

MEMOIRE D'HABILITATION A DIRIGER DES RECHERCHES (HDR)

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From the Simulation of Complex Biological Systems to the Design of Artificial Morphogenetic Systems, and Back

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POUR OBTENIR L'HABILITATION A DIRIGER DES RECHERCHES DE L'UPMC

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Acknowledgments

This part of my memoir was the most difficult to write, as I have been incredibly fortunate to have many supporters throughout my “complex” career, in academia and industry, among friends and family, who all played a critical role in shaping my knowledge, building my motivation, supporting me financially, encouraging me when in doubt, and helping me make important decisions at turning points. I choose to recognize their contribution here for the most part in chronological order.

A physics alumnus of Ecole Normale Supérieure in Paris, I completed my PhD in 1991 (at age 25) in computational neuroscience at ESPCI, and then was appointed to a postdoctoral position at the Institute of Neuroinformatics at the Ruhr University, Bochum in Germany. I want to salute my two supervisors of this past era, **Elie Bienenstock** (today professor at Brown University) and **Christoph von der Malsburg** (today director of FIAS, Goethe University, Frankfurt), respectively, who believed in me, despite my relative immaturity, and introduced me to the early and exciting beginnings of self-organization models in recurrent neural networks—at the interface between spike correlations and connection graphs, long before temporal coding and STDP became commonplace. Their influence was decisive in my passion for “complex systems” thinking in cognitive science and beyond.

Following this first postdoc, in 1995, I decided to pursue opportunities in the software industry. After a stay in Paris, I relocated to the San Francisco Bay Area in 1998 and assumed lead roles in several start-ups, from e-commerce to bioinformatics. I want to recognize, among others, my tutors in the core R&D team of Neuron Data, **Bruno Jouhier** (chief architect) and **Jean-Marie Chauvet** (co-founder and CTO), who did not hesitate to hire a dreamy scientific programmer and train him to be a professional software engineer and architect—a new skill that would prove invaluable in my later comeback to academia. I am also twice thankful to my friend **Isabelle Guyon**, who not only was the first researcher to show me neural networks back in 1987, leading to my PhD, but also years later in 2000 called on me to join BIOwulf Genomics, a data mining company she had created in Berkeley.

In parallel to my industry period in Paris, from 1995 to 1998, I had the privilege to conduct part-time academic research at CREA, the research center in cognitive science and self-organization of Ecole Polytechnique. I am forever indebted to my mentor **Jean Petitot** (professor at EP, future director of CREA, and reviewer of this HDR) for welcoming me and starting ground-breaking work together on the link between cognitive linguistics and neural dynamics, under the auspices of his morphodynamical theory (see Project COGNIMORPH, p57). This study, going to the core of the dual physicalist/symbolic nature of cognition, remains today a key component of my neuroscientific tenets—together with Elie’s views on compositionality (see Project SYNBLOCK, p50). Jean’s immense polymath work and generous spirit toward young researchers are a continued source of inspiration.

It was also Jean who kept contact with me throughout my industrial exile and never ceased to believe that I had more to say in research. His encouragement to pursue our collaboration, combined with my preference for staying in the US, eventually pushed me to the gates of the University of Nevada, Reno (UNR) in 2004. It was there where I resumed my academic career after a 6-year hiatus. I am grateful to the colleagues who appointed me as a research/visiting assistant professor, thus enabling my re-entry into university: first **Philip H. Goodman** (professor of medicine) the enthusiastic and inspiring director of the Brain Computation Lab and designer of the NeoCortical Simulator platform, with whom I started the NEUROFORM project (p63); then **Frederick C. Harris** (associate professor) and **Yaakov Varol** (chairman) of the Department of Computer Science and Engineering, who welcomed my proposal to create an original graduate seminar on complex systems and later invited me to teach courses from the main computer science curriculum.

My seminar attracted other faculty members, in particular **Guy Hoelzer** (future chairman of Biology) and **Thomas Nickles** (chairman of Philosophy), both strong advocates of developing a complex systems research and teaching program at UNR. Guy is also the originator and driving force behind our EVOSPACE project (p35), and it was a great pleasure to work closely with him on designing the model and analyzing the results (programmed by our student **Rich Drewes**). I thank him for including me in his vision. It opened new perspectives to me in evolutionary dynamics, which I am looking forward to combining with my own work in biological development.

Indeed, it was during those fertile years at UNR that a cornerstone of my current research, the DEVO project (p11), or “embryomorphic engineering”, was born. This model of architected morphogenesis, which I single-handedly invented and implemented, represents a personal accomplishment that I am especially proud of. Besides the early influence of Jean Petitot, who among other things triggered my curiosity on the philosophical question of the “form”, I want to cite two authors whom I have never met but whose brilliant books were major catalysts of my model: *How the Leopard Changed Its Spots* by the late Brian Goodwin (1994), and *The Art of Genes* by Enrico Coen (2000). They represent the “structuralist” lineage of embryologists, from Goethe, D’Arcy Thompson

and Waddington, which was left out of the Modern Synthesis of evolution and genetics, but recently revived by “evo-devo”—integrating genes *and* biomechanical shaping for a full account of variation.

I eventually returned to Paris in October 2006 and, within one week of landing, a new adventure began. It started at a dinner with **Paul Bourguine** (director of CREA), whom I had met years earlier. How can only a few words describe Paul? He is *the* tireless and invaluable powerhouse of the French and European complex systems communities. Exceptionally and passionately committed to fostering research and teaching, Paul invests all his time, enthusiasm and expertise to the benefit of cohorts of peers and students. He combines his talent with indefatigable optimism and mirth to organize innumerable conferences, submit (and obtain) dozens of large grant proposals, create several Master’s and PhD programs, write major ANR and EC calls, and establish new networks, new institutes, new foundations, even a new university—in short, move entire mountains, within the complicated web of French academia, all the way to the government, big industry and Europe.

Thanks to Paul Bourguine and **Nadine Peyri ras** (developmental biologist, CNRS Gif-sur-Yvette), I was offered a position in the FP6 *Embryomics* project that they were co-leading (see p5). Less than a year later, in September 2007, I was recruited as the first guest researcher of the Complex Systems Institute Paris Ile-de-France (ISC-PIF) recently founded by Paul. At this point, I want to thank **R gion Ile-de-France**, in particular its former vice-president for research and innovation **Marc Lipinski**, for providing most of the institute’s funding and the researchers’ salaries as part of its “Major Focus Domains” program. Then, it was not too long before Paul asked me to replace him as director, so he could focus on other challenges. Our executive board approved the change to start in January 2009.

Since my return to academia, I have strengthened or initiated important scientific relationships and created several original research projects with various institutions in the US, France, Europe and Canada. In addition to my previous publications, this new period in itself has led to a flurry of journal and conference articles, book chapters and edited books, invited talks and seminars, organization of workshops and conferences, grant writing, review and committee duties, etc. (see CV p80). I want to point out the critical role that was played by several of my co-authors, collaborators and close colleagues in the success of this whole enterprise. I thank them heartily for their initiatives, assistance, encouraging remarks, and hard work. Beside the names cited above, in particular: **Hiroki Sayama** (Binghamton University SUNY), co-chairman and co-editor of our *Morphogenetic Engineering (ME)* workshops and book; **Mihaela Ulieru** (Canada Research Chair, University of New Brunswick), whose energy catalyzed my invention of the PROGNET model (p26) and enabled its implementation (by her student **Adam MacDonald**); **Jacob Beal** (BNN Technologies and CSAIL, MIT) and **Olivier Michel** (LACL, University Paris-Est Cr teil), for integrating me into the communities of spatial and amorphous computing; **Rolf W rtz** (INI, Ruhr University Bochum), for inviting me to his workshop and book projects on organic computing; **Yves Fr gnac** (INAF, CNRS Gif-sur-Yvette; professor at Ecole Polytechnique), for asking me to co-organize his series of student seminars on brain and cognition (and for reviewing this HDR); **Marco Dorigo** (IRIDIA, Universit  Libre de Bruxelles), for inviting a special session on *ME* to his ANTS conference; **Hugues Bersini** (IRIDIA), for enrolling Paul and me into the chairmanship of ECAL 2011; **Evelyne Lutton** (INRIA Saclay) and **Nicolas Bredeche** (LRI, Universit  Paris-Sud Orsay), for joining and contributing to my idea of a new INRIA team called “MESOBIONICS”; **Julien Delile**, my PhD student co-supervised with Nadine, for putting up with my erratic schedule and still producing great work in the DEVO project (p21); **Jean-Louis Giavitto** (IBISC, Universit  d’Evry) for guiding me during this HDR effort and reviewing it; and the members of the jury not yet cited here, **Wolfgang Banzhaf** (reviewer), **Guillaume Beslon**, **Yves Burnod**, and **Amal El Fallah** (see affiliations on cover), for giving their time to read it and comment it.

Heading an institute envisioned by Paul *while* doing research (and writing my HDR) is not an easy task. The ISC-PIF is a multidisciplinary research center and network (“GIS”) sponsored by R gion Ile-de-France and 15 French academic partners. It involves yearly fund-raising and designing an activity program with operating budget (workshops and summer schools, postdocs and engineers, project grants) and capital budget (lab space renovation/equipment, computing clusters). My special thanks go to the institute’s staff, especially our administrative assistants **Genevi ve Tual** and **Noemi Abrescia**, and communication manager **Daniel da Rocha** for working hard to make all of this a success. I am also grateful to the **steering committee’s** members (<http://iscpif.fr/committees>) for their useful advice and, this year 2010, to my new co-directors, **Arnaud Banos** and **David Chavalarias**, talented researchers already busy with their own labs, who have accepted to lead major tasks of our vast operation. **Marcel Skrobek**, our new secretary general also provides invaluable help with office management, in close link with our benevolent administration, the **CNRS Regional Delegation DR5**.

Finally, these acknowledgments would not be complete without my warmest thanks and love to all my family and friends, in particular the ones who have closely followed and supported my career: Mom, Grandma, Alice and Jan, Pierre and Martine, Dad, Carl and Molly, Dan, and my partner Greg.

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to my dear aunt Alice, gone too early

From the Simulation of Complex Biological Systems to the Design of Artificial Morphogenetic Systems, and Back

Abstract

The main theme of my research is the computational modeling and simulation of complex multi-agent systems, in particular biological, neural and techno-social, which can also inspire novel principles in intelligent systems design. I am especially interested in “self-made puzzles”, i.e., the self-organization of complex, articulated morphologies from a swarm of heterogeneous agents, through dynamical, developmental, and evolutionary processes. For example, these emergent patterns can be innovative structures in multicellular organisms, autonomic networks of computing devices, or “mental representations” and imagery made of correlated spiking neurons.

My work currently addresses two domains: (a) neural computation, where a central question is to understand how the symbolic level of cognition (artificial intelligence) can arise from the underlying complex dynamical system of the brain (neural networks); and (b) artificial life, preoccupied with explaining how orderly complexity can spontaneously develop and evolve without the need for a higher symbolic level. In other words, the cognitive challenge I pursue consists of reconstructing the emergence of the human symbolic faculty to help create intelligent machines. As for the engineering challenge, it is rather about removing the symbolic human bias from intelligent system design and creating autonomous efficient systems that could grow and adapt without explicit programming. These two challenges are naturally closely linked and their concepts mutually transferable.

Artificial Life: Biological Modeling & Bio-Inspired Engineering Part of my efforts has been focused on promoting a new field of research, Embryomorph Engineering or, more broadly, Morphogenetic Engineering, exploring the artificial design and implementation of autonomous systems capable of developing complex, heterogeneous morphologies without central planning or external drive. I have conducted various studies toward this goal, starting with multi-agent models of biological development that combine pattern formation (arising from gene regulation networks contained in each cell, themselves triggered by diffusion of positional gradients between cells) and self-assembly (arising from biomechanical forces). I have extended these principles to the self-organization of precise network topologies by “programmed attachment” of nodes (instead of random “preferential attachment”). At another scale, I have also investigated spatially explicit models of evolutionary dynamics and endogenous speciation among large populations of genome-encoded individuals.

Neural Dynamics: Large-Scale Spiking Neural Networks My other research endeavor is to bridge the lingering gap between symbol-based AI architectures and node-based neural computation, thus establish an intermediate, or mesoscopic, scale of description of cognitive functions. Representations at this scale are embodied in local yet large-scale dynamical states of bioelectrical activity. The working hypothesis is that this activity consists of “spatio-temporal patterns” that can be composed together to form quasi-discrete entities. My goal is to understand the laws of self-organization, and induced organization, of the neural signals supporting those entities, and from there outline a new theoretical framework for mesoscopic neurodynamics with compositional properties. At a mesoscopic level, the brain should essentially be construed as a “pattern formation machine”, generating specific dynamical states or regimes made of myriads of bioelectrical neuronal signals – not unlike many other biological collective phenomena such as bird flocking, ant colonies or multicellular development itself (except dynamical “neuron flocking” happens in phase space and across a complex network topology).

1. Overview of Research Program

Information and Communication Technology (ICT) systems are qualitatively fundamentally different from natural complex systems (CS). Traditional engineered ICT products are generally made of a number of unique, heterogeneous components assembled in complicated but precise ways, and are always intended to work deterministically following the specifications given by their designers (Fig. 1.1d). By contrast, self-organization in natural complex systems (physical, biological, ecological, social) often emerges from the repetition of agents obeying identical rules under stochastic dynamics (Fig. 1.1a).

For sure, nontrivial behavior can emerge from relatively simple agent rules—a fact often touted as the hallmark of complex systems—however, most patterns spontaneously created by natural self-organization (spots, stripes, waves, trails, clusters, hubs, etc.; see Ball 1999, Bourguin & Lesne 2006) can be described with a small number of statistical variables. They are either random or shaped by external boundary conditions, or both, but never truly exhibit an *intrinsic architecture* like ICT systems possess on the hardware and software levels. There are, however, major exceptions that blur this dichotomy between ICT and CS and show a possible path toward what could become tomorrow's (a) ICT-like / ICT-controlled CS and (b) CS-inspired ICT:

ICT-like / ICT-controlled CS On the one hand, major families of natural complex systems strikingly demonstrate the possibility of combining pure self-organization *and* elaborate architectures (Fig. 1.1b): the self-assembly of myriads of cells into the body plans and appendages of organisms, the synchronization of constellations of neuronal signals into cognitive states of the brain, or the stigmergic collaboration of swarms of social insects toward giant constructions. Multicellular organisms are composed of segments and parts arranged in specific ways, yet they entirely self-assemble in a decentralized fashion, under the guidance of genetic and epigenetic instructions spontaneously evolved over millions of years and stored in every cell. In modern biotechnological endeavors such as synthetic biology (e.g., Endy 2005, Knight 2003), these instructions could be modified in specific ways to steer the emergent collective behavior of cellular populations toward desirable outcomes for biomedical applications. Similarly, spiking neural activity in the brain also exhibits unique properties of *structured self-organization* into non-random “spatiotemporal patterns” (e.g., Bienenstock 1995), or “dynamic shapes”, which are the basis for mental representations and all cognitive functions. Finally, social insects are also able to collectively construct complicated nests without global plan or architect (Bonabeau et al. 1999).

CS-inspired ICT Conversely, large-scale artificial ICT systems already exhibit complex systems effects—albeit still mostly uncontrolled and unwanted at this point. Segmentation and distribution of large computing systems over a multitude of smaller and relatively simpler components has become both a growing need and an inevitable reality in many domains of computer science & engineering, AI, and robotics (e.g., Tanenbaum & van Steen 2002). Instead of fighting this trend, ICT should ride it higher and gradually transition from a state of exogenously imposed order toward increasing organizational and functional autonomy. Faced with an explosion in system size at all scales, whether hardware (integrated parts), software (program modules), or networks (applications and users), engineers will be led, more or less willingly, to give up the rigid design of systems in every detail and rethink them in terms of CS (Fig. 1.1c; e.g., Minai et al. 2006, Würtz 2008). They should focus on “meta-design”, i.e., the generic conditions allowing the endogenous self-assembly, self-regulation and evolution of these systems. How do biological organisms achieve morphogenetic tasks so reliably? Can we export their self-formation capabilities to engineered systems?

Thus, while CS already include natural systems that seemingly exhibit all the attributes of ICT systems, ICT systems are already becoming natural objects of study for CS researchers. Both of these cross-boundary examples point to a new field that would explore the design and implementation of autonomous systems capable of developing complex and *desired* functional architectures with little or no central planning. In other words, they are captivating examples of *programmable self-organization*—a hybrid concept not sufficiently explored so far, neither in natural CS (for the

“programmable” part), nor in traditional ICT engineering (for the “self-organization” part).

Along these directions, I am interested in clarifying the fundamental principles of an “informed physics” or, its flip side, a “physical computation”, in particular the continuous-to-discrete transition from microscopic elements to structured macroscopic patterns, via mesoscopic levels of organization. My focus is on (i) *cognitive problems*, where the goal is to understand the emergence of a symbolic architecture from the underlying neural dynamics (schematization, categorization, pattern recognition in perception and language) and (ii) *evo-devo problems*, where the challenge is the meta-design of decentralized systems that do not make use of a symbolic level (biological modeling and bio-inspired computing, artificial development, evolutionary computation).

(a) natural random self-organization

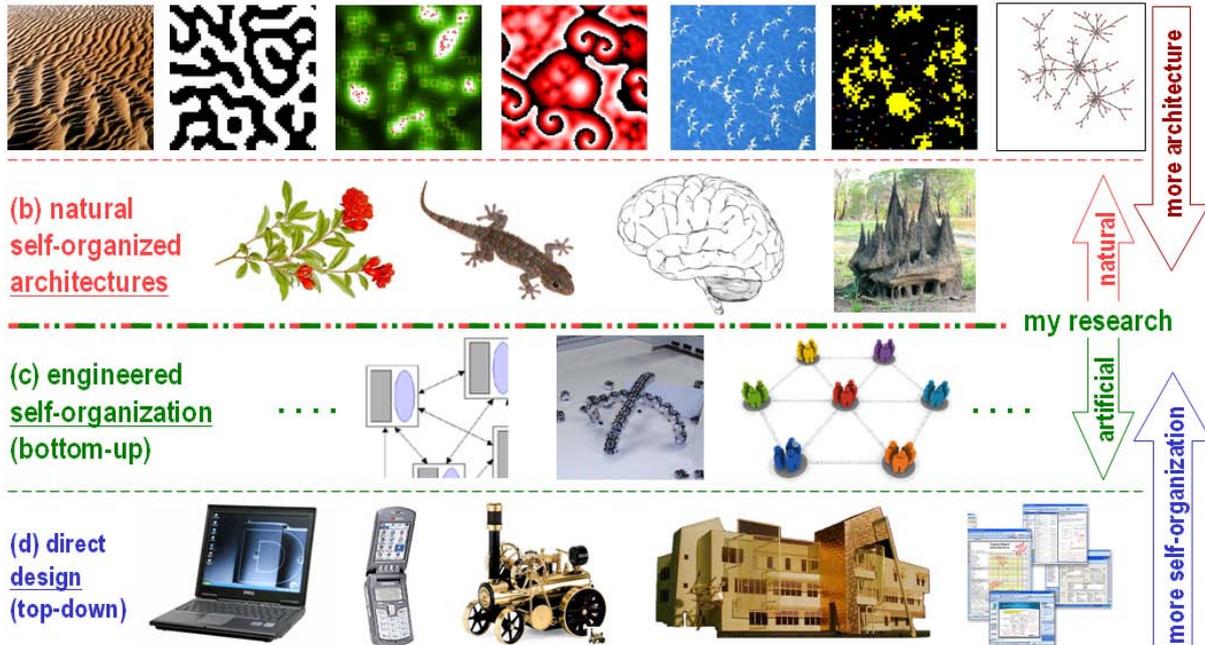


Figure 1.1: Four families of systems representing various degrees of self-organization vs. design, and randomness vs. architecture. (a) Most natural complex systems are characterized by stochasticity, repetitivity and statistical uniformity. From left to right: sand ripples from wind convection, activator-inhibitor pattern formation, slime-mold aggregation, traveling waves in BZ reaction, bird flocking, insect heap-clumping, and power-law networks (all NetLogo simulations except the first photograph). (d) At the other extreme, all human-made artifacts (computers, devices, vehicles, buildings, software) are centrally and precisely designed, leaving almost no room for autonomy. There, self-organization and emergence are a nuisance, not desired effects. (c)-(d) My research is positioned in the middle: I strive to (i) understand how certain natural self-organized systems exhibit a strong (non-random) architecture, by proposing new models for class (b): multicellular organisms, including the activity of their nervous system, and social insect constructions. Conversely, I also want to (ii) instill self-organized principles into artificial intelligent systems, i.e., invent new systems for class (c): multi-agent software, robotic swarms, techno-social networks, and much more.

Recognizing and Reintroducing Programmability in Complex Systems

Complex systems are generally defined as large sets of elements that interact locally among each other and with their nearby environment to produce an emergent collective behavior at a macroscopic scale. They are characterized by a high degree of decentralization, and the ability to self-assemble and self-regulate. Most CS are also *adaptive* (and dubbed “CAS”; Holland 1992) in the sense that they are able to learn and/or evolve toward further innovation by feedback from their external fitness, i.e., overall level of success in their environment, onto their internal structure and behavior of the elements (whether through direct learning mechanisms and/or indirect selection processes).

The elements or “agents” composing a CS follow local rules that can be more or less

sophisticated. Often, these rules are themselves internally structured as networks of smaller entities. For example, one cell can be modeled as a self-regulatory network of genetic switches, one social agent (ant, software process) as a network of decision rules, one neural unit as a local assembly of neurons (dual excitatory/inhibitory oscillator system, synfire chain). On the other hand, agents can also interact collectively at the level of clusters or subnetworks (organs, assemblies, cliques) that combine in a modular fashion to form larger collectives. Thus, from both perspectives, CS can often be described as “networks of networks” on several hierarchical levels. The higher levels connecting elements or clusters of elements are generally spatially extended (cell tissues, cortical areas, ant colonies, computer networks), whereas the lower levels inside elements are generally nonspatial (gene nets, neural assemblies, rule trees). Elements follow the dynamics dictated by their inner networks and also influence neighboring elements through the emission and reception of signals (chemical, electrical, software packets).

In this vast interdisciplinary field of CS research, my own research ambition is to look beyond the usual fascination for spontaneous or “free” order, i.e., unconstrained or unstructured patterning (Fig. 1.1a), and explore another critical question that concerns the interplay of *programmability* with self-organization (Fig. 1.1b-c). Indeed, it is an often underappreciated ability of CS to exhibit *controllable* properties, at the same time (or despite the fact) that they are self-organizing. It seems that “complex” is too commonly (mis)construed as “homogeneous”, “monolithic” and/or “random”. Yet, there can be a wide diversity of agents and *heterogeneity* of patterns, via positions; a CS can be *modular*, hierarchical, and architecturally detailed at multiple scales; it can also consist of *reproducible* structures arising from programmable agents. Thus, with the dual goal to “re-engineer emergence” and promote *emergent engineering* (Doursat & Ulieru 2008), whether in CS-inspired artificial systems or ICT-controlled natural systems, the most important challenge is not simply to observe how *any* kind of self-organization can happen, but it is to understand how self-organization is, and can be, *guided*. Here, relevant models will likely not be found in the traditional “statistical” approaches to CS (Fig. 1.1a), such as random patterning (e.g., Gierer & Meinhardt 1972, Pearson 1993), flocking (e.g., Vicsek et al. 1995) or networking (e.g., Barabási & Albert 1999, Newman 2006, Barrat et al. 2008), but rather in the genuinely *morphological* aspects of CS, such as biological development (Fig. 1.1b). The difference between these two qualitative classes of CS resides in (i) the relative sophistication of the elements and (ii) their ability to combine in sufficiently various ways to form precise and reproducible architectures.

Naturally, this ambition seems to lead to paradoxical objectives: Can autonomy be planned? Can decentralization be controlled? Can evolution be designed? The answer lies in a change of scale: instead of a top-down enforcement of macroscopic structures, the new controls take the form of *local instructions inside every microscopic agent of the system*. These instructions can also be diversified, depending on the agent types and positions, introducing the required degree of heterogeneity for a system to exhibit a new type of behavior, more sophisticated than patterning, flocking or clustering.

Summary of Research Topics

My work currently addresses two domains: (a) *neural computation*, where a central question is to understand how the symbolic level of cognition (artificial intelligence) can arise from the underlying complex dynamical system of the brain (neural networks); and (b) *artificial life*, preoccupied with explaining how orderly complexity can spontaneously develop and evolve without the need for a higher symbolic level. In other words, the cognitive challenge I pursue consists of reconstructing the emergence of the human symbolic faculty to help create intelligent machines. As for the engineering challenge, it is rather about removing the symbolic human bias from intelligent system design and creating autonomous efficient systems that could grow and adapt without explicit programming. These two challenges are naturally closely linked and their concepts mutually transferable.

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without central planning or external drive. I have conducted various studies toward this goal, starting with multi-agent models of biological development that combine pattern formation (arising from gene regulation networks contained in each cell, themselves triggered by diffusion of positional gradients between cells) and self-assembly (arising from biomechanical forces). I have extended these principles to the self-organization of precise network topologies by “programmed attachment” of nodes (instead of random “preferential attachment”; Barabási & Albert 1999). At another scale, I have also investigated spatially explicit models of evolutionary dynamics and endogenous speciation among large populations of genome-encoded individuals.

Ambition: *“Meta-designing” the development, function and evolution of self-organized complex systems that do not use a symbolic level.*

- How do embryonic cells construct an entire organism without a blueprint map?
- How do complexity, innovation and fitness spontaneously evolve (without a “watchmaker”)?
- How can biological organisms inspire a novel engineering paradigm based on decentralized, self-adapting collectivities of agents, instead of explicit rules and external design?
- How can we create a network of agents that would spontaneously diversify, multiply and self-organize to work collectively on a given task (e.g., swarm robotics, immune security)?

Keywords: *artificial development, self-assembly, pattern formation, spatial computing, evolutionary computation.*

- multi-agent models of morphogenesis, based on gene regulation networks
- decentralized but programmable pattern formation, self-assembly and shape development
- spatially extended cellular automata models of population genetics, evolution and ecology

Neural Dynamics — Large-Scale Spiking Neural Networks

My other research endeavor is to bridge the lingering gap between symbol-based AI architectures and node-based neural computation, thus establish an intermediate, or *mesoscopic*, scale of description of cognitive functions. Representations at this scale are embodied in local yet large-scale *dynamical states* of bioelectrical activity. The working hypothesis is that this activity consists of “spatio-temporal patterns” that can be composed together (Bienenstock 1995, 1996) to form quasi-discrete entities. My goal is to understand the laws of self-organization, and induced organization, of the neural signals supporting those entities, and from there outline a new theoretical framework for mesoscopic neurodynamics with compositional properties. At a mesoscopic level, the brain should essentially be construed as a “pattern formation machine”, generating specific dynamical states or regimes made of myriads of bioelectrical neuronal signals – not unlike many other biological collective phenomena such as bird flocking, ant colonies or multicellular development itself (except dynamical “neuron flocking” happens in phase space and across a complex network topology).

Ambition: *Understanding and reconstructing the emergence of a symbolic level from a complex dynamical system.*

- How is the infinite diversity of analog (visual, auditory) stimuli segmented, grouped and reduced to a few logical categories?
- How is discrete symbolic meaning “carved out” from the continuous physical environment?
- How are neural signals organized in the brain and what kind of complex coordinated (and reproducible) spatiotemporal patterns do they form?
- How does this pattern formation of a spatiotemporal kind provide the basis for structured “mental objects” and their hierarchical composition?

Keywords: *segmentation, schematization, categorization, perception, language, ontology.*

- mesoscopic emergence and interaction of spatiotemporal patterns of activity and connectivity
- based on: stochastic-firing, excitable, oscillatory and subthreshold neuron models
- creating: synchronization, traveling waves, coherence induction, synfire chains, compositionality
- for: pattern recognition and categorization, in perception and language

2. Artificial Life: Biological Modeling & Bio-Inspired Engineering

Computational, spatially explicit models of development and evolution with possible outcomes toward hyperdistributed, decentralized engineering systems.

The fireworks were by Gandalf: they were not only brought by him, but designed and made by him; ... The lights went out. A great smoke went up. It shaped itself like a mountain seen in the distance, and began to glow at the summit. ... Out flew a red-golden dragon – not life-size, but terribly life-like: fire came from his jaws, his eyes glared down; there was a roar, and he whizzed three times over the heads of the crowd.

—J. R. R. Tolkien, *The Fellowship of the Ring*

This area of my research is positioned at the interface between the science and the engineering of complex systems, around biological topics and bio-inspired principles. It covers both the computational modeling of biological self-organization phenomena (in particular development and evolution) and the design of decentralized, autonomous and adaptive artificial systems inspired by these phenomena (especially in ICT and robotics). It aims to establish mutually beneficial transfers between these two poles, by providing new paradigms to engineering and, in turn, by equipping biological observation techniques with new models and control methods. In this way, it ultimately hopes to contribute to important future applications and potential fallouts, whether of biomedical nature (e.g., how models of development can be relevant to cancer or stem cell research) or technological nature toward a new generation of distributed processors, architectures and robotics (e.g., how a swarm of mini-robots can self-organize).

The CREA lab and ISC-PIF institute where I work were leaders or partners of four recent major European and ANR projects (to which I collaborated in 2006-2008), including *Embryomics* (Peyri ras et al. 2005) and *BioEmergences* (Bourgine et al. 2006). These projects pioneered the development of methods and algorithms for reconstructing the complete dynamics of multicellular development observed by microscopy. Describing this process as a dynamic tree annotated in space and time, they founded a new discipline, “embryomics”, named after the -omics family (genomics, proteomics, etc.). The embryo of an organism refers to the system-level description of the multiscale dynamics of its early stages of development, correlating genotype and phenotype. In this framework, biologists produce and annotate time-lapse series of organism development, while mathematicians and computer scientists process these images to reconstruct and model collective cell dynamics. This effort resulted in sophisticated software platforms capable of handling large amounts of 4-D imaging data (i.e., voxel movies) by a workflow of segmentation and tracking algorithms (e.g., Zanella et al. 2007, Lombardot et al. 2008; Fig. 2.1). It is therefore an inverse problem of complex systems: starting from a large set of spatiotemporal data and detecting their correlations, the goal is to arrive at theoretical models explaining their changes. The post-genomic era is in great need of such systemic approaches at the cellular organization level to achieve a better understanding of biological processes and make progress in medical applications.

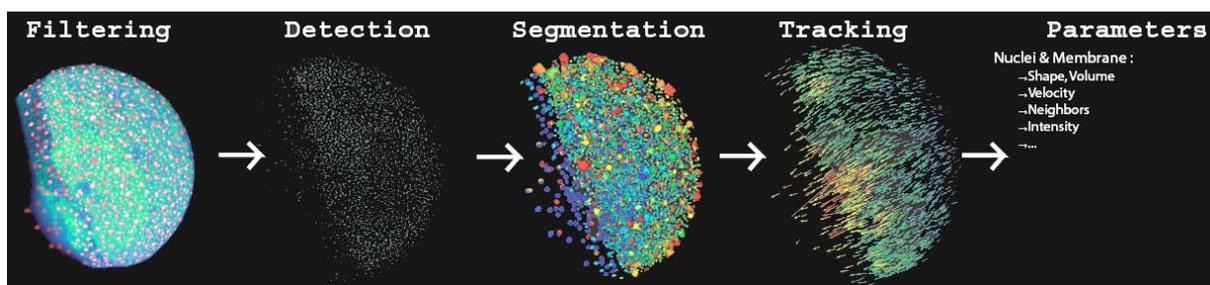


Figure 2.1: Typical image processing workflow at the core of the *Embryomics* and *BioEmergences* projects (from Faure et al. 2007; see Publications in Section 2.1).

In parallel to this biological modeling endeavor, works in Artificial Life (Alife), especially *artificial development* and *evolution*, aim to create a new generation of intelligent computational complex systems, consisting of a multitude of (electronic or hybrid synthetic-organic) micro-programmed elements interacting locally. The objective here is to incorporate self-organization into the traditional concepts of architecture, function and design—and vice versa. This new “complex systems engineering” (e.g., Braha et al. 2006, Minai et al. 2006, Würtz 2008) must meet the growing necessity of hyper-distributed and self-organized architectures. Beyond statistical and random phenomena (pattern formation, collective movement, power laws, etc.), the main challenge is to reintroduce *programmability* and *reproducibility* in the emergence of spontaneous order—in short: to regain control of emergence. It is therefore necessary to understand how complex self-organizing systems can also be heterogeneous, modular and hierarchical.

Alife Systems

The field of Alife is chiefly concerned with the simulation of life-like, organismal processes through computer programs or robotic devices that generally are of a distributed nature and operate on a multitude of interacting components. Researchers in Alife attempt to design and construct systems that have the characteristic of living organisms or societies of organisms out of nonliving parts, whether virtual (software agents) or physical (electromechanical components, chemical materials, etc.). Alife is therefore a bottom-up attempt to recreate or synthesize biological phenomena with the goal of producing adaptive and intelligent systems. In this sense, it can be contrasted with the traditional top-down analytical approach of Artificial Intelligence (AI) based on symbolic systems. Alife is one of the most important and rapidly developing research domain within the landscape of complex systems. In particular, it actively promotes biology-inspired engineering as a new paradigm that would complement or replace classical physics-based engineering. Alife opens entirely new perspectives in software, robotic, electrical, mechanical or even civil engineering. Can a sophisticated device or building architecture construct itself from a reservoir of small components? Can a robot rearrange its parts and evolve toward better performance without explicit instructions? Can a swarm of software agents self-organize and collectively innovate in problem-solving tasks?

Among the great variety of biological systems that inspire and guide Alife research, three broad areas can be identified according to the scale of their elementary components: (a) at the microscopic scale, chemical, cellular and tissular systems; (b) at the mesoscopic scale, organismal and architected systems; and (c) at the macroscopic scale, collective and societal systems. Artificial molecular and cellular models focus on the spontaneous organization of complex chemical and organic structures, such as DNA/protein self-assembly (e.g., Rothmund 2006) or organism development (e.g., Eggenberger 1997). Applications are linked to nanotechnologies for biomedical or integrated electronic purposes (“smart materials”, MEMS, etc.). On the anatomical and functional level, robotic parts (limbs, sensors, actuators, etc.) and local behavioral modules are coupled and integrated to produce a global behavior in one autonomous device, aiming toward adaptivity and nonsymbolic intelligence. This is the scope of “reactive”, “behavior-based” (Brooks 1985) or “embodied” robotics (e.g., Pfeifer & Bongard 2006), exemplified by insect-like robots and evolving or reconfigurable mechanical morphologies (e.g., Sims 1994, Lipson & Pollack 2000). Finally, entire colonies of virtual or robotic creatures also constitute important objects of interest for their unique properties of collective self-organization and diversity-inducing evolution. Generically termed “swarm intelligence”, new methodologies such as ant colony optimization (ACO; Dorigo & Stützle 2004, Bonabeau et al. 1999) or particle swarm optimization (PSO; Kennedy & Eberhart 1995) are derived from the observation of animal societies and applied to problem-solving tasks.

Toward Complex, Decentralized Engineering

The interdisciplinary field of Alife originated from cellular automata (CA) and, by its very definition, necessarily covers or intersects with several other *distributed* systems paradigms—which are the rule in biotic systems—such as neural networks, complex networks (from gene regulation to ecosystems), swarm intelligence (insect colonies, collective motion), or generative and developmental systems

(embryogenesis, morphogenesis). Yet, despite the inherent propensity of Alife to study decentralized and self-organized process, researchers in evolutionary computation (EC, which comprises genetic algorithms), one of the most powerful concepts that Alife ever imported from biology into AI, have generally taken a quite different path and, in stark contrast with natural biological systems, have essentially focused on centralized, classically designed, and non-developmental systems. Their efforts have been mainly invested in *optimization* problems, where “emergence” actually becomes more of a nuisance than a desired property. Yet, it is striking that the founder of genetic algorithms, John Holland, constantly refers to evolutionary search *within the framework of complex adaptive multi-agent systems* (Holland 1992, 1996, 1998) and was himself a co-founder of the Santa Fe Institute—whereas today’s EC conferences include only a minority of such complex systems topics. Thus, after all, there is still surprisingly little complex systems thinking in Alife, especially EC—while, conversely, there is also surprisingly little engineering thinking in the complex systems community (see paragraph on “Artificial Evo-Devo” below).

Although themselves emerging from a hundred billion neurons, our human cognitive faculties create the illusion of a central consciousness or viewpoint and require great effort to comprehend truly parallel processes. We are strongly biased toward identifying central causes, and spontaneously tend to ascribe the generation of order and meaning to a single entity endowed with a lot of information (one gene, one cell, one neuron, one individual). Even when we know that this entity does not have intentions or does not even exist as such, we cannot help but follow anthropomorphic stereotypes: controller, organizer, manager, designer, etc. This is why we traditionally refer to systems containing multiple, intricate causal and influence links as “complex”—whereas in fact those so-called complex systems might well turn out to be “simpler” than our familiar artefacts with their uniquely ordered and precise arrangement. Heteronomous human-designed order is the most sophisticated of all forms of organization. In living systems, by contrast, autonomous decentralized order is the natural norm because it is the most cost-effective: information is distributed over a large number of relatively ignorant agents, making it easier to create new states of order by evolving and recombining their local interactions. To imitate Ulam’s famous quip about nonlinear vs. linear systems, the pervasiveness of self-organized systems (vs. designed systems) make them the “nonelephant” species of systems science—yet they remain the least familiar of them. Biological systems are not engineered and human-made systems could learn a lot from them (Minai et al. 2006).

Therefore, we need to find other ways of describing the complex systems than imposing concepts coming from complicated human-made systems, such as “architecture”, “processing”, “control”, “input/output”, “feedforward/feedback”, etc. (a) The appropriate level of *functional description* is that of higher *pattern formation*, not agent-to-agent transmission. (b) Yet, at the same time, these patterns cannot be directly shaped but must emerge in a bottom-up fashion: thus the right level of *design and control* is the *agent* and its local interactions with other agents. As long as these two levels are confused—either by trying to design the patterns top-down, or trying to describe the system’s dynamics agent by agent, link by link—complex systems will remain inextricably complex.

Evolutionary Development

In the variation/selection couple of Darwinian evolution, variation has become the poor child of biology’s Modern Synthesis. Darwin discovered the evolution of species, based on random variation and nonrandom natural selection, and established it as a central fact of biology. During the same period, Mendel brought to light the laws of inheritance of traits. In the twentieth century, his work was rediscovered and became the foundation of the science of genetics, which culminated with the revelation of DNA’s role in heredity by Avery and its double-helix structure by Watson and Crick. By integrating evolution and genetics together, the “modern synthesis” of biology has demonstrated the existence of a fundamental correlation between genotype and phenotype. Mutation in the first is causally related to variation in the second. Yet, 150 years after Darwin’s and Mendel’s era, the nature of the link from genes to organismal forms, i.e., the actual molecular and cellular basis of the *mechanisms* of development, are still unclear. To quote Kirschner and Gerhart (2005, p. ix): “When Charles Darwin proposed his theory of evolution by variation and selection, explaining selection was his great achievement. He could not explain variation. That was Darwin’s dilemma. . . . To understand novelty in evolution, we need to understand organisms down to their individual building blocks, down

to their deepest components, for these are what undergo change”.

While most of the attention was turned to selection, it is only in recent years that understanding variation (as the generation of phenotypic innovation) by comparing the *developmental* processes of different species became the primary concern of *evolutionary development*, or “evo-devo”, a rapidly expanding field of biology (e.g., Coen 2000, Carroll et al. 2001, Müller & Newman 2003, Kirschner & Gerhart 2005). The genotype-phenotype link cannot remain an abstraction if we want to unravel the *generative* laws of development and evolution—and ultimately transfer them to artificial self-organized systems. The goal is to unify what Darwin called the “endless forms most beautiful” of nature (Carroll 2005), and reduce them to *variants* around a common theme (Webster & Goodwin 1996). The variants are the specifics of genetic information; the common theme is the developmental dynamics that this information guides. Modern synthesis postulates this reduction in principle but has never truly explained it physically. *How* does a static genome dynamically unfold in time and 3-D space (Edelman 1988)? *How* are morphological changes correlated with genetic changes?

Artificial Evo-Devo

Looking at the full evolutionary *and* developmental picture should also be a primary concern of systems engineering and computer science when venturing in the new arena of autonomous architectures. Optimization techniques inspired by biology in its traditional modern-synthesis form have also, like their model, principally focused on evolution and given rise to evolutionary computation and genetic algorithms based on metaphorical “genes”, “reproduction”, “mutation” and “selection”. However, the great majority of these approaches rely on a direct mapping from artificial genomes to artificial phenotypes, which includes very few or no elements of morphogenesis. One ambition of my research work is to contribute to new avenues in evolutionary engineering, such as artificial embryogeny (AE, Stanley & Miikkulainen 2003, Bentley & Kumar 1999, Miller & Banzhaf 2003), amorphous computing (Abelson et al. 1999, Coore 1999, Nagpal 2002, Werfel & Nagpal 2006), spatial computing (Beal & Bachrach 2006), autonomic computing (Kephart & Chess 2003), organic computing (von der Malsburg et al. 2006, Würtz 2008), natural computation (e.g., Nunes de Castro 2006), complex systems engineering (Minai et al. 2006), ambient intelligence (Marzano & Aarts 2003) and pervasive or ubiquitous computing (Weiser 1993), by stressing the importance of fundamental laws of *developmental variations* as a prerequisite to selection on the evolutionary time scale of artificial systems (Stanley & Miikkulainen 2003)—a thesis mirroring the evo-devo paradigm in natural, biological systems (see, e.g., Kauffman 1993, 2008, Goodwin 1994). In the EC framework, it means an *indirect* or *implicit* mapping (as opposed to direct or explicit) from genotype to phenotype. Fine-grain, hyperdistributed architectures (i.e., many light-weight agents, as opposed to a few heavy-weight agents) such as multicellular organisms might be in a unique position to provide the “solution-rich” space needed for successful selection and *spontaneous innovation, through developmental modularity and composition*.

Most families of typical emergent patterns in complex systems (spots, stripes, waves, trails, clusters, hubs, etc.; see Ball 1999, Bourguine & Lesne 2006) can be described with a small number of statistical variables. They are generally uniform and repetitive, displaying a “poorness of information” akin to textures—but never exhibit a true, intrinsic *architecture* (Fig. 2.2) like engineered products do. One monumental exception to this relative homogeneity is biological development. Morphogenetic processes demonstrate the possibility of combining pure self-organization *and* elaborate structures. Multicellular organisms are composed of segments and parts arranged in specific ways that might resemble the devices of human inventiveness. Yet, they entirely self-assemble in a decentralized fashion, under the guidance of genetic and epigenetic information spontaneously evolved over millions of years and stored in every cell. In other words, they are examples of *programmable self-organization*—a concept not sufficiently explored so far, neither in complex systems science (for the “programmable” part), nor in traditional engineering (for the “self-organization” part). How do biological organisms achieve morphogenetic tasks so reliably? Can we export their self-formation capabilities to other complex systems? “Directing decentralization” is a seemingly paradoxical endeavor, but its resolution could reside in the change of level on which design operates, to become “meta-design”: instead of building a puzzle directly at the architectural level (by design or evolution), shape its *pieces* in a generic way (by design or evolution) so that they build it for you.

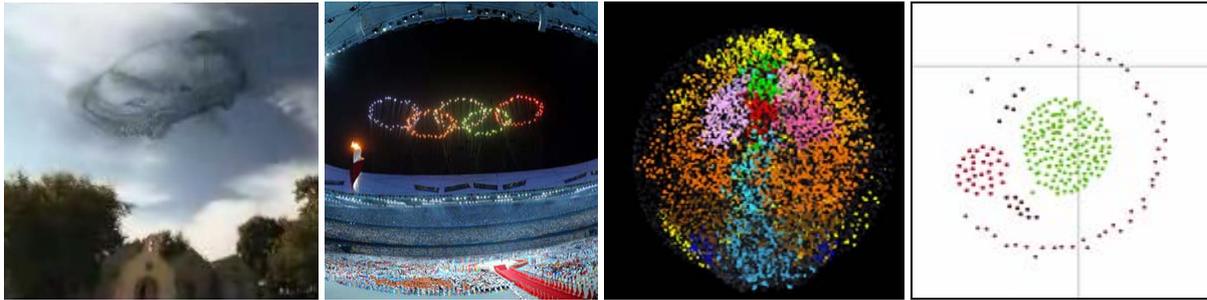


Figure 2.2: Various metaphorical illustrations of the exotic concept of non-random, “architected swarm” (whether self-organized or not in their actual implementation). From left to right: CG animation of a car-shaped bird flock in a Citroën commercial (template-based trick); Olympic rings-shaped fireworks in Beijing (five separate rocket launches); Actual image processing and tracking of the complex choreography of cell trajectories during zebrafish embryogenesis (*Embryomics* and *Bioemergences* project); Genuine surprising morphogenetic self-organization in a simulation of artificial collective motion mixing 4 different “species” (Sayama 2007).

Projects

This part presents three Alife projects that address all levels of system organization, multicellular morphogenesis, functional architectures, and population dynamics. Their topology can vary from regular or irregular lattices with nearest neighbor connectivity, to network topologies containing long-range links. The former type is spatially extended, generally in 2-D or 3-D, while the latter type generally does not rely on a background notion of space or Euclidean distance.

2.1. Project DEVO: Biological and Artificial Development

Multi-agent modeling and simulation of the fundamental principles of the “self-made puzzle” of embryonic development, based on self-assembly, pattern formation and genetic regulation, with exportation to artificial systems.

Abstract: The spontaneous making of an entire organism from a single cell is the epitome of a self-organizing *and* programmable complex system. Through a precise spatiotemporal interplay of genetic switches and chemical gradients, an elaborate form is created without explicit architectural plan or engineering intervention. This original study, which I single-handedly designed and developed, proposes a multi-agent simulation and exploitation of these fundamental morphogenetic mechanisms.

2.2. Project PROGNET: Programmed Attachment Networks

The self-assembly of complex but precise network topologies by programmed attachment: An extension of the artificial development project from 2-D/3-D multicellular organisms to n-D networks.

Abstract: In this original model of autonomous network construction and dynamics, which I created during a collaboration with **Mihaela Ulieru** (Canada Research Chair; Computer Science Department, University of New Brunswick), nodes execute the same program in parallel, communicate and differentiate, while links are dynamically created and removed based on “ports” and “gradients” that guide nodes to specific attachment locations. As the network expands, nodes switch different rules on and off, creating chains, lattices, and other composite topologies.

2.3. Project EVOSPACE: Spatial Evolutionary Dynamics

A spatially extended model of endogenous speciation in the absence of external environmental constraints.

Abstract: A commonly held view in evolutionary biology is that *speciation*, i.e., the emergence of genetically distinct and reproductively incompatible subpopulations, is driven by external environmental constraints. **Guy Hoelzer, Rich Drewes** (University of Nevada, Reno) and myself have developed a spatially explicit model of a biological population to study the emergence of spatial and temporal patterns of genetic diversity *in the absence* of predetermined domains. We propose a 2-D cellular automata model showing that an initially homogeneous population might spontaneously segment into different species through sheer *isolation by distance*.

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The spontaneous making of an entire organism from a single cell is the epitome of a self-organizing and programmable complex system. Through a precise spatiotemporal interplay of genetic switches and chemical gradients, an elaborate form is created without explicit architectural plan or engineering intervention. This original study, which I single-handedly designed and developed, proposes a *multi-agent* model and simulation (or, equivalently, “agent-based” model; see Macal & North 2006, Treuil et al. 2008) to understand and exploit these fundamental morphogenetic mechanisms.

Overview: From Embryogenesis to Embryomorphic Engineering

On the one hand, research in *self-assembling* (SA) systems, whether natural or artificial, has traditionally focused on pre-existing components endowed with fixed shapes (e.g., Whitesides & Grzybowski 2002). Biological development, by contrast, dynamically creates new cells that acquire selective adhesion properties through differentiation induced by their neighborhood (e.g., Wolpert et al. 2006). On the other hand, biological *pattern formation* (PF) phenomena (Turing 1952, Gierer & Meinhardt 1972, Young 1984, Nijhout 1990, Kondo & Asai 1995, Meinhardt 1998) are generally construed as orderly states of activity on top of a quasi-continuous and fixed 2-D or 3-D cell substrate. Yet, again, the spontaneous patterning of an organism into regions of gene expression arises within a multicellular medium in perpetual expansion and reshaping. Finally, both phenomena (SA and PF) are often thought of in terms of *stochastic events*—whether mixed components that randomly collide in self-assembly, or spots and stripes that crop up unpredictably from instabilities in pattern formation (Fig. 2.1.1). Here too, these notions need significant revision if they are to be extended and applied to embryogenesis. Cells are not randomly mixed but pre-positioned where cell division occurs. Genetic identity regions are not randomly distributed but highly *regulated* in number and position.

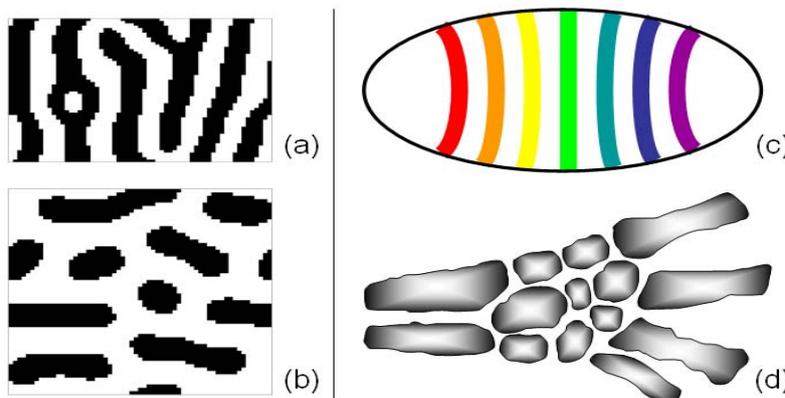


Figure 2.1.1: “Free” vs. “guided” morphogenesis. A simple activator-inhibitor model with cellular automata, such as Young’s (1984), creates (a) stripes and (b) spots in variable positions and unpredictable numbers. By contrast, (c) the stripes and (d) the spots of developing animal segments are tightly controlled by multiple sets of genes, leaving very little room for chance arrangements (from Doursat 2008b).

This work presents a spatial computational model of *programmable* and *reproducible* morphogenesis that integrates SA and PF under the control of a nonrandom gene regulatory network (GRN) stored inside each cell of a swarm. The differential properties of cells (division, adhesion, migration) are determined by the regions of gene expression to which they belong, while at the same time these regions further expand and segment into subregions due to the self-assembly of differentiating cells. To follow an artistic metaphor (Coen 2000), SA is similar to “self-sculpting” and PF to “self-painting”. The model can be construed from two different vantage points: either (a) pattern formation on *moving* cellular automata, in which the cells spatially rearrange under the influence of their own activity pattern, or (b) collective motion in a *heterogeneous* swarm, in which the cells gradually differentiate and modify their interactions according to their positions and the regions they form. It offers a new abstract framework, which I call *Embryomorphic Engineering* (coined after

Neuromorphic Engineering) to explore the causal and programmable link from genotype to phenotype that is needed in many emerging computational disciplines, such as artificial embryogeny (Stanley & Miikkulainen 2003, Bentley & Kumar 1999, Miller & Banzhaf 2003).

Summarized Description of the Model

First, the motion of a homogeneous swarm of cells (pure SA) and the patterning by gradient propagation on a fixed swarm (pure PF) are introduced separately. Then, these two components are combined to form reproducible growing patterns (SA + PF). The genetic program controlling these arrangements inside every cell is also explained. Finally, this combination is repeated as modules ($SA^{(k)} + PF^{(k)}$) inside a larger, heterogeneous system to create complex morphologies by recursive refinement of details.

Development of One Module

Self-assembly by division and adhesion (SA) In its current version, the embryomorphic model consists of a 2-D swarm of cells with dynamically changing neighbor interactions calculated by a Delaunay-Voronoi tessellation (Fig. 2.1.2). Each cell follows two major laws of cellular biomechanics in a simplified format: (i) cell *division*, coded by a uniform probability p for any cell to split into two, and (ii) cell *adhesion*, represented by elastic forces derived from a quadratic potential V with resting length r_e , hard-core radius r_c , and scope of visibility r_0 , similarly to collective motion models (Vicsek et al. 1995, Grégoire & Chaté 2004) but with a zero velocity vector. These parameters are collected in genotype G_{SA} . Laws of motion are derived from a spring-damper system with negligible mass/inertia effects. Under potential V , starting from a compressed swarm, cells quickly relax to a resting state, in which they tend to form a quasi-regular hexagonal mesh.

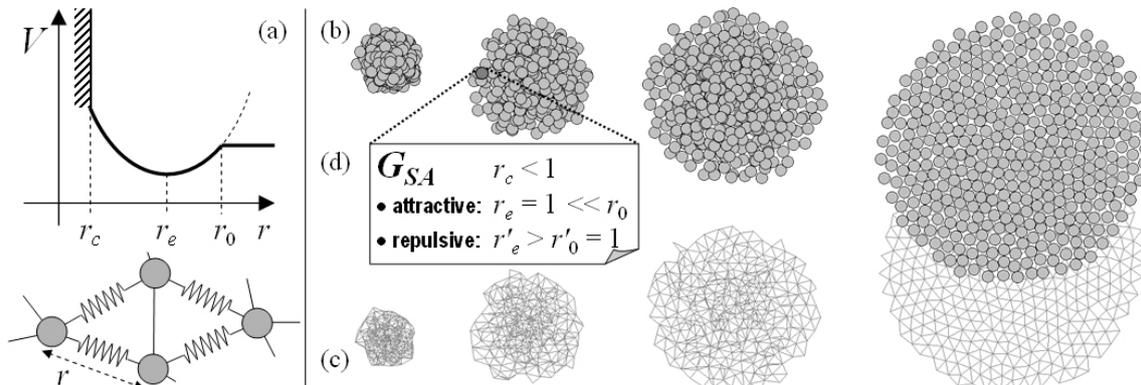


Figure 2.1.2: Deployment of a homogeneous swarm (SA). (a) Agent-level interaction potential V similar to elastic springs. (b) Relaxation of a 400-agent swarm from an initially compressed state. (c) The same swarm viewed from its mesh of pairwise interactions obtained by Delaunay triangulation and pruning of edges longer than r_0 . (d) Genetic SA parameters inside every agent (here, attractive mode only) (from Doursat 2008d).

Propagation of positional information in gradients (PF-I) Pieces of a jigsaw puzzle are defined not only by their position and shape but also by the “image” they carry. In the self-organized swarm, this translates into state variables inside each cell that determine their PF activity. The present model distinguishes between two kinds of PF-specific state variables (i.e., signals that cells continuously exchange and process): *gradient* variables (PF-I) and *pattern* variables (PF-II).

Gradient values (PF-I) propagate from neighbor to neighbor and establish *positional information* across the swarm (Wolpert 1969). For example, a cell W containing a counter variable $g_W = 0$ increments this counter to 1 before passing it to its neighbors, which in turn instruct their neighbors to set it to 2, and so on (Fig. 2.1.3). The result is a roughly circular wave pattern of g_W values centered on W . Together with W , three other gradients, E , N and S contribute to form a 2-D coordinate system via “equatorial” midlines WE and NS (in which cells have identical counter values). Note that the four

sources W , E , N , S are not placed by hand but also self-position by migrating away from each other inside the swarm. Discrete counter increments and midlines are used to create positional information in amorphous and spatial computing systems, too (Coore 1999, Nagpal 2002, Beal & Bachrach 2006).

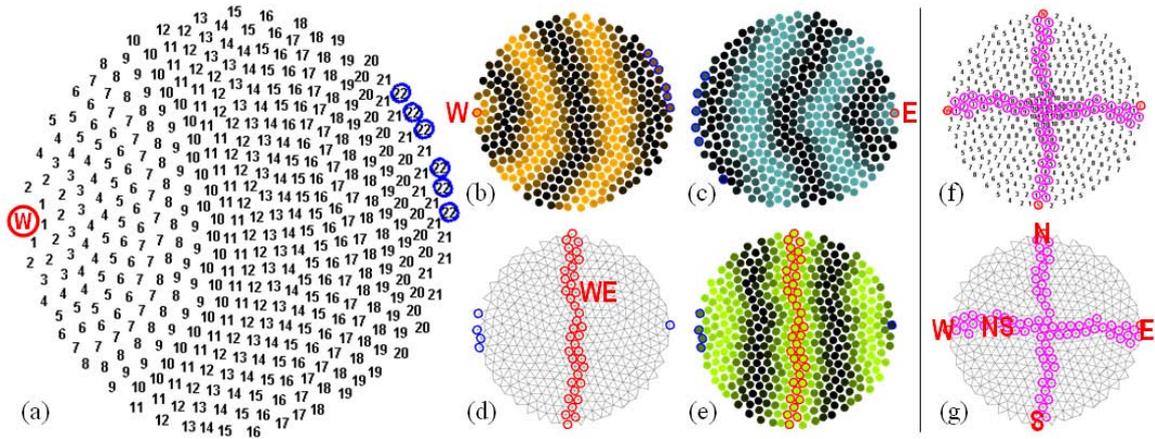


Figure 2.1.3: Propagation of positional information (PF-I). (a) Circular gradient of counter values originating from source agent W (blue circles mark end points). (b) Same gradient values viewed by a cyclic color map. (c) Opposite gradient coming from antipode agent E . (d) Set of agents WE whose W and E counters are equal ± 1 . (e) Planar gradient triggered by WE . (f,g) Complete coordinate compass, with NS midline (from Doursat 2008d).

Programmed patterning by gene expression levels (PF-II) Pattern values (PF-II) correspond to gene expression levels that are calculated on top of the X and Y gradient values to create different *cell types* (which in turn affect the SA behavior; see SA + PF integration below). This calculation relies on a *gene regulatory network* (GRN), whose weights constitute the genetic parameters of the PF process and are denoted by G_{PF} (Fig. 2.1.4). Thus the core architecture of the virtual organism is a network of networks, i.e., an irregular 2-D lattice of identical GRNs locally connected to each other via “chemical signalling” nodes (Mjolsness et al. 1991, Salazar-Ciudad et al. 2000, von Dassow et al. 2000).

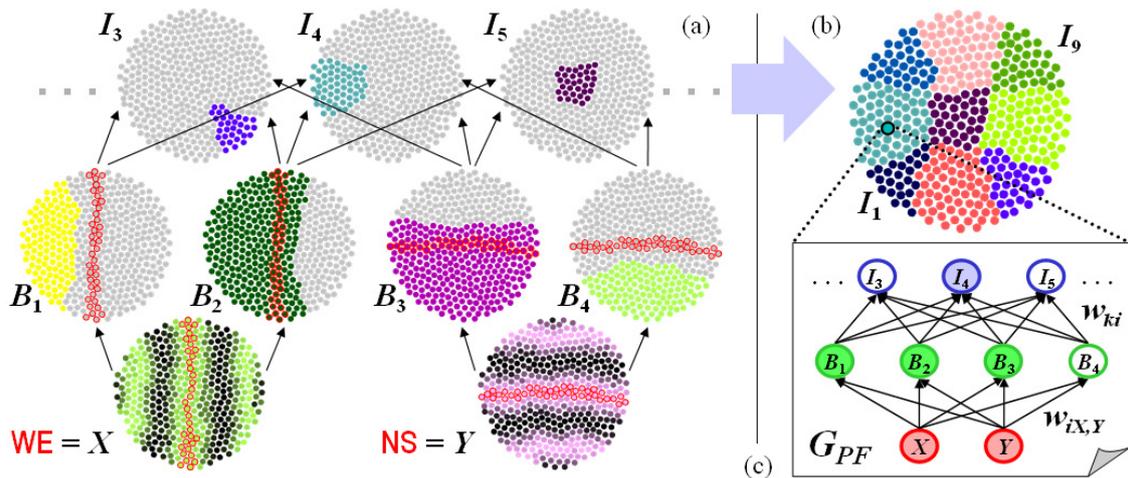


Figure 2.1.4: Programmed patterning (PF-II). (a) The same swarm viewed under different colormaps highlighting the agents' internal patterning variables X , Y , B_i and I_k (virtual equivalent of *in situ* hybridization in biology). (b) Consolidated view of all identity regions I_k for $k=1..9$. (c) Gene regulatory network used by each agent to calculate its expression levels, here: $B_1 = \sigma(1/3 - X)$, $B_3 = \sigma(2/3 - Y)$, $I_4 = B_1 B_3 (1 - B_4)$, etc. (from Doursat 2008d).

The patterning process represents the emergence of *heterogeneity*, i.e., the segmentation of the swarm into “identity regions” corresponding to high levels of expression of particular genes I_k of the GRN. A

well-known example is the early striping of *Drosophila* (see review in Carroll et al. 2001) controlled by a 5-layer hierarchy of segmentation genes along the anteroposterior axis (maternal, gap, primary and secondary pair-rule, segment polarity). The present model relies on a 3-layer caricature of the same principle along the two intersecting X and Y axis: (1) the bottom layer of the GRN contains the two positional variables g_{WE} and g_{NS} seen above; (2) the middle layer contains “boundary” genes B_i that segment the embryo into horizontal and vertical half-planes of strong and weak expression levels via 2-D step functions; (3) the top layer contains the identity nodes I_k derived from positive and negative products of B_i 's, i.e., various intersections of the B_i half-planes.

Simultaneous growth and patterning (SA + PF) After describing the self-assembly of a non-patterned swarm (SA) and the patterning of a fixed swarm (PF), the embryomorph SA and PF behaviors are combined to create growing patterns at every stage (Fig. 2.1.5). Cells continually adjust their positions according to the elastic SA constraints, *while* continually exchanging gradient values and PF signals over the same dynamic links. This dual dynamics is guided by the combined genotype $G = (G_{SA}, G_{PF})$. Daughter cells inherit all the attributes of mother cells, including G and internal PF variables (current gradient counters and gene levels). The SA variables (coordinates and adhesion/signalling edges of the lattice) are recalculated from a position close to the original cell. Both sets of variables are immediately updated, as the newly born cell starts contributing to SA forces and the traffic of PF gradients that maintain the pattern's consistency at all times in the swarm.

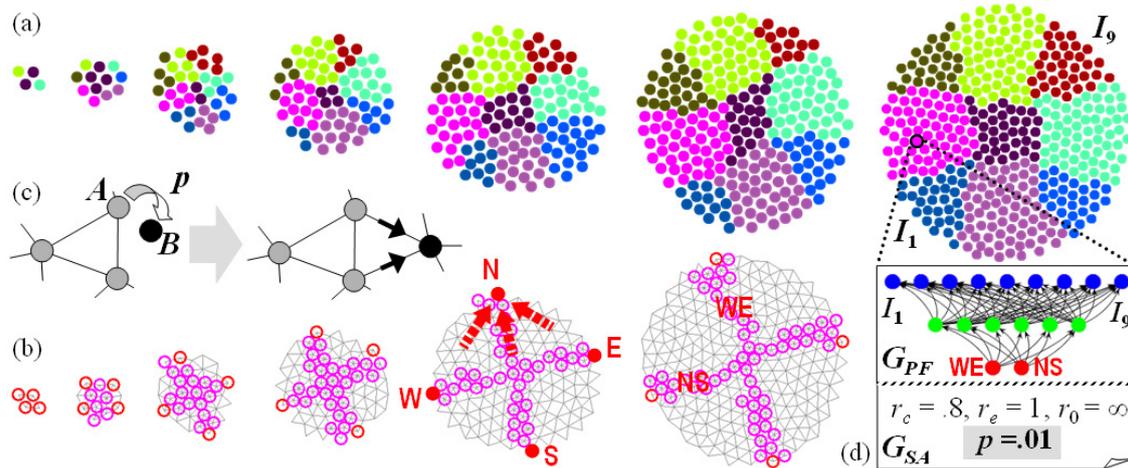


Figure 2.1.5: Simultaneous growth and patterning (SA+PF). (a) Swarm growing from 4 to 400 agents by division. (b) Swarm mesh, highlighting gradient sources and midlines. Gradients and pattern are continually maintained by source migration, e.g., N moves away from S and toward WE . (c) Agent B created by A 's division quickly submits to SA forces and PF traffic. (d) Combined genetic programs inside each agent (from Doursat 2008d).

Multiscale Modular Development

Modular, recursive patterning (PF[k]) Natural embryological patterns, however, do not develop in one shot but in numerous incremental stages (Coen 2000). An adult organism is produced through modular, recursive growth and patterning. In *Drosophila*, regions of the embryo that acquire leg, wing or antenna identity (“imaginal discs”) start developing local coordinate systems of morphogen gradients to support the pre-patterning and construction of the planned organ (see review in Carroll et al. 2001). Correspondingly, the present embryomorph model includes a pyramidal *hierarchy* of network modules able to generate patterns in a recursive fashion (Fig. 2.1.6). First, the base network $G_{PF}^{(0)}$ establishes main identity regions as above, then subnetworks $G_{PF}^{(k)}$ triggered by the identity nodes I_k of $G_{PF}^{(0)}$ further partition these regions into smaller, specialized compartments at a finer scale. This type of fractal patterning has also been explored in generative algorithms such as “L-systems” (Siero et al. 1982, Prusinkiewicz & Lindenmayer 1990). These systems, however, are mostly self-similar, and use symbolic rules and explicit geometrical features instead of coupled dynamical units.

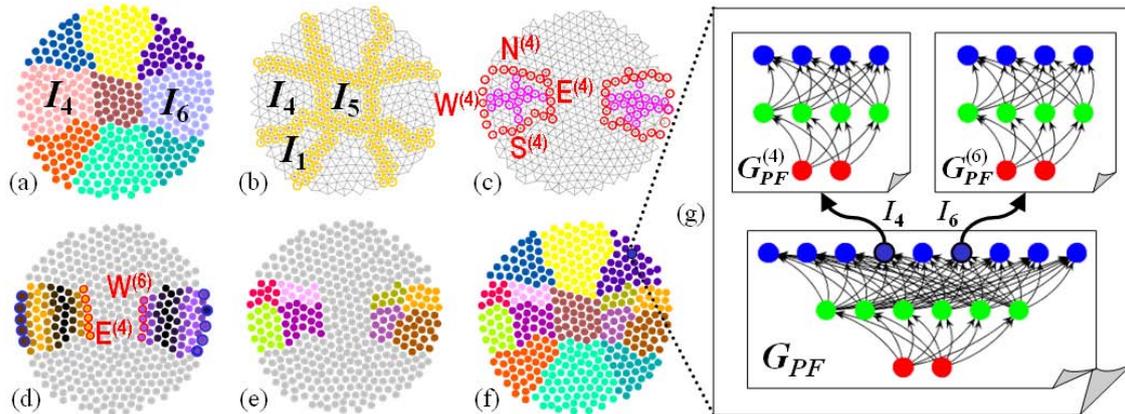


Figure 2.1.6: Modular, recursive patterning (PF[k]). (a) 9-region swarm, as in Fig. 2.1.4b. (b) Agents at the border between two domains are highlighted in yellow circles. (c) These border agents become new gradient sources (red circles) at a lower scale inside certain identity regions. (d) Missing border sources arise from the ends (blue circles) of other gradients. (e,f) Subpatterning of the swarm in I_4 and I_6 . (g) Corresponding hierarchical gene regulation network (from Doursat 2008d).

Modular, anisotropic growth (SA[k]) So far missing from the model is a true topological *deformation* dynamics, or “morphodynamics”, that can confer non-trivial shapes to the organic system beyond simple blobs. To this aim, cells must be able to *diversify their SA characteristics, depending on their PF type and spatial position*, thus closing the feedback loop between genetics and geometry (e.g., Coen et al. 2004). In particular, they have to exhibit *inhomogeneous, anisotropic* cell division (varying p) and *differential adhesion* (varying V). For example, the growth of limb-like structures can be achieved by a coarse imitation of meristematic plant offshoots (Fig. 2.1.7). In this process, only the tip or “apical meristem” of the organ is actively dividing at any time (whereby cells forming the tip self-identify as being the local maxima of a gradient generated by the base of the limb). Moreover, potential V is attractive only among cells within the limb region, while it is repelling between the limb and other areas. Just like inhomogeneous division, differential adhesion is an essential condition of complex shape formation (Hogeweg 2000, Marée & Hogeweg 2001).

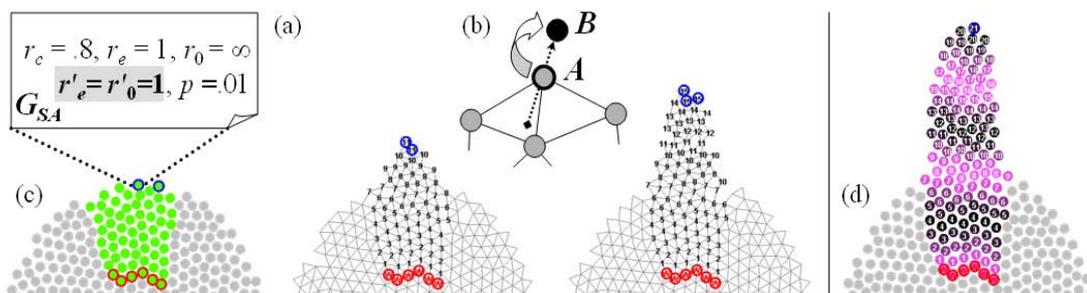


Figure 2.1.7: Modular, anisotropic growth (SA[k]). (a) Genetic SA parameters are augmented with repelling V values r'_e and r'_0 used between the growing region (green) and the rest of the swarm (gray). (b) Daughter agents are positioned away from the neighbors’ center of mass. (c) Offshoot growth proceeds from an “apical meristem” made of gradient ends (blue circles). (d) Cyclic coloring of the gradient underlying this growth (from Doursat 2008d).

Modular growth and patterning (SA[k] + PF[k]) Putting everything together, full morphologies can develop and self-organize from a few cells (Fig. 2.1.8). These morphologies are *complex, programmable* and *reproducible*. They are architecturally complex because they can be made of any variety of modules and parts that are not necessarily repeated in any periodic or self-similar way. They represent programmable phenotypes emerging because they emerge from the same given genotype carried by every cell of the swarm. They are reproducible, as their structure and shape are not left to chance but tightly controlled by the genotype. Naturally, the exact positions of the cells at the microscopic level are still random, but not the positions of the mesoscopic and macroscopic

regions that they form. Moreover, the modularity of the phenotype is a direct reflection of the modularity of the genotype. The hierarchical SA and PF dynamics recursively unfolds inside the different regions and subregions that it creates. Each module $G^{(k)} = (G_{SA}^{(k)}, G_{PF}^{(k)})$ can be reused by exact duplication, but can also diverge from other blocks through different internal genetic SA and PF parameters, potentially giving each region a different morphodynamic behavior and different gene activity landscape. Duplication followed by divergence is the basis of serial homology (e.g., vertebrae, teeth, digits), a major natural evolutionary mechanism (Carroll et al. 2001). The integration between SA and PF is controlled by the identity nodes I_k : these nodes switch on the execution of subordinate modules $G^{(k)}$, i.e., their gene expression activity (parametrized by $G_{PF}^{(k)}$) to create new local segmentation patterns, and their mechanical behavior (parametrized by $G_{SA}^{(k)}$) to create new morphodynamical behaviors.

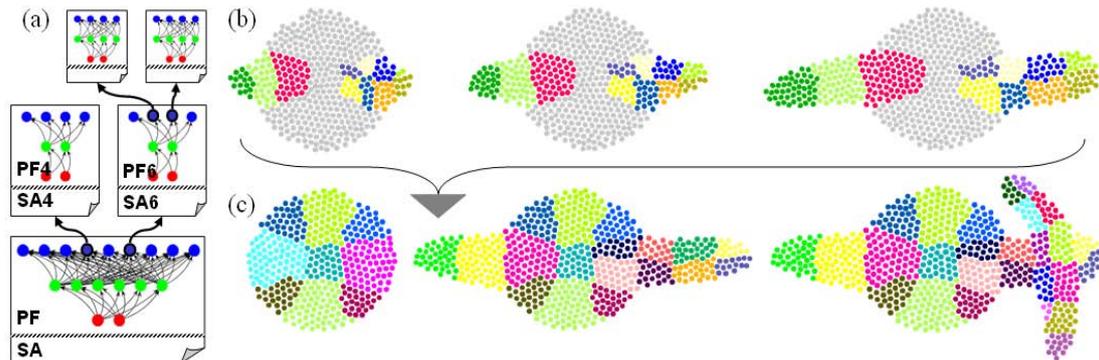


Figure 2.1.8: Modular growth and patterning (SA[k] + PF[k]). (a) Example of a three-tier modular genotype giving rise to the artificial organism on the right. (b) Three iterations detailing the simultaneous limb-like growth process (Fig. 2.1.7) and patterning of these limbs during execution of tier 2 (modules 4 and 6). (c) Main stages of the complex morphogenesis, showing full patterns after execution of tiers 1, 2 and 3 (from Doursat 2008d).

Evolution: The Generation of Variation by Modules

This part presents preliminary experiments involving *hand-made mutations* of the genotypes of embryomorph systems and their corresponding phenotypes. For now, these systems are purely developmental and do not serve a specific function. No organism “fitness” is defined (neither structural, nor functional) and no selection is performed by systematic search. This will be part of future projects (see below). The goal here is to illustrate the link between genotype modularity and phenotype modularity, and the programmable and predictable effect that mutations in the former can have on the evolution of the latter, *via a self-organized developmental process*, suggesting that modularity is an essential condition of evolvability (Schlosser & Wagner 2004, Callebaut & Rasskin-Gutman 2005, Watson & Pollack 2005).

Figures 2.1.9-11 show several examples of modular embryogenesis and how certain mutations in the genotype correlate with quantitative or qualitative changes in the phenotype. The organism of Fig. 2.1.9a is taken as the reference or “wild type”. To simplify the illustration, its genotype is composed of only two different modules: a base module establishing the body plan (lower module) and a specialized module in charge of growing a limb-like appendage (upper module). As described previously, each module consists of two types of “genes” or genetic parameters: self-assembly genes G_{SA} , coding how cells divide and spread spatially, and pattern formation genes G_{PF} , coding how cells acquire their types. In the simplified display of Figs. 2.1.9-11, the gene regulatory network of G_{PF} is not shown. Instead, only the type of checkered pattern it produces (explained below) and the switch identity genes are displayed.

Quantitative Variations

Varying limb thickness by GRN weights (PF) In Fig. 2.1.9b, the same organism has been affected

by a “thin-limb” mutation of the base body plan. Although not shown, the weights of the base module’s gene regulatory network G_{PF} have been modified in such a way that they now create a checkered pattern with a narrower central row allowing less space for the limbs to grow, hence making them actually thinner. The reverse, “thick-limb” mutation is shown in Fig. 2.1.9c, with coefficient 2. This is a good example of the compactness of the developmental genotype (Floreano & Mattiussi 2008, Stanley & Miikkulainen 2003) and its large-scale effect on the phenotype: just varying the sensitivity of a couple of genes can result in dramatic morphogenetic changes.

Varying limb length by division signals (SA) By modifying the division rate and/or the stop conditions of proliferation, the size of various parts of the embryo can also be modulated. For example, in Figs. 2.1.9d and 2.1.9e cell proliferation is regulated only in the limbs, respectively by stopping it sooner ($g' = 10$) and later ($g' = 40$). In Fig. 2.1.9f, both body plan and limbs stop growing beyond gradient values $g' = 8$, producing a phenotypic shape that is proportionally smaller to the wild type. Note that similar effects can also be achieved by decreasing or increasing the probability of division p , while keeping the maximum gradient values constant (see Fig. 2.1.10c).

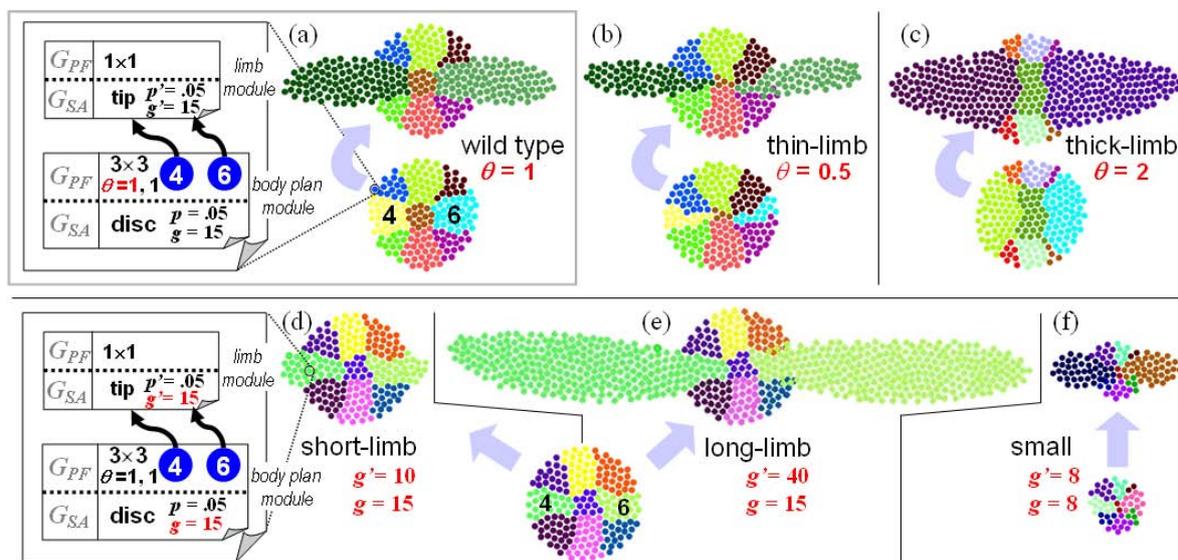


Figure 2.1.9: Simulations from the multiagent model showing quantitative variations. (a)-(c) Varying limb thickness by modifying GRN weights (see text). (d)-(f) Varying length and size by stopping division earlier/later (see text) (from Doursat 2009g).

Structural Variations

Changing limb position by module switching In Fig. 2.1.10, the modularity of the limb component is demonstrated through various mutations reminiscent of experiments on biological organisms such as *Drosophila*. The identity genes marking the regions (“imaginal discs”) responsible for the growth of a specific appendage (see review in Coen 2000, Carroll et al. 2001) can be literally turned on or off in new regions with respect to the wild type of Fig. 2.1.9a. For example, in Fig. 2.1.10a, a virtual case of “antennapedia” (the growth of a leg where there should be an antenna) is obtained by connecting a new identity region to the limb module, here region I_2 instead of region I_6 . This means *rewiring* the gene regulatory network G_{PF} to reflect the fact that the limb genes’ regulatory sites in the DNA have mutated and now accept gene I_2 ’s proteins as a promoters instead of gene I_6 ’s proteins. In the three-limb mutation of Fig. 2.1.10b, these regulatory sites have duplicated themselves before mutating, accepting gene I_2 *in addition* to gene I_6 (not just in replacement), so that the limb module is now executed three times instead of twice.

Serial homology by duplication & divergence Later in the course of evolution, similar copies of the same organ can diverge and acquire specialized characteristics, as Fig. 2.1.10c illustrates. In this

scenario, three copies of the entire limb module were produced by duplication. Then, these copies can mutate independently from each other, e.g., through different cell division rates p' creating a shorter or longer limbs. Serial homology is a major evolutionary process, resulting from *duplication* followed by *divergence* (Carroll 2005, Gerhart & Kirschner 2005). Biological organisms often contain numerous repeated parts in their body plan. This is most striking in the segments of arthropods (several hundreds in millipedes; see the simulated “arthromorphs” of Dawkins 1996) or the vertebrae, teeth and digits of vertebrates. After duplication, these parts tend to diversify and evolve more specialized structures (lumbar vs. cervical vertebrae, canines vs. molars, etc.). Homology exists not only within individuals but also between different species, as classically shown by comparing the forelimbs of tetrapods from the bat to the whale. Homology could also be explored as an important routine of artificial self-developing systems.

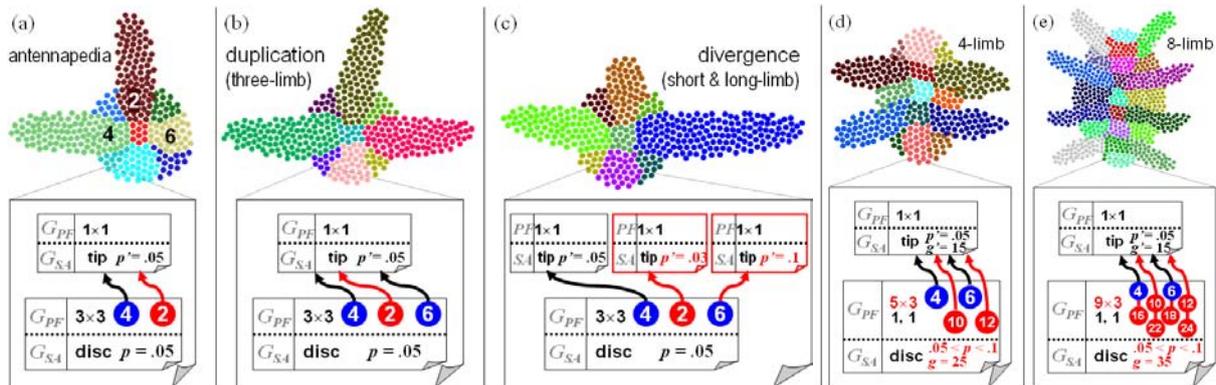


Figure 2.1.10: Simulations showing structural variations. (a)-(c) Changing limb configuration by switching the limb-triggering genes and/or duplicating the limb module (see text). (d)-(e) Adding limbs by body plan expansion (see text) (from Doursat 2009g).

Adding limbs by body plan expansion In the scenario of Fig. 2.1.10d-e, new limbs are generated not by reusing the same body plan differently (Fig. 2.1.10a-b) or by duplicating the limb module (Fig. 2.1.10c), but rather by expanding the gene regulatory network G_{PF} of the body plan in order to create new regions of gene identity that can host limb growth. The embryo’s geography is increased from a $3 \times 3 = 9$ -type checkered pattern to a $5 \times 3 = 15$ -type (Fig. 2.1.10d) or a $9 \times 3 = 27$ -type pattern (Fig. 2.1.10e). The SA part of the body plan is also slightly modified to accommodate these new regions. It assumes an oval shape resulting from a *nonuniform* distribution of the division rate p that follows the NS midline gradient (see Fig. 2.1.3), i.e., greater toward the north and south poles and lower in the center.

Adding digits by modular hierarchy Finally, along the same principles, Fig. 2.1.11 shows a few cases of simulations of *three-tier* organisms. Fig. 2.1.11a is taken as the new wild type. After the usual development of two limbs from the 3×3 body plan, extra “digits” grow from these limbs, guided by the top module of the hierarchical genotype. To make room and support the growth of these new digits, limbs have expanded their internal pattern from 1×1 to 2×4 (see previous section). Fig. 2.1.11a presents a double bilateral symmetry, with respect to both horizontal and vertical axes. Fig. 2.1.11c is a further mutation of Fig. 2.1.11b, in which region I_6 ’s limb has accelerated its growth and expanded its checkered pattern to support the development of two new digits, whereas, on the contrary, region I_4 ’s limb has continued to regress back to an undifferentiated stump. Figure 2.1.11d gives an overview of a possible phylogenetic tree based on the different forms detailed above. Dashed branches suggest “convergent” speciation pathways.

Future Directions

Embryomorphic engineering is inherently interdisciplinary, as it closely follows biological principles at an abstract level, but does not attempt to model detailed data from real genomes or organisms.

Thus, it sits at crossroads between different families of works, from developmental and systems biology to artificial life, in particular spatial computing, evolutionary programming and swarm robotics. It is an original attempt to integrate the three mechanisms of SA, PF and GR discussed above. Only few previous theoretical models of biological development or bio-inspired artificial life systems have combined them in various ways. The evo-devo works of Eggenberger (1997), Hogeweg (2000), Salazar-Ciudad & Jernvall (2002), or with lesser morphogenetic abilities Shapiro et al. (2003), Nagpal (2002), are among these notable achievements. Other interesting studies have explored the combination of two out of three: SA and PF, no GR—self-assembly based on cell adhesion and signalling pattern formation, but using predefined cell types without internal genetic variables (e.g., Marée & Hogeweg 2001); PF and GR, no SA—non-trivial pattern formation from instruction-driven intercellular signalling, but on a fixed lattice without self-assembling motion (e.g., von Dassow et al. 2000, Coore 1999); SA and GR, no PF—heterogeneous swarms of genetically programmed, self-assembling particles, but in empty space without mutual differentiation signals (e.g., Sayama 2007).

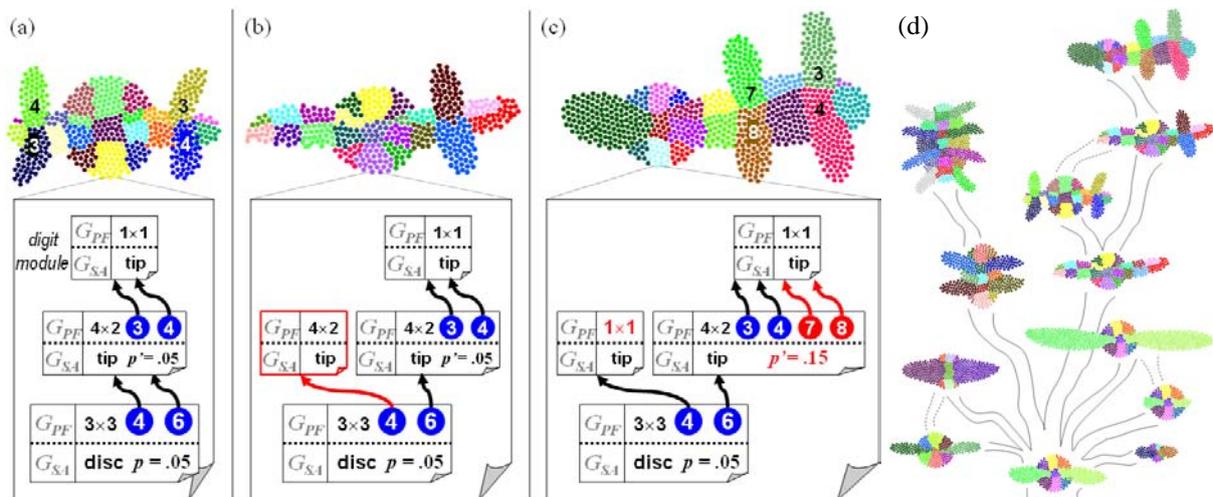


Figure 2.1.11: (a)-(c) Adding digits via a third tier in the modular hierarchy of the developmental genotype (see text). (d) A possible phylogenetic tree (from Doursat 2009g).

Abstracting from biological development, an important goal is also to contribute to a novel engineering paradigm of system assembly that would replace omniscient architects with large-scale decentralized collectivities of agents. Many research works (see next section) have investigated the possibility of obtaining self-formation capabilities from a variety of complex computing components: nano-units, software agents, robot parts, mini-robots, etc. Since functionality is distributed over a great number of components, it would be an insurmountable task to assemble and instruct each of them individually. Rather, in a way similar to biological cells, these components should be easily mass-produced, initially as identical copies of each other, and only acquire their specialized positions and functions by themselves within the system, once mixed together (Abelson et al. 1999). Thus beyond the proof-of-concept simulations presented above, a more systematic exploration is needed. The next steps must involve the mass-production of virtual organisms during an evolutionary search. This in turn requires the definition of a purpose or *function* to these organisms, and a *fitness functional* of how well this function is fulfilled by each developed individual.

From form to function While the task of “meta-designing” laws of artificial *development* inspired from biology is challenging, it only constitutes the first part of an embryomorphic engineering effort. Another important question is *functional* meta-design: once a self-developing infrastructure is mature, what computing capabilities can it support? What do its cell-agents and organ-regions actually represent in practice? In biological organisms, although cell physiology often partakes in development (e.g., electrical signals of neurons guiding synaptogenesis), there seems to be a broad distinction between developmental genes and the rest of the genome. In computing systems, these two modes could also be decoupled into two different sets of agent variables. After reaching developmental

maturation, and while still fulfilling maintenance and self-repair tasks, the morphogenetic SA and PF activity (i.e., division, position information and patterning signals) would give way to another type of activity subserving functional computation. Obviously, the type of computation would entirely depend on the nature of the agents.

In fact, in many computing domains, the problem is reverse: there is already a demand for precise self-formation capabilities in a variety of distributed systems made of otherwise functionally computing agents, and morphogenetic-like approaches have also been proposed in some applications. For example, MIT's "amorphous computing" has set the stage for a myriad of micro-processors containing the same instructions to self-organize without exact blueprint map or functional reliability, unlike traditional VLSI (e.g., Abelson et al. 1999, Coore 1999, Nagpal 2002). Such self-assembling components can also represent mobile sensors and actuators in complex self-managing networks (Beal & Bachrach 2006). In software applications (servers, security, etc.), a swarm of small-footprint software agents could diversify and self-deploy to achieve a desired level of application functionality and service (e.g., "immune" security; Hofmeyr & Forrest 2000). In robotics, too, whether articulated parts of reconfigurable devices (Lipson & Pollack 2000, Komosiński & Rotaru-Varga 2001, Hornby & Pollack 2002, Goldstein et al. 2005), or mobile formations of mini-robots (Gross et al. 2006, Christensen et al. 2007, Winfield et al. 2005), there is also great demand for guidance by complex but controllable morphologies. It is also an important challenge in complex techno-social networks made of myriads of mobile devices, software agents and human users, all relying on local rules and peer-to-peer communication (Dressler 2007; see Section 2.2 below).

From ontogeny to phylogeny After adding function to growth, one must also define how the embryomorphic system *evolves*, i.e., how it *varies* (randomly) and how it is *selected* (non-randomly). Different selection strategies are possible, either focusing on prespecified forms, or prespecified functions, or allowing unspecified outcomes. When selecting for form, a hard reverse engineering problem must be addressed: given a desired phenotype, what is the genotype that can produce it? While deterministic reverse compilation is possible in some cases (Nagpal 2002), parameter search is difficult in general. Fitness criteria that reward only the target shapes create jagged landscapes of unreachable peaks. A smoother approach is to define a "shape distance" as an increasing function of favorable mutations. It is conjectured here that this kind of gradual search might actually benefit, not suffer, from the high genotype dimensionality of an embryomorphic model, compared to the direct mappings of genetic algorithms. Hierarchical gene regulatory networks might be better at providing the fine-grain mutations required by the gentle-slope search toward increasingly sophisticated innovation (Dawkins 1996, Nilsson & Pelger 1994). Complex systems inherently have greater variational power, as they allow combinatorial tinkering on highly redundant parts.

However, beside gaining self-repair properties, why constrain a self-assembling system to produce a predefined shape? More benefits might come from such systems by selecting for function while leaving freedom of form. Gradual optimization could rely on a distance of performance to predefined goals, instead of shapes, allowing the most successful candidates to reproduce faster and mutate. Functional selection under free form or organization is the strategy adopted by most evolutionary computation works that also contain elements of distributed architectures or (small-size) complex systems. For example, this is the case of the logical functions computed by randomly composed multi-instruction programs in *Avida* (Lenski et al. 2003), the locomotion abilities created by randomly articulated multi-segment robots in *Golem* (Lipson & Pollack 2000) or *Framsticks* (Komosiński & Ulatowski 1999), or the shooting skills of intelligent video game agents emerging from randomly assembled multi-neuron networks in *NERO* (Stanley et al. 2005). However, most of these works are based on macroscopic genotype-phenotype encodings. Again, it is argued here, although not yet proven, that a larger number of agents, such as in multicellular embryogenesis, would be even more favorable to a successful evolutionary search.

Spinoff Projects

In summary, I intend to push the DEVO project from its current abstract state into two directions: one direction toward more realistic biological development and one direction toward more practical artificial development.

Biological development: Toward a more realistic model of morphogenesis

- add more realistic details derived from biological observations and measures of multicellular developmental behavior
- design a more sophisticated model of biomechanics (the “SA” part), based on 3-D polygonal cell geometry and active structural reshaping (e.g., tensegrity)
- use a finer model of gene regulation dynamics (the “PF” part), based on differential equations of concentration kinetics in recurrent gene circuits (Sharp & Reinitz 1998), and the concept of dynamical “attractor” states (Kauffman 1969, 1993)
- fine-tune the parameters of, and mutual feedback between, biomechanics and gene regulation by conducting an evolutionary exploration of the genotype → phenotype causal link, where the fitness function is defined as the resemblance with specific stages of natural embryogenesis (epiboly, gastrulation, somitogenesis, etc.)

Artificial development: Toward a more practical morphogenetic engineering system

- build an application of morphogenetic self-formation to swarm robotics (virtual and physical)
- establish a link with spatial and amorphous computing, e.g., reimplement the model in *MGS* language (Giavitto & Michel 2002, Giavitto & Spicher 2008) or MIT’s *Proto* language (Beal & Bachrach 2006)
- study the balance between endogenous dynamics and environmental influences (polymorphism)
- demonstrate the theoretical usefulness of “devo” in “evo” through quantitative, statistical measures over many trials

These future directions will take shape through several “spinoff projects”, each in collaboration with one or more colleagues whom I personally know: either we are already close collaborators, or we have frequently met, or at the minimum I have already visited them in their lab and have had extensive discussions with them. They all have expressed a clear interest in working or continuing to work with me on these topics.

Project DEVO-MECAGEN

How the embryomorphic DEVO model can expand into a biologically realistic multiscale computational and mathematical model of animal morphogenesis, based on mechano-chemical coupling between genetic and cellular dynamics.

Collaborators: Nadine Peyri ras, Development, Evolution, Plasticity of the Nervous System (DEPSN), CNRS, Gif-sur-Yvette – Paul Bourguine, Center of Research in Applied Epistemology (CREA), Ecole Polytechnique, Paris – Julien Delile, PhD student, “Frontiers in Life Sciences” Doctoral Program.

Abstract: [From our common ANR grant application *Mecagen*, February 2009] This project aims to construct a theoretical model of the multiscale dynamics of the early stages of animal morphogenesis, under the control of quantitative reconstructions of experimental development. This theoretical reconstruction will take the form of a discrete multi-agent computational model combined with a continuous mathematical formulation. In this approach, embryonic development is construed as an emergent, self-organized phenomenon based on the individual behavior of cells and their genetically

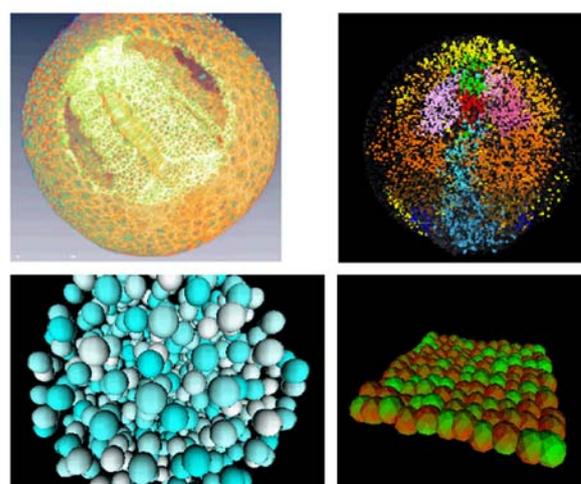


Figure 2.1.12: Top: 3-D voxel snapshot of a developing zebrafish and its reconstruction by image processing (*Embryomics* and *BioEmergences* projects). Bottom: Preliminary 3-D embryomorphic simulations (DEVO-MECAGEN project).

regulated, and regulating, biomechanics. Measurements will be made from 4-D imaging observations of the first 15 hours of a model vertebrate's embryogenesis—the zebrafish *Danio rerio*. The MECAGEN project will draw from the previous FP6-NEST projects *Embryomics* and *BioEmergences* to implement (a) the quantitative multiscale reconstruction of the morphodynamics of *Danio rerio*'s early embryogenesis, from the egg to the beginning of somitogenesis, and (b) the modeling of the gene regulation, cellular dynamics and biomechanical constraints that govern morphogenesis (Fig. 2.1.12). Model and experiments will be coupled in a feedback loop, whereby the model is optimized and falsified by experimental trials of gain and loss of function.

Project DEVO-SYMBIOTIC

Translation of the basic principles of the embryomorphic DEVO model (pattern formation, collective motion, and gene regulation) into a stack of formal languages ultimately compiled and implemented in a synthetic biological substrate or “bioware”.

Collaborators: Jean-Louis Giavitto, Computer Science, Integrative Biology and Complex Systems (IBISC), Université d'Evry Val d'Essone / Genopole – Olivier Michel and Antoine Spicher, Laboratory of Algorithmic, Complexity and Logic (LACL), Université Paris 12 Val-de-Marne

Abstract: [From our common ANR grant application *Synbiotic*, January 2010] Synthetic biology is an emerging science that promotes a standardized design and manufacturing of biological system components without natural equivalents (Endy 2005). It is currently in search of design principles to achieve a reliable and secure level of functionality from reusable biological parts (such as BioBricks; Knight 2003). Beyond genetic engineering problems, which require the development of dedicated software tools, computer scientists identify this challenge with systems design (e.g., electronic circuits or large software systems). In this context, the objective of DEVO-SYMBIOTIC is to design and develop tools to literally “compile” (as in programming languages) the overall behavior of a population (of bacteria) into cellular processes local to each entity (one bacterium). The ultimate motivation is to exploit the collective properties of a bacterial population to create artificial biosystems that can meet various needs in the fields of health care, nanotechnology, energy and chemistry. This long-term core research project is a type of “unconventional” computing at the interface between computer science and biological engineering. It relies on the development of new approaches (spatial computing, amorphous and autonomic computing) to deal with new classes of applications characterized by the emergence of global behaviors in a large population of entities that are irregularly located and dynamically interconnected.

Project DEVO-EVO

Using the embryomorphic DEVO model as a virtual phenotype platform for the theoretical exploration of “tinkered” and convergent evolution, in particular through the duplication and rewiring of complex gene regulation networks.

Collaborator: Ricard Solé, Complex Systems Lab, Catalan Institution for Research and Advanced Studies (ICREA), Universitat Pompeu Fabra, Barcelona

Abstract: [From RS's James S. McDonnell Foundation Research Award *Origins of Innovation in Tinkered Networks*, 2006] Nature abounds in complex forms and structures and seems to have an infinite power of generating complexity. Yet, biological complexity is the result of an apparently inefficient mechanism of change: *tinkering*. Indeed, evolution operates by extensively reusing previous structures, and it is unable to “foresee” the future, as an engineer would. An additional feature of evolution is the presence of widespread *convergence* of innovations: common solutions are found to common problems. Evolution often reinvents similar structures and functional traits by tinkering from available components, as if only some special solutions could be achieved. Are there

common rules imposing limitations on what is possible? This project involves an exploration of the question of how tinkered evolution generates successful innovations and why these innovations usually converge to common solutions. Complex networks, such as gene regulatory networks, have been shown to display common patterns of organization, often resulting from simple rules of duplication and rewiring. Tinkered networks exhibit a high fragility under the removal or damage of hubs and a high robustness under random mutations. The presence of these common traits might pervade the convergent designs found in nature. Understanding the origins of this dual character of tinkering, i.e., its efficiency and limited repertoire, can be achieved by studying the underlying landscapes where these evolutionary paths take place. A model of development of embodied organisms will be constructed in order to explore the requirements for pattern formation to allow animal diversity to emerge and flourish, and determine the role of emergent dynamics versus selection under tinkered evolution.

Project DEVO-PROTO

Construing the embryomorphic DEVO model as a spatial computing paradigm, and porting it to the MIT Proto language.

Collaborator: **Jacob Beal**, BBN Technologies / Computer Science and Artificial Intelligence Laboratory (CSAIL), MIT, Cambridge, Massachusetts

Abstract: [From JB’s original programming language *Proto*; Beal & Bachrach 2006] Many complex systems are “spatial computers”—collections of local computational devices distributed through a physical space, in which the difficulty of moving information between any two devices is strongly dependent on the distance between them, and the “functional goals” of the system are generally defined in terms of the system’s spatial structure. Systems that can be viewed as spatial computers are abundant, both natural and man-made, and include sensor networks, robotic swarms, engineered biofilms, cells during morphogenesis, ad-hoc peer-to-peer wireless networks, cellular automata, and FPGAs. MIT Proto is a language and toolkit that makes it easy to write complex programs for spatial computers using a continuous space abstraction. Rather than describe the behavior of individual devices, the programmer views the space filled by the devices as an amorphous medium—a region of continuous space with a computing device at every point—and describes the behavior of regions of space. These programs are automatically transformed into local actions that are executed approximately by the actual network of devices. When the program obeys the abstraction, these local actions reliably produce an approximation of the desired aggregate behavior.

Project DEVO-BOTS

How the embryomorphic DEVO model can be expanded and applied to large swarms of robots that evolve and adapt together into different organisms based on bio-inspired approaches.

Collaborators: **Alan F. T. Winfield**, Faculty of Environment and Technology, Bristol Robotics Lab (BRL), University of the West of England, Bristol – and/or – **Marco Dorigo**, Institut de Recherches Interdisciplinaires et de Développements en Intelligence Artificielle (IRIDIA), Université Libre de Bruxelles

Abstract: [Text example from the FP7-FET project *Symbion*, in which BRL is a partner] The aim is to investigate and develop novel principles of behavior, adaptation and learning for self-assembling robot “organisms” based on artificial evolution and evolutionary computational approaches (Fig. 2.1.13). The plan is to combine bio-inspired evolutionary paradigms with robot embodiment and swarm-emergent phenomena thus enabling the “organism” to autonomously manage its own hardware and software organization. We hope that such artificial organisms will become self-configuring, self-healing, self-optimizing and self-protecting from hardware and software points of view. This may lead

not only to extremely adaptive, evolvable and scalable robotic systems, but might also enable the robot organisms to reprogram themselves without human supervision; to develop their own cognitive structures and, finally, to allow new functionality to emerge: the most suitable for the given situation.



Figure 2.1.13: Project *Symbion*'s mockup illustration (from <http://www.symbion.eu>)

Symbion will for the first time consider a truly symbiotic multi-cellular construction of real-world artificial organisms. Elementary robots equivalent to single cells will build artificial-life-forms with a central nervous system, common energy resources and homeostasis at the level of the whole organism. The heterogeneous elementary robots will be capable of autonomous aggregation and disaggregation into/from the organism (without human assistance) and will be capable of autonomous energy collection (survival) in their habitat.

Relevant Publications

Full Papers – Books, Journals, Conferences, Workshops, Reports

- Bourgine, P., Campana, M., Cunderlik, R., Drblikova, O., Faure, E., Lombardot, B., Luengo-Oroz, M.A., Melani, C., Remesikova, M., Rizzi, B., Savy, T., Zanella, C., Kollar, J., Colin, I., Desnoullez, S., Funabashi, M., Duloquin, L., Randoux, S., Courtade, E., Hirsinger, E., Santos, A., Beaurepaire, E., Herbomel, P., Suret, P., Lutfalla, G., Nicolas, J.-F., Doursat, R., Sarti, A., Mikula, K. & Peyri ras, N. (2010) Embryomics: Reconstructing the cell lineage tree as the core of the embryo. ***In Preparation.***
- Doursat, R. (2006b) The growing canvas of biological development: Multiscale pattern generation on an expanding lattice of gene regulatory networks. *InterJournal: Complex Systems* 1809.
- Doursat, R. (2008a) The self-made puzzle: Integrating self-assembly and pattern formation under non-random genetic regulation. *InterJournal: Complex Systems* 2292.
- Doursat, R. (2008b) Organically grown architectures: Creating decentralized, autonomous systems by embryomorphic engineering. In *Organic Computing*, R. P. W rtz, ed., pp. 167-200, Springer-Verlag.
- Doursat, R. (2008d) Programmable architectures that are complex and self-organized: From morphogenesis to engineering. *11th International Conference on the Simulation and Synthesis of Living Systems (ALIFE XI)*, August 5-8, 2008, University of Southampton, Winchester, UK. In *Artificial Life XI*, S. Bullock, J. Noble, R. Watson & M. A. Bedau, eds., pp. 181-188, The MIT Press.
- Doursat, R. (2008f) The growing canvas of biological development: Multiscale pattern generation on an expanding lattice of gene regulatory networks. In *Unifying Themes in Complex Systems Vol VI*, A. A. Minai, D. Braha & Y. Bar-Yam, eds., Springer-Verlag. ***This volume selected 77 papers from over 300 presented at the ICCS 2006 conference.***
- Doursat, R. (2008g) Spatial self-organization of heterogeneous, modular architectures. *Spatial Computing Workshop (SCW 2008)*, at *2nd IEEE International Conference on Self-Adaptive and Self-Organizing Systems (SASO 2008)*, October 20-24, 2008, Venice, Italy.
- Doursat, R. (2009g) Facilitating evolutionary innovation by developmental modularity and variability. *Generative & Developmental Systems Workshop (GDS 2009)*, at *18th Genetic and Evolutionary Computation Conference (GECCO 2009)*, July 8-12, 2009, Montreal, Canada.
- Doursat, R., Sayama, H. & Michel, O., eds. (2010) *Morphogenetic Engineering: Toward Programmable Complex Systems*, in *NECSI "Studies on Complexity" Series*, Springer-Verlag. ***In Preparation.***

Abstracts (for Presentations or Posters) – Conferences, Workshops

- Doursat, R. (2006a) The growing canvas of biological development: Multiscale pattern generation on an expanding lattice of gene regulatory networks. *6th International Conference on Complex Systems (ICCS 2006)*, June 25-30, 2006, New England Complex Systems Institute (NECSI), Boston, MA.
- Doursat, R. (2007a) Embryomorphic engineering: How to design hyper-distributed architectures capable of autonomous segmentation, rescaling and shaping. *Unconventional Computation Conference (UC 2007)*, March 21-23, 2007, Los Alamos National Laboratory (LANL) and Santa Fe Institute (SFI), Santa Fe, NM. OCP Science ***Best Poster Award in Unconventional Computing*** (2008) *International J. of Unconventional Computing* 4(2): i-ii.

- Doursat, R. (2007e) The self-made puzzle: Integrating self-assembly and pattern formation under non-random genetic regulation. *7th International Conference on Complex Systems (ICCS 2007)*, October 28-November 2, 2007, New England Complex Systems Institute (NECSI), Boston, MA.
- Doursat, R. (2008c) From morphogenesis to embryomorphic engineering. “*From Amorphous to Spatial Computing*” Workshop, July 7-8, 2008, Paris, France.
- Doursat, R. (2008e) A morphogenetic model of controlled self-organization. *5th European Conference on Complex Systems (ECCS 2008)*, September 14-19, 2008, Hebrew University, Jerusalem, Israel.
- Doursat, R. (2009c) Heterogeneous collective motion or moving pattern formation? The “self-made puzzle” of embryogenesis under the light of multi-agent modeling. “*Morphogenesis in Living Systems*” Conference, May 14-16, 2009, Université Paris Descartes, France.
- Faure, E., Lombardot, B., Luengo-Oroz, M., Campana M., Peyriéras, N., Doursat, R. & Bourguine, P. (2007) Active machine learning for embryogenesis. *4th European Conference on Complex Systems (ECCS 2007)*, October 1-5, 2007, Technische Universität Dresden, Germany.

Invited Keynote Presentations & Talks (with Abstracts) – Conferences, Workshops

- Doursat, R. (2007b) Embryomorphic systems meta-design: Preparing for self-assembly, self-regulation and evolution. *7th Understanding Complex Systems Symposium (UCS 2007)*, May 14-17, 2007, Department of Physics, University of Illinois at Urbana-Champaign, IL.
- Doursat, R. (2007c) Multiscale Embryomorphic Architectures. *Workshop on Scaling in Biological and Social Networks*, July 9-13, 2007, Santa Fe Institute (SFI), Santa Fe, NM.
- Doursat, R. (2007f) How to plan self-organization, control decentralization, and design evolution: Addressing the paradoxes of complex systems engineering with metaphors from biological development. *2nd International Conference on Bio-Inspired Models of Network, Information, and Computing Systems (BIONETICS 2007)*, December 10-13, 2007, Budapest, Hungary. **Keynote address.**
- Doursat, R. (2009a) Mouvement collectif hétérogène ou formation de motifs en mouvement? Le puzzle auto-façonné de l’embryogenèse à la lumière des modèles multi-agents. *5ème École interdisciplinaire d’échanges et de formation en biologie (Berder 2009)*: “Spatialisation et localisation”, March 29-April 4, 2009, Formation du CNRS, Berder (Brittany), France.
- Doursat, R. (2009b) The self-made puzzle: Complex systems science as a design activity. *Workshop on “Aesthetic at the Heart of Science”*, in *The European Future and Emerging Technologies Conference (FET 2009)*: “*Science Beyond Fiction*”, April 21-23, 2009, Prague, Czech Republic.
- Doursat, R. (2009d) Embryomorphic engineering: How elaborate, modular architectures can be self-organized, too. *1st International Morphogenetic Engineering Workshop (MEW 2009)*, June 19, 2009, Complex Systems Institute, Paris, France.
- Doursat, R. (2009e) Heterogeneous collective motion or moving pattern formation? The self-made puzzle of embryogenesis under the light of multi-agent modeling. *2nd Paris Workshop on Multi-Agent Systems in Biology at Meso or Macroscopic scales (MASBio 2009)*, June 23, 2009, Université Pierre et Marie Curie, Paris, France.
- Doursat, R. (2009f) Evolutionary developmental systems as “self-made puzzles” that can be programmed: Lessons from biological morphogenesis. Invited panelist (of 6), *Generative & Developmental Systems Workshop (GDS 2009)*, at *18th Genetic and Evolutionary Computation Conference (GECCO 2009)*, July 8-12, 2009, Montreal, Canada.
- Doursat, R. (2009h) Heterogeneous collective motion or moving pattern formation? The two sides of embryogenesis combined by multi-agent modeling into a “self-made puzzle”. *Workshop on Quantitative Tissue Biology and Virtual Tissues (Biocomplexity X)*, October 28-November 1, 2009, The Biocomplexity Institute, Indiana University, Bloomington, IN.
- Doursat, R. (2009i) Causing and influencing patterns by designing the agents: Complex systems made simpler. *4th Workshop on Causality in Complex Systems*, co-organized by DSTO, CSIRO (Australia), and ONR, AFRL (US), in association with the *Conference on Spatial Simulation for the Social Sciences (S4)*, November 25-27, 2009, Institut des Systèmes Complexes, Paris Ile-de-France.
- Doursat, R. (2010c) [TBA]. *2nd International Conference on Morphogenesis in Living Systems (MLS 2010)*, May 27-29, 2010, Université Paris Descartes, France.

2.2. Project PROGNET: Programmed Attachment Networks

The self-assembly of complex but precise network topologies by programmed attachment: An extension of the artificial development project from 2-D/3-D multicellular organisms to n-D networks.

In this original model of autonomous network construction and dynamics, which I created during a collaboration with **Mihaela Ulieru** (Canada Research Chair; Computer Science Department, University of New Brunswick), and which was later implemented under my guidance by **Adam MacDonald**, MSc student at UNB, nodes execute the same program in parallel, communicate and differentiate, while links are dynamically created and removed based on “ports” and “gradients” that guide nodes to specific attachment locations. As the network expands, nodes switch different rules on and off, creating chains, lattices, and other composite topologies.

Introduction

Imagine self-assembling circuits, computers, cars, buildings, etc., composed of a swarm of small components, parts, and modules (self-propelled or carried by mini-robots) that would aggregate in an orderly fashion without following a central direction or global blueprint. Imagine a self-reconfiguring manufacturing plant (Ulieru et al. 2002), a self-stabilizing energy grid (Silberman 2001, McMillin et al. 2006, Grobbelaar & Ulieru 2006, Carreras et al. 2009), or a self-deploying emergency taskforce (Ulieru & Unland 2004), all relying on a myriad of mobile devices, software agents and human users that would build their own network on the sole basis of local rules and peer-to-peer communication. Whether in 3-D devices or *n*-D techno-social webs, decentralized automation based on *emergent architectures* promises to be the new paradigm of systems engineering and control. Traditionally, the role of an engineer is that of an active designer, who enforces hierarchical, top-down, linear thinking—even if “complicated”, but not “complex”. By contrast, new types of unplanned emergent behavior lead the engineer to only *guide* existing bottom-up interactions among a multitude of components (Carreras et al. 2007, 2009, Ulieru 2007). We need to *design for emergence*, i.e., for systems that fundamentally and continually adapt and evolve. It is hoped that it would bring many beneficial “self-*x*” properties improving, complementing or even replacing current human-led design and planning efforts (Boardman & Sauser 2007). For example, it could allow remote operations in hostile places, faster organization without the usual delays tied to a central command node, greater robustness and reactivity to new events or environments, better scalability if the system needs to grow, and possibly the greatest achievement of all: the ability to learn and evolve.

The past few years have seen a remarkable increase in research activities across many disciplines to bring this future closer to us. In fact, the march toward decentralization and self-organization has already spontaneously begun—but we are not prepared for it. The explosion in size and complexity of information and communication technologies (ICT) and, generally, all networked systems (Internet, utility infrastructures, business, urban planning, transportation, military, health, etc.) has preceded our ability to fully master them. To some degree, engineers and planners are losing sight of their own creation, which has grown beyond the capacity of a single mind. Considering how Internet, for example, has evolved into today’s complicated network prone to many pitfalls (Willinger & Doyle 2002), one notices that the classical engineering paradigm has in fact led to a spiral of increasing but unwanted complexity characterized by continual “patching”, hence fragility. The traditional view of control engineering is that the controller is a separate entity that monitors and affects the main system, generally by feedback from its output variables onto its input variables (Isermann 1981). In the paradigm shift towards emergent engineering, this system/controller pair becomes fragmented into a myriad of micro-system/micro-controller pairs (represented in the model below as simple agents and their individual rules; see also Müller-Schloer & Sick 2008). Rather than attempting to stabilize the whole complex system in a centralized manner, the emergent controller is implemented in the form of generic control mechanisms located in every component.

Thus instead of trying to cling to an increasing elusive global control, we should now ride the wave of complexity and focus on the *generic and distributed conditions* that will organize it. It

becomes necessary to drastically revise the traditional top-down perspective on systems design and control, which aimed at imposing order *exogenously*, and rather let systems grow, function, and stabilize—even adapt and improve—*endogenously*, in a bottom-up fashion. In future emergent engineering, the role of humans toward machines will shift from “micro-managers” to “lawmakers”.

An Abstract Model of Self-Made Network

Toward this goal, I present here an original model of autonomous network construction and dynamics, which I created as a generalization of the embryomorph project (Section 2.1) from 2-D/3-D multicellular organisms to n -D networks, and its potential for concrete applications. The challenge is to design a set of rules or protocols that individual agents in a multitude should follow to independently create links between each other, such that the end result is a network that consistently represents an intended structure. This ability to form programmed structures in a distributed, self-organized way, can be then applied to a number of real-world situations where networking accuracy and reliability is important. Here, agents will be called “nodes”, which can for example represent human users equipped with personal digital assistant (PDA) devices communicating via wireless connectivity. They can also represent software agents (see, e.g., Wooldridge 2002) acting as proxies for physical machines, devices or other resources that need to function together, e.g., in a manufacturing chain. In any case, nodes execute the same program in parallel, but gradually differentiate according to local and limited positional information. The self-assembly program carried by each node includes routines for the exchange of messages and the dynamical creation or removal of links. It relies on a combination of “ports” and internal state variables derived from discrete “gradients”. Ports and gradients guide the new nodes to specific attachment locations in the developing network. As the network expands and node positions change, nodes adapt by switching different subsets of rules on or off—analogue to gene activation/repression in biological DNA—thus triggering the growth of specific structures.

This part describes the basic mechanisms used by the model of self-constructing networks from an abstract viewpoint. We start with elementary chains and lattices, and progress toward more complicated, composite topologies, including branching and randomized redundancy. Initially, a simulation consists of an empty system with no nodes. Over time, the system periodically adds new nodes, which communicate and form a network of links in order to build a specifically engineered structure. This global structure is geometrically predesigned, but the local rules within the nodes take a different form. They represent a logical program of instructions, which is identical in each node and defines its actions given a specific state of the information it contains.

Constructing simple chains Chains are the simplest self-assembling structures. In this first scenario, nodes possess two ports, X and X' , and two corresponding gradient values x and x' . Ports can be “occupied” (linked to other node ports) or “free” (not linked), while free ports can be “open” (available for a link) or “closed” (disabled). New nodes that just arrived in the system’s space, or nodes that are not yet connected, have both ports open and gradients set to 0. A node i can create a link with another node j only through a pair of complementary open ports, here X and X' , with one link per port. Thus the only possible links between i and j are $i_X \leftrightarrow j_{X'}$ and $i_{X'} \leftrightarrow j_X$. As soon as a new link is made, its two ports are occupied, i.e., cannot accept new links, and gradients are immediately updated according to the following rules: (a) a free port always maintains its value at 0 (gradient source), and (b) value x is sent out on link $X' \rightarrow X$ with an increment of +1, so that X receives a new value $x' = x + 1$ (and conversely with x' , $X \rightarrow X'$ and $x = x' + 1$). This is similar to the gradient rule of the embryomorph model presented in Section 2.1.

Figure 2.2.1 shows the self-assembly of a short chain. A new node can connect to any available open and complementary port at random, including the most recent and oldest nodes of the chain: all valid links (here, two at any time) have an equal probability to be formed. The gradient counters keep track of the nodes’ positions in the chain. This allows, for example, to build chains of a fixed length n by closing any remaining open ports as soon as $x + x' = n - 1$. Again (see Section 2.1), discrete counter increments are also the method of choice for spreading positional information in amorphous and spatial computing systems (Coore 1999, Nagpal 2002, Beal & Bachrach 2006). In the present

model, the role of the gradient source can be transferred to another node, thereby shifting gradient chains in successive corrective waves, as nodes continually communicate with each other to adjust their counters. Figure 2.2.1b shows an example of a step-by-step decomposition of a gradient update after a new node (dashed) has connected to the system. In general, the new x value of a node i , denoted by $x_i(t+1)$, is set to $x_j(t) + 1$ if j is the neighbor attached to i_X (same with x' and $i_{X'}$). This ensures a natural propagation of gradient value corrections and converges after $O(n)$ time steps.

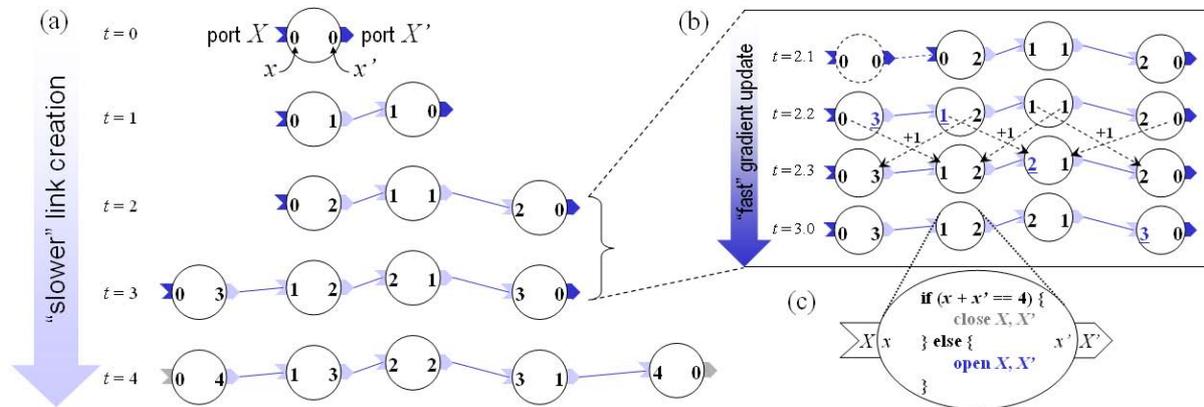


Figure 2.2.1: Self-assembly of a simple chain. (a) The five main steps leading to a 5-node chain. Through the *link creation* routine, incoming nodes attach to either open ports, X or X' (dark blue), of the forming chain. When a link is created, its ports become “occupied” (light blue) and gradient values are updated in all nodes (see b). When chain length is 5 (i.e., $x + x' = 4$), all open ports are closed (gray; see c). (b) Detailed substeps of the value-passing *gradient update* routine. (c) *Port management* routine of the “DNA” program in each agent: ports close when length is 5 (from Doursat & Ulieru 2008b).

Node routines Thus all nodes carry the same program (their “genotype” or “DNA”), which consists of three main routines: *gradient update* (G), *port management* (P), and *link creation* (L). The gradient update routine G (explained above, see Fig. 2.2.1b) is generic code that provides nodes with the positional information they need to make further decisions, and is used in all network structures (see next sections). The port management routine P (Fig. 2.2.1c) contains the heart of the logic that is specific to the topology of a target architecture—whether a chain, a lattice or a more complicated composite graph. For example, in the case of a 5-node chain, it simply commands a node to shut its ports whenever $x + x' = 4$ (the “open” and “close” commands apply only to free ports, and are ignored on occupied ports). Finally, the link creation routine L (Fig. 2.2.1a) is also generic logic that prompts new nodes to pick one of the open ports of the network at random to make a new connection. Routines G and P are executed only by the nodes that are already involved in the network, paving the way for newcomer nodes to execute routine L .

Lattice formation by guided attachment With *two* pairs of ports, (X, X') and (Y, Y') , and two pairs of associated gradient variables (x, x') and (y, y') , also set to 0 when the node is new, lattices can grow (Fig. 2.2.2). Here, two nodes i and j can form four possible links involving pairs of complementary ports, i.e., $i_X \leftrightarrow j_{X'}$ or $i_{X'} \leftrightarrow j_X$ or $i_Y \leftrightarrow j_{Y'}$ or $i_{Y'} \leftrightarrow j_Y$ (Fig. 2.2.2a). If left without structure-specific constraints (i.e., only routines G and L , but no P), the networking process will grow branches that criss-cross randomly, where each branch maintains its own gradient system along its length (Fig. 2.2.2b). To be able to program a more orderly network, such as a regular square lattice of fixed size $n \times m$, routine P must contain specific port-shutting commands that strictly regulate the pool of open ports at any time during the life of the structure. Node attachment must be directed toward a restricted set of available locations, resembling blinking beacons on a landing runway (Fig. 2.2.2c). Then, through routine L , a new node can randomly choose among one of these few locations.

Robustness by cluster redundancy The previous examples involved exact structures of connections that were programmed at node-level by a (quasi) deterministic algorithm. Despite minimal randomness in the choice of locations for new attachments, there was a unique possible final outcome:

a chain or a lattice planned in advance. While we want to preserve this essential aspect of *programmability* (the whole focus of this work), it is also important to reintroduce an element of *variability* and *redundancy* in the system—albeit at a smaller scale. In biological development, the position and number of individual cells is very imprecise, while the structures and organs they form are reliably placed. Similarly, programmed network self-assembly can also afford to be irregular at the microscopic level of the nodes, while retaining an orderly arrangement at the higher, mesoscopic levels of *clusters* of nodes.

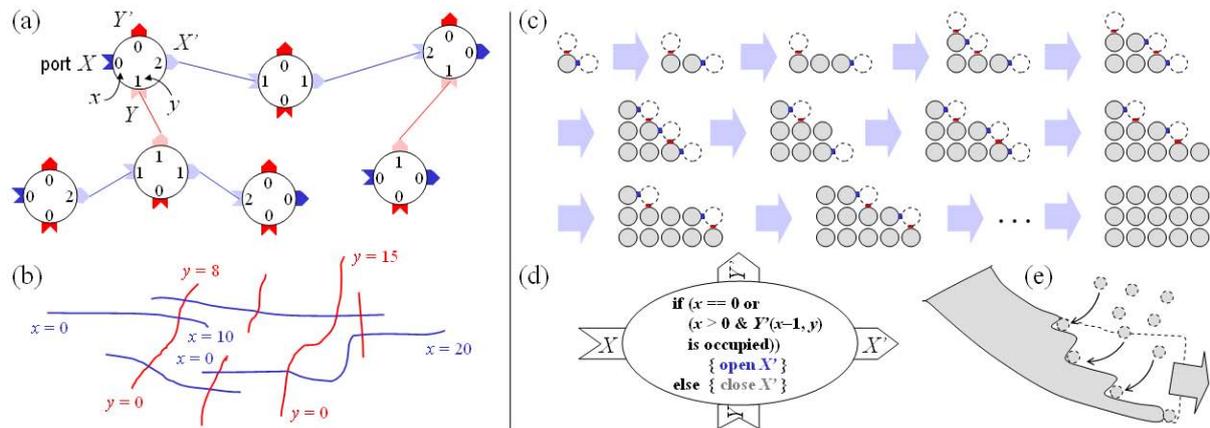


Figure 2.2.2: Self-assembly of a lattice. (a) Nodes have four ports, X , X' , Y , and Y' , and can form either $X \leftrightarrow X'$ or $Y \leftrightarrow Y'$ links. (b) Without any port management routine P , node chains (schematized by curved lines) form and intersect in a random manner. (c) Condensed view of an example of 5×3 lattice self-assembly in orderly “waves” of node attachment: the only available spots offered by open ports are internal “corners”. (d) An excerpt of the P routine in every node (rules P_2 and P_3 explained in the text). (e) A generic illustration of lattice-building attachment waves (from Doursat & Ulieu 2008b).

One solution to implement this idea is to simply “thicken” chains and lattices (Fig. 2.2.3) by replacing single nodes with clusters of nodes. This can be done through one additional port, C (as in “cluster” or “clique”) that allows multiple nodes with identical x and y gradient coordinates to form random connections with each other. The C port represents an extra “nonlinear” dimension added to the single pair of ports (X, X') of linear 1-D chains, or the two pairs of ports (X, X'), (Y, Y') of bilinear 2-D lattices. Another new feature is that nodes are also allowed to make multiple connections per port, whether X , Y or C (Fig. 2.2.3a). As a result, nodes cluster into families according to their gradient values. Thus, in the case of a chain, a new node has two possibilities of attachment: it can either thicken or lengthen the chain. Similar to cellular proliferation in morphogenetic tissues and organs, this proliferation of nodes in structured networks introduces redundancy and “failover” safety. Overall, it remains a deterministic structure (guided by the genotype of the attachment rules G , P and L) but with fine-grain stochasticity.

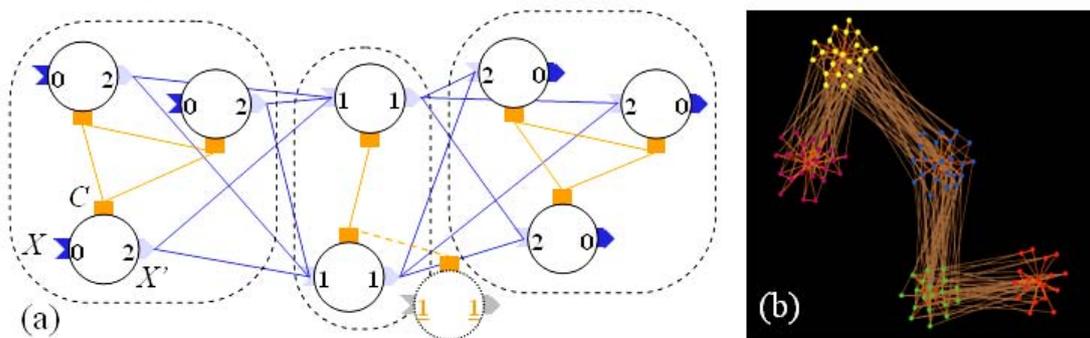


Figure 2.2.3: Cluster chain. (a) Detailed 3-cluster chain: internal (orange) links connect the C ports of nodes with same (x, x') values, while (blue) links *between* clusters form the chain. A new node (gray) connecting through C adopts the cluster’s values. (b) Simulation with 5 clusters and ~ 20 nodes/cluster (from Doursat & Ulieu 2008b).

Branching and modular structures by local gradients More complicated structures can then be developed by composing multiple chains and lattices. To allow the creation of *modules* with their own identities and local positional information, one can find again inspiration from biology, in particular the concepts of *modularity* and *homology* that are central in evo-devo (Carroll et al. 2001, Müller & Newman 2003, Kirschner & Gerhart 2005). Modules are similar to “limbs” that have distinct morphologies and geographies. They are implemented here by distinguishing chain segments and branches through independent coordinate systems based on different “tags” a, b, c , etc. To start with a simple example, a chain can branch off from the middle of another chain (Fig. 2.2.4). The gradient ports in the initial chain of the system are denoted by (X_a, X'_a) , while the ports of the branches will be (X_b, X'_b) , (X_c, X'_c) , and so on. Accordingly, routine L is modified so that links cannot be created between ports with different tags.

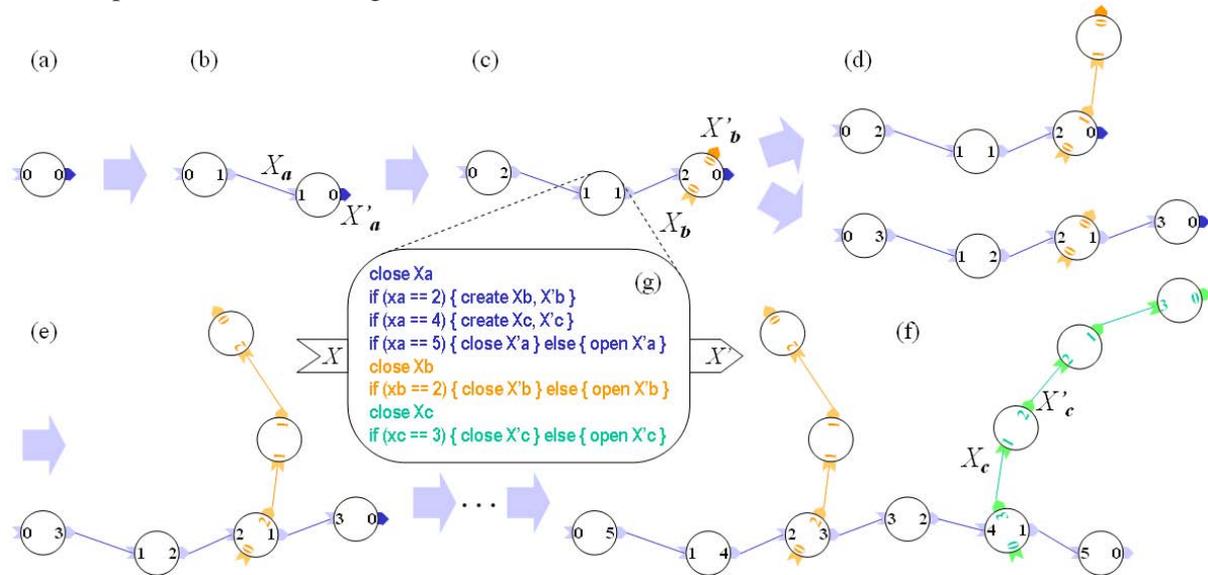


Figure 2.2.4: Branching scenario (see text). (a,b) Beginning of chain a . (c) Branch b starts. (d) Two possible next steps. (e) Chain b stops at length 3. (f) Final outcome, including a 4-node branch c . (g) This exact structure is prescribed by the port management program P carried by each node (from Doursat & Ulmer 2008b).

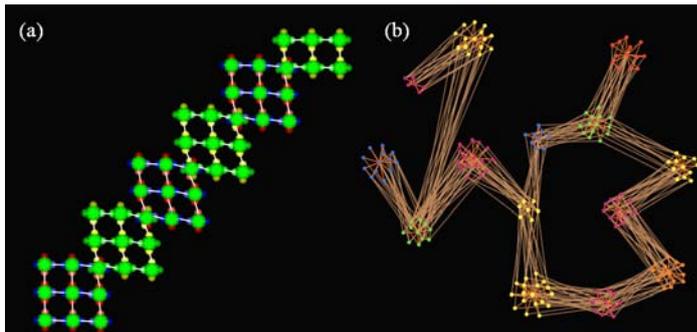


Figure 2.2.5: Two simulations of programmed modular networks. (a) Branching 3×3 lattices attached by their corners. (b) Complex branching chain of node clusters, including a cycle (from Doursat & Ulmer 2008b).

assembling, its last node $(x_a, x'_a, y_a, y'_a) = (2, 0, 2, 0)$ creates a new quartet of ports (X_b, X'_b, Y_b, Y'_b) that spins off a new 3×3 lattice tagged b , and so on. Finally, whether based on 1-D chains or 2-D lattices, modular composite structures can also be “thickened” with clusters of nodes by adding a C port to each node, as explained in the previous section. An example of complex programmed network made of a branching chain (including a cycle) of clusters is shown in Fig. 2.2.5b.

In the elementary scenario of Fig. 2.2.4, when the third node has attached (i.e., when $x_a = 2$), the P routine commands that a new pair of ports (X_b, X'_b) be created on that node and only port X'_b be open (Fig. 2.2.4c). Afterwards, new nodes can attach to either open port, X'_a (lengthening the initial chain) or X'_b (starting the new branch; Fig. 2.2.4d). The order of node attachment, however, does not influence the final structure. Another example of branching structure based on lattices instead of chains is shown in Fig. 2.2.5a: here, once a 3×3 lattice tagged a has finished self-

Future Directions

The previous section described abstract principles of self-made networks that have a purely endogenous ability to form precise topologies. It established new foundations for the emergence of non-random, programmable patterns exhibiting intrinsic structures that are neither repetitive nor imposed by the environment. Starting from these premises, the model will be completed with other important features in order to be applicable to concrete problems: (1) physical space, (2) external events, (3) agent functionality, and (4) action plans.

Physical space Most real-world networks combine non-spatial graph topologies (e.g., connecting software agents or organizations) with Euclidean graph topologies (e.g., connecting people and equipment on the field) at different degrees. For example, many cyber-physical systems inherently have a dual spatial/nonspatial nature, as they often include a physical infrastructure at a “lower” communication level, with a virtual overlay network at a “higher” application level (Ulieru & Unland 2004, Grobbelaar & Ulieru 2007). The abstract mechanisms of programmed attachment described above create purely non-spatial graphs that are displayed in 2-D figures only for convenient viewing. Nodes can potentially “see” all other nodes and the discrete gradient information is internal to the graph. Thus if nodes must represent agents and devices interacting in real space, the dynamics must be modified to take into account the effects of metric distance. Space can intervene at two levels: by limiting the scope of pre-attachment detection (nodes can connect only to nearby nodes, within a certain radius), and by giving a mechanical meaning to the nodes and links. For example nodes can be interpreted as electrically charged particles, and links as elastic springs, as in force-based layout algorithms (Fruchterman & Reingold 1991).

External events Naturally, the propensity to create structured network formations must also be influenced and modified by the environment in which those formations will function. In a rapidly changing situation, it is critical that programmed networks be able to dynamically co-develop with the situation (i.e., disassemble and reassemble into different configurations, by switching on and off different sets of rules stored in their nodes) and/or co-evolve (by creating new rules on the fly). In the model above, node attachment was based on port availability driven only by positional gradient values. This internal dynamics must now interact with the external dynamics of the system’s context, along with its boundary conditions and unexpectedly occurring events (Figs. 2.2.6-7). Environmental landmarks can play different roles in the self-structuring process: they can act toward the growth process as *triggers* (warning signals starting a new network formation), *attractors* (points of particular interest pulling a network formation toward them) or *obstacles* (avoidance areas bending or stopping a network formation).

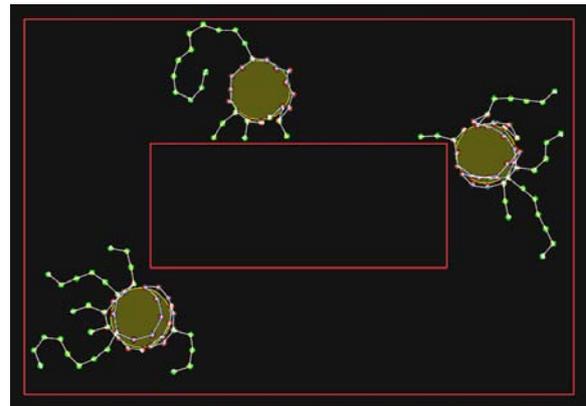


Figure 2.2.6: This numerical simulation of self-organized network morphologies—in which nodes execute a program similar to Fig. 2.2.4—shows that they can exhibit a high degree of adaptation to environmental constraints, such as spatial boundary conditions. Each network is based on the same node program (genotype), yet grows differently (“polymorphism” of the phenotype) as it senses its environment (e.g., anti-collision rules between the nodes and walls) (from Ulieru & Doursat 2010).

Agent functionality Another important aspect not included in the abstract model is the diversity of functional roles that agents may take on, in addition to their self-assembly capabilities. In practical situations the problem is in fact reverse: the challenge is to make already functional and specialized agents (PDAs, software agents) interact in a less centralized and more autonomous way (e.g., by carrying automated positioning devices that guide them toward optimal places). In any case, the model must now mix various *predefined* agent identities before they further differentiate by gradient position inside the structure. This natural heterogeneity of agents could be reflected in the model by a

heterogeneity of ports and gradients, and diversified attachment rules that depend on agent types. This would result in various *subnetworks* of two kinds: “intra-category” subnetworks linking agents of the same type and “inter-category” subnetworks combining agents of different types together.

Action plans Finally, the adequacy or “fitness” of the deployed network to the situation, both in its structure and function, might still have to depend on a two-way communication between the agents and a remainder of centralized command. Effective deployment might not always be able to rely on pure peer-to-peer self-organization at the local level. Depending on the problem at hand, certain types of techno-social networks might still need some amount of global monitoring and orchestration. Dynamical adaptation to a situation basically happens at two levels: (a) quick adaptation to local circumstances at the level of the agents (e.g., attraction, collision avoidance) *under the same rules of deployment* (Fig. 2.2.7a-d) and (b) major changes of strategy at the command level that *change the rules of deployment* (Fig. 2.2.7e). High-level action plans would set only the global course of the action (e.g., based on symbolic codenames), while the low-level implementation details are carried out by individual agent protocols (real-time positioning and linking). Action plans would be compiled down into local rules of attachment and broadcast to all agents. Thus, the network could adapt to new episodes by reprogramming the agents on the fly to create new formations.

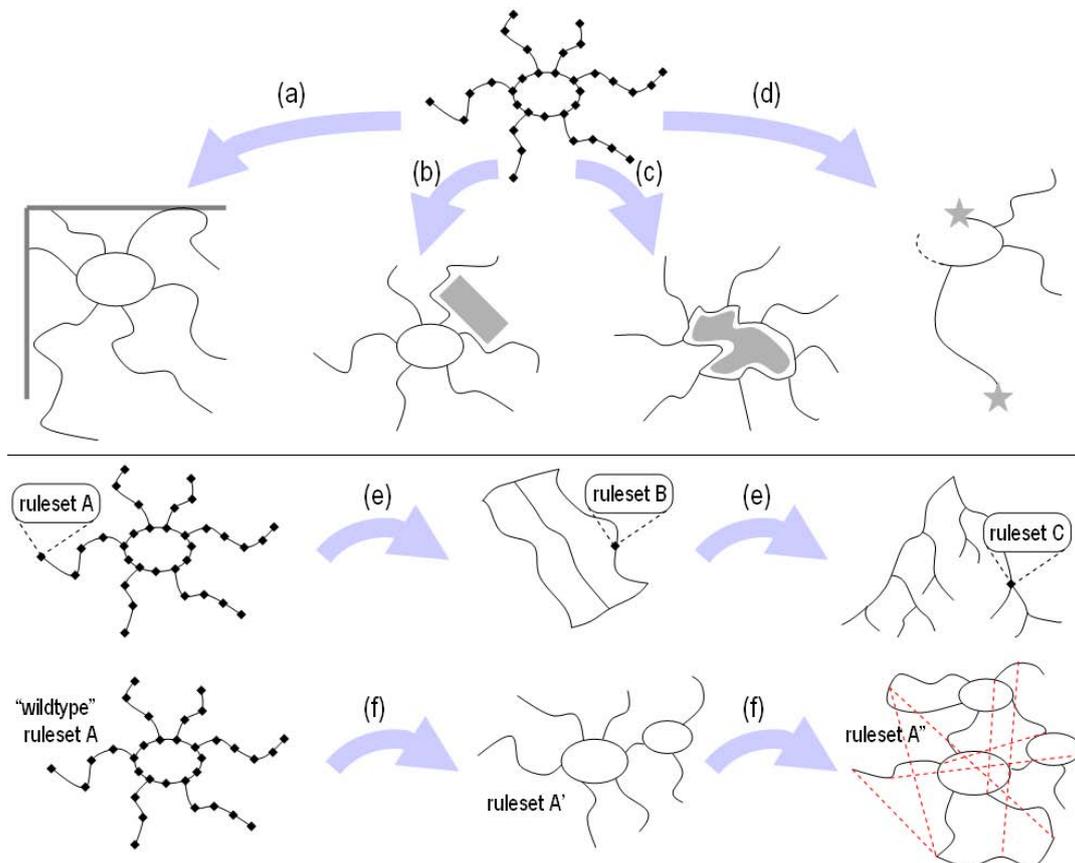


Figure 2.2.7: Schematic illustration of developmental vs. evolutionary changes. **Top: Polymorphism.** Endogenous network topologies (driven by an internal genotype) should have the ability to modify their growth according to the environment, under the *same* rules of self-assembly (same genotype), i.e., exhibit some degree of plasticity. For example, a free growing structure could (a) hit an obstacle and stop growth locally, (b) work around an obstacle, (c) be attracted by, and mold around a location of interest, (d) be triggered by, and connect certain cues in the environment. **Bottom: Evolution.** Endogenous topologies can also modify their rules (genotype) and create new modules and new structures. This is more drastic than polymorphism, as it involves qualitative innovation rather than limited quantitative plasticity. For example, (e) by switching between different prepared rulesets (stored or broadcast to all agents) or (f) by mutating and trying out new rulesets that were not written in advance. Note that, unlike biological evolution, this artificial evolution could happen on the same fast time scale as the development of the structure (“on-the-spot evolution”).

In summary, future work should expand the abstract algorithmic rules (gradient update G , port management P , and link creation L) to take into account spatial extension, external events, agent diversity, and hierarchical command. By implementing these four principles, in addition to intrinsic self-connectivity, scenarios of a self-organized *and* structured network could become practical. It would involve groups of agents that can create specific, but adaptive, spatial architectures to deal with specific situations. This dynamical process would be continuously adjusting to the dynamics of the external circumstances, including unexpected events and new effects.

Spinoff Projects

Project PROGNET-SOS

Emergent Engineering for the Management of Complex Crisis Situations

Possible collaborators: Mihaela Ulieru, Canada Research Chair; Computer Science Department, University of New Brunswick – Valeriy Viatkin, Program Director of Software Engineering, Department of Electrical and Computer Engineering, University of Auckland, New Zealand

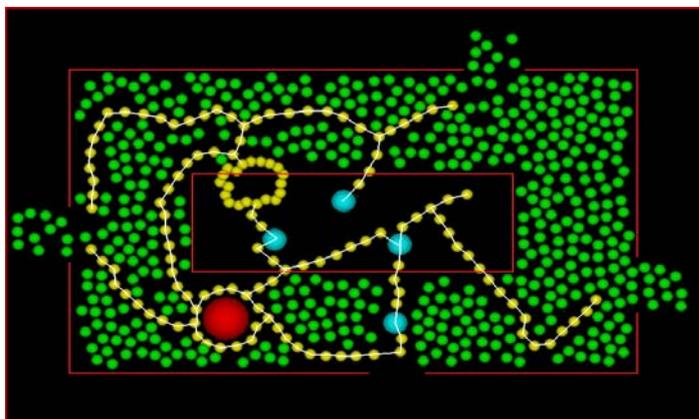


Figure 2.2.8: Schematic mockup view (not a simulation) of a possible SOS scenario within the space of a stadium, which would combine programmed networking and dynamic interaction with the environment. Growing cordons of security agents (orange) encircle the threat (red), guide the crowd (green) toward the exits, carry victims to emergency vehicles (blue, driving in and out through gates under the bleachers), and create special enclosed spaces on the field (cycle) (from Doursat & Ulieru 2008b).

Abstract: [From (Doursat & Ulieru 2008a)] We propose a methodological framework termed *emergent engineering* for deploying large-scale “eNetwork” systems in Self-Organized Security (SOS) scenarios (Ulieru 2008). It involves an abstract model of *programmable* network self-construction in which nodes execute the same code, yet differentiate according to position. These principles could lead to a future SOS application, in which a new type of *controllable* self-organization is able to dynamically co-evolve the system with its environment. During emergency response to an acute and developing disaster, several first responders come together in a collaborative endeavor and form joint teams, or “SOS networks”, to contain and manage a crisis situation. These teams are dynamic, short-lived *meta-organizations* deployed on the fly

from units belonging to different organizations such as military forces, police, firefighters, paramedics, or non-governmental organizations (Fig. 2.2.8). SOS consists of networks of agents interacting intensely with each other and generating a collective behavior that co-evolves with the environmental dynamics. The key issue when deploying emergency operations in an SOS system is to find the right balance between individual protocols and high-level policies in order to achieve the best possible collective meta-organizational behavior.

Project PROGNET-ENERGYWEB

Providing a framework for reducing energy consumption and encouraging the adoption of renewable energy sources by fostering the active involvement of prosumers and leveraging their potential for bottom-up innovation in a complex techno-social system.

Possible collaborators: Mihaela Ulieru, Canada Research Chair; Computer Science Department,

University of New Brunswick – **Daniele Miorandi, Iacopo Carreras**, Center for REsearch And Telecommunication Experimentation for NETworked communities (CREATE-NET), Trento – **Falko Dressler**, Autonomic Networking Group, Universität Erlangen

Abstract: [From our common FP7-ICT grant application *EnergyWeb*, April 2008] EnergyWeb aspires to develop the tools, theory, and methodology that can enable a novel, decentralized and collaborative energy grid paradigm (Silberman 2001, McMillin et al. 2006). It focuses on a projected future development in which energy production and consumption are distributed at the microscopic level of individual users, or “prosumers”. As a consequence, the degree of complexity increases dramatically as massive numbers of prosumers interact, making the EnergyWeb system fundamentally a complex system, akin to large self-organized sensor and actor networks (Dressler 2007) and autonomic computing (Kephart & Chess 2003). The migration from a centralized power production architecture to a distributed and autonomous grid production poses many new and important challenges. It cuts across various disciplines, including complex systems, network theory, agent-based modeling and simulations, distributed control, peer-to-peer architectures, economics, marketing and sociology. The spontaneous dynamics of traditional models of agent coalition (synchronization, clustering, pattern formation, swarm intelligence, etc.) need to be complemented with innovative *control dynamics*. In this context, an open research question is thus how to reintroduce a certain dosage of “programmability” inside free self-organization, but instead of being a top-down, external enforcement of global structures, the new controls would take the form of local internal instructions. Both the control and evolution of self-organization must rely on the existence of a “microprogram” inside every agent of the system, i.e., a set of parameters or instructions otherwise referred to as “genotype”. Through their genotype, agents can be controlled to display specific characteristics and can also be gradually modified toward new and improved behaviors. The more sophisticated the genotype becomes, the richer the variety and complexity of the overall performance, or “phenotype”, can be. Therefore, genetic-like regulation at the agent level could also be the key to controlling self-organization in techno-social complex systems such as EnergyWeb.

Relevant Publications

Full Papers – Books, Journals, Conferences, Workshops, Reports

Doursat, R. & Ulieru, M. (2008b) Emergent engineering for the management of complex situations. *2nd International Conference on Autonomic Computing and Communication Systems (Autonomics 2008)*, September 23-25, 2008, Telecom Italia Labs, Turin, Italy.

Doursat, R. & Ulieru, M. (2010) [TBA]. *In Preparation*.

Ulieru, M., Palensky, P. & Doursat, R., eds. (2009) *IT Revolutions: 1st International ICST Conference, Venice, Italy, December 17-19, 2008, Revised Selected Papers*, LNICST 11, Springer-Verlag.

Ulieru, M. & Doursat, R. (2010) Emergent engineering: A radical paradigm shift. *ACM Transactions on Autonomous and Adaptive Systems (TAAS)*. *To appear*.

Invited Keynote Presentations & Talks (with Abstracts) – Conferences, Workshops

Doursat, R. (2008h) Paradox in approaching complexity: From natural to engineered complex systems. *IT Revolutions 2008*, December 17-19, 2008, Telecom Italia Future Centre, Venice, Italy.

Doursat, R. (2010a) Embryomorphic engineering: From biological development to self-organized computational architectures. *4th EmergeNET Meeting: Engineering Emergence (EmergeNET4)*, April 19-20, 2010, St William’s College, York, UK. *Keynote address*.

Doursat, R. (2010b) Architecture and self-organisation: Heading for the best of both worlds. *Gartner Enterprise Architecture Summit*, May 17-18, 2010, London, UK. *Keynote address*.

Doursat, R. (2010d) [TBA]. *2nd Summer Solstice International Conference on Discrete Models of Complex Systems (SOLSTICE 2010)*, June 16-18, 2010, LORIA, CNRS, Nancy, France.

Doursat, R. & Ulieru, M. (2008a) Guiding the emergence of structured network topologies: A programmed attachment approach. “*Dynamics On and Of Complex Networks II*” *Workshop (DOON II)*, at *5th European Conf. on Complex Systems (ECCS 2008)*, September 14-19, 2008, Hebrew University, Jerusalem, Israel.

2.3. Project EVOSPACE: Spatial Evolutionary Dynamics

A spatially extended model of endogenous speciation in the absence of external environmental constraints.

A commonly held view in evolutionary biology is that *speciation*, i.e., the emergence of genetically distinct and reproductively incompatible subpopulations, is driven by external environmental constraints. **Guy Hoelzer**, **Rich Drewes** (University of Nevada, Reno) and myself have developed a spatially explicit model of a biological population to study the emergence of spatial and temporal patterns of genetic diversity *in the absence* of predetermined domains. We propose a 2-D cellular automata model showing that an initially homogeneous population might spontaneously segment into different species through sheer *isolation by distance*.

Speciation in Spatial Evolutionary Dynamics

The most common framework for understanding the process of biological speciation is a geographical one (Silvertown & Antonovics 2001). For example, instances of speciation are typically allocated into three categories based on the extent of geographical separation between the daughter species (Fig. 2.3.1a). *Allopatric speciation*, in which a species range becomes severed and leads to population fragments that are not linked by gene flow, has been viewed as the most common means of speciation (Mayr 1942). This process is easy to understand, because the independence of evolutionary processes (mutation, drift, selection) in populations that no longer communicate with one another would inevitably lead to reproductive incompatibility between such populations given enough time in isolation. It is also easy to observe the “fingerprints” of allopatric speciation in many instances, such as the endemism of terrestrial species on islands (e.g., Darwin’s finches; Grant & Grant 1997).

The other two categories involve speciation in the face of gene flow, and it is less clear what the compelling “fingerprints” of these processes might look like. In the second category, *parapatric speciation*, one species becomes two, where the daughter species occupy contiguous ranges. This has most often been modeled as a consequence of habitat variation and divergent local adaptation by subpopulations (e.g., Gavrillets 2004). *Sympatric speciation*, in which the ranges of the daughter species overlap, has similarly been modeled as a consequence of habitat variability (e.g., Dieckmann et al. 2004). Models of sympatric speciation suggest that discretely different microhabitats or resources are most effectively exploited by permitting specialization by two species rather than one.

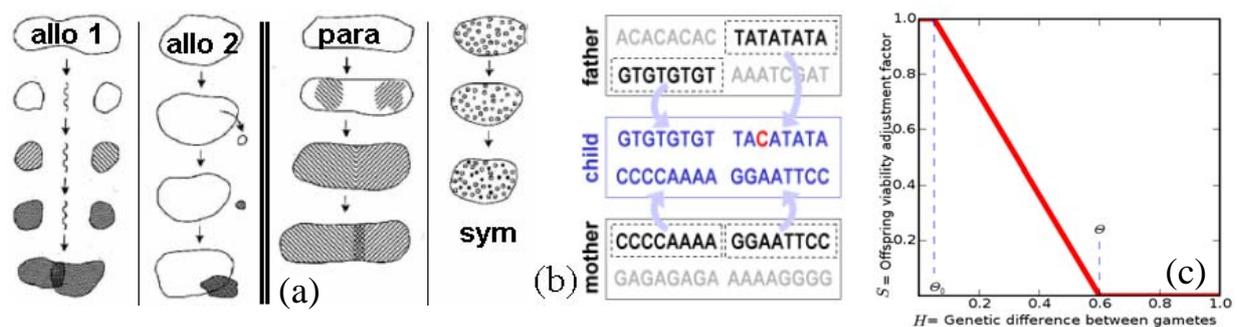


Figure 2.3.1: (a) Schematic illustration of the different geographical modes of speciation: allopatric (1: dichopatric, 2: peripatric), parapatric, and sympatric. (b) Rules of virtual genomics and sexual reproduction in the model (see text). (c) Outbreeding depression curve in the model: offspring survival probability as a function of genetic difference (see text) (from Hoelzer et al. 2008).

A common theme among all three of these categories is that speciation is induced by divisive, external factors and that the inherent tendency of biological populations is to remain unified in the absence of these factors. In other words, the conventional wisdom is that it is the environment that tears species apart. One well-known, but rare, situation where this view breaks down is in the case of ring species (such as seagulls; Irwin et al. 2001). In this paper we describe a model of a spatially extended

biological population suggesting that biological populations inherently and regularly tend to tear themselves into reproductively incompatible daughter species *without influence by external factors*. It illustrates the potential for functional decoherence (speciation) under “isolation-by-distance” (Wright 1943, Slatkin 1993).

Grid Model

We have implemented a generalized cellular automaton model of evolutionary processes called EVOSPACE. The simulated world is an $N \times N$ grid, where each cell is occupied by a certain number of individuals from a population. An individual contains genetic information in the form of a set of chromosomes and can migrate and mate with other individuals within a certain distance. A chromosome consists of a string of characters that can take one of four values representing the nucleotide bases A, C, G, and T. The number and length of chromosomes are the same for all individuals. During mating, an offspring is constructed by randomly selecting and combining two haploid genomes from the two diploid parents, possibly introducing random mutations in the process (Fig. 2.3.1b). Thus reproduction in our model is sexual, because genomes from two parents are combined to produce the offspring; but individuals are also hermaphrodites, as any adult can potentially mate with any other adult.

At every generation, i.e., time step in the model, migration, mating and mutations create similarly structured but genetically distinct offspring for the next simulated generation. First, individuals can randomly move on the grid world within bounds determined by a *dispersal distance*. Then, they can choose a mate within similar bounds. Finally, after mating, each offspring is placed in a random cell in the vicinity of one of the parents while the parents die, so only one generation lives on the grid at each time step. The mean reproductive rate in the population is regulated each generation to buffer swings in population size resulting from a variety of factors, such as stochastic mortality (see below). This is achieved by randomly removing individuals or generating additional offspring. Simulations begin at generation 0 with a population of genetically identical individuals, set to some fraction of the maximum potential population size, and the system is allowed to evolve for hundreds to millions of generations.

For the experiments described in this work, the habitat across the grid environment is homogeneous, so location per se does not influence the fitness of individuals. However, we introduce one important dependency: the offspring’s *survival probability* as an increasing function of the *genetic difference* or “incompatibility” between merging gametic genomes. Expressing the genetic difference between two chromosomes as a fraction between 0 (nucleotide identities at all positions of the DNA sequence were identical) and 1 (nucleotide identities at all positions of the DNA sequence were different), offspring resulting from gametes with a genetic difference greater than a threshold θ has zero survival probability (we use $\theta = 0.6$ in this study). This function of declining reproductive compatibility with genetic difference, or *outbreeding depression* (Fig. 2.3.1c), is central to the exploration of speciation in this model because reproductive isolation between sexual species lies at the core of the concept of speciation. It is, in fact, the fundamental criterion embodied in the definition most commonly assumed in the context of evolutionary biology, the “Biological Species Concept” (BSC) (Mayr 1942). Our rule for reproductive isolation between species is somewhat more restrictive than the BSC requires, because real species can be genetically compatible, but behaviorally incompatible. For a comprehensive discussion of reproductive compatibility functions in speciation models see Gavrilets (2004).

Results

To measure the performance of the model and produce graphs clearly showing that our model can exhibit speciation, we use different types of statistical quantities, among which *mismatch distribution histograms* and *genetic cluster plots*. To assess the emergence of genetically distinct subpopulations, all measurements are based on a common definition of genetic difference between gametes, as described above, which influences offspring viability.

Mismatch distribution histograms (Rogers & Harpending 1992) reveal the frequency distribution of genetic differences among the genomes in the population(s). The horizontal axis is the genetic difference and the vertical axis shows the number of pairs of gametes found with that degree of genetic difference (Fig. 2.3.2). In this plot, a population of genetically *random* individuals appears as a single distinct peak at .75 (with a small standard deviation), because of the 25% probability that two bases are identical at any particular position of the DNA sequence. In the case of a population of genetically *identical* genomes—the starting condition for our simulations—the plot shows a single sharp peak at 0. As mutations lead to genetic divergence, the general tendency for peaks is to spread out and travel to the right in the mismatch distribution.

Observing time-sequence movies of these mismatch distributions under different model conditions reflects the spatiotemporal patterns of gain and loss of genetic diversity, especially as it reveals the origin and existence of distinct subpopulations (traveling waves along the distribution). We present a series of snapshots in Fig. 2.3.2 as a glimpse into the dynamics of these systems. In the absence of outbreeding depression, the single initial peak on the histogram centered on 0 spreads and moves to the right, as predicted. When the space is large enough, this primary peak becomes centered on a genetic difference of 75%, as expected under the Jukes-Cantor mutation model (Jukes & Cantor 1969). However, for certain combinations of grid size (sufficiently large), dispersal distance (sufficiently short), and mutation rate, additional dynamical patterns emerge. We were particularly interested in tracking the diversity waves described by Rogers & Harpending (1992). Indeed, small secondary peaks arise at low levels of genetic difference (left side of the mismatch distribution), move to the right and often persist long enough to merge with the primary peak. This observation is consistent with previous findings on spatial self-organization under isolation-by-distance (e.g., Sayama et al. 2000, Hoelzer 2001, Hogeweg & Takeuchi 2003, Rauch et al. 2003).

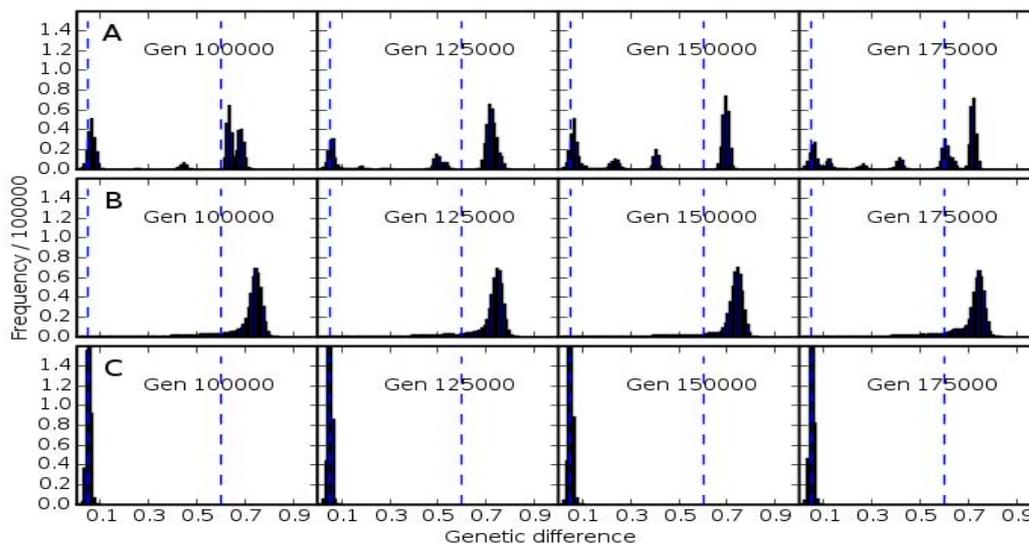


Figure 2.3.2: Time series of mismatch distribution histograms. Snapshots of frequency histograms of the genetic difference of randomly selected pairs of individuals from three runs, setting (A) low movement distance $\delta = 1.5$ with outbreeding depression $\theta = 0.6$, (B) low movement distance $\delta = 1.5$ with no outbreeding depression, and (C) larger movement distance $\delta = 5.0$ with $\theta = 0.6$. Plots are shown horizontally for a sequence of four generations (100,000, 125,000, 150,000, and 175,000) within each of the conditions A, B, C. Note that the number of peaks does not correspond directly to the number of distinct genetic types in the population (from Hoelzer et al. 2008).

The patterns we detect in intraspecific dynamics are greatly enhanced by introducing the outbreeding depression function. Along with sharpening the degree of spatial organization that emerges (see next section), outbreeding depression strongly increases the frequency, amplitude and persistence of the secondary peaks appearing in the mismatch distributions. As these peaks move to the right of θ , the subpopulations being compared encounter an increasingly stringent demographic disadvantage, because when individuals from those subpopulations mate with each other their offspring are

decreasingly viable. Divergence occurs as a consequence of mutation in our model, so divergence continues as the demographic cost of outbreeding depression increases the chance of subpopulation extinction. Nevertheless, sometimes a peak becomes established to the right of θ indicating a comparison between subpopulations that have diverged to the point where individuals from these subpopulations can no longer interbreed. We believe that in this way our model is realistically modeling important aspects of speciation.

We have further found that the development of new, stable peaks to the right of θ (new species, we argue) is quite sensitive to the interrelationship of the spatial scale of the simulation (grid size and dispersal distance), the mutation rate, and other factors. If the mutation rate is slightly too high, then overall genetic diversity increases rapidly until it is too hard to find viable mating pairs within reproduction range and the whole population goes extinct. If the mutation rate is slightly too low, subpopulations go extinct before speciation can be completed. We are working now to systematically examine parameters under which speciation occurs (see “Future work” below).

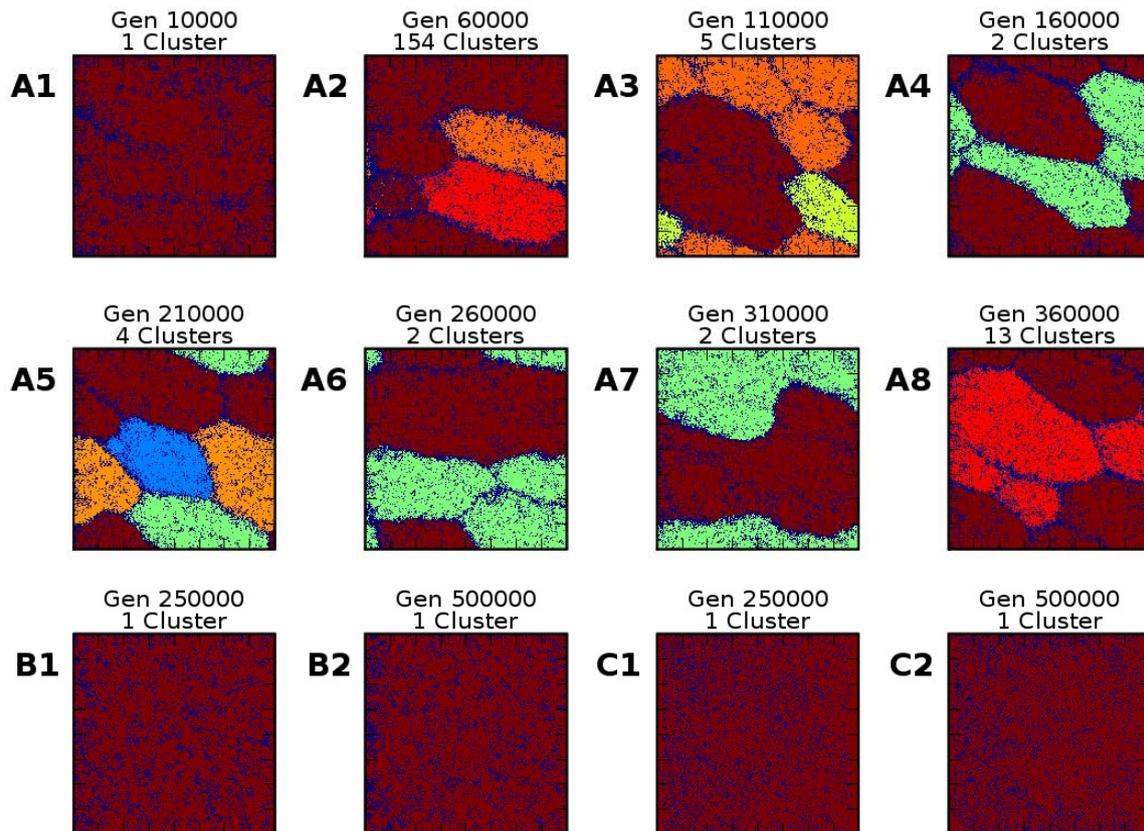


Figure 2.3.3: False-color depiction of genetic clustering on the world grid. Dark blue represents unoccupied cells or cells not connected to any cluster. Each other color represents genomes identical at more than 40% (i.e., genetic difference < 60%). Using this threshold in combination with $\theta = 0.6$ helps identify different species with different colors. (Note that colors were assigned anew in each plot; the clustering algorithm is probabilistic; and some clusters are too small to discern.) Plots (A1) through (A8) depict snapshots of the clustering state at eight different generations with distance $\delta = 1.5$ and outbreeding depression threshold $\theta = 0.6$. Plots (B1) and (B2) were generated under $\delta = 1.5$ without outbreeding depression and show no evidence of clustering at the difference threshold of 60%. The (C) plots, for $\delta = 5.0$ and $\theta = 0.6$, present a similar lack of clustering (from Hoelzer et al. 2008).

Genetic cluster plots prove useful in examining the *spatial* clustering of distinct subpopulations. Whereas the mismatch distribution provides good insight into the existence of distinct, internally homogeneous subpopulations, it does not demonstrate whether clusters are spatially segregated on the lattice or show where they are located. Genetic cluster plots are obtained by grouping pairs of individuals that have a genetic distance lower than a given level and displaying those groups in

different colors (Fig. 2.3.3). These plots clearly illustrate the spatial self-organization that emerges in our model. Visual examination indicates that the genetically homogeneous subpopulations revealed by the histogram plots also form distinct spatial clusters that occupy coherent, non-overlapping regions of the lattice. The borders between these regions tend to be unoccupied, or occupied with hybrid individuals that are not genetically similar enough to any neighboring region to be classified with them.

Spatial plots such as isolation-by-distance and genetic clustering also demonstrate the strong sharpening effect of outbreeding depression. The intrinsic tendency of the grid world toward spatial order is greatly enhanced by introducing a dependence between compatibility and viability. It could be said that outbreeding depression plays a negative feedback role analogous to long-range inhibition in morphogenetic reaction-diffusion processes (Turing 1952, Gierer & Meinhardt 1972). In this analogy, mating plays the positive feedback role of short-range activation. Together, these effects contribute to the spontaneous formation of “spots” by encouraging neighboring elements to be similar and, at the same time, distant elements to be different. In a sense, our model represents “evolutionary pattern formation” at the scale of populations of organisms instead of molecules or cells.

Future Directions

New Measurement Tools

We have already begun to statistically characterize the self-organizing behavior of the unconstrained version of EVOSPACE. We propose to do a thorough job of this as a basis for comparison with strategically constrained versions of the model. We specifically plan to characterize the following:

- the threshold of boundary emergence as a function of the dispersal kernel and spatial scale;
- the characteristic number of individuals in newly emerging subpopulations
- the characteristic number of individuals in larger subpopulations that become unstable and subdivide;
- the frequency distribution of lineage persistence times for both genetic lineages and subpopulations;
- how all of these statistics are modified in the proximity of (1) hard edges at the limit of the landscape (straight, convex and concave edges) and (2) partial barriers to dispersal within the range of the system.

This will lead to a quantitative demographic description of the spatial evolutionary dynamic at the scale(s) of emergent subpopulations (and species defined by total reproductive isolation).

Phase Space Exploration

We also plan to take advantage of the computational power of a computing grid to systematically explore key dimensions of phase space for the EVOSPACE model. EVOSPACE reaches a state of dynamic equilibrium where traces of the genetic homogeneity of the initial conditions have disappeared in roughly 50K generations, although this “burn-in” phase can vary with run conditions. Therefore, each simulation run on the grid will extend for 200K generations. There are four fundamental parameters we plan to investigate by systematically tuning their values, and run simulations for different combinations of factors:

Dispersal distance is adjusted using the EVOSPACE variable δ , the radius of the individual movement neighborhood and the mating neighborhood. This variable will be set at increments of 1-cell starting at $\delta = 1.5$ and ending at the point where the system behaves as though it were well mixed (we estimate this to be about $\delta = 8$ on an 800x800 grid).

Mutation rates There is a range of mutation rates under which spatial self-organization will occur, given other parameter values. If mutation rate is too low, the system effectively mixes the little

variation that exists. In other words, the system is able to drift fast enough to keep up with mutation without subdividing. If the mutation rate is too high, the system is unable to spatially organize fast enough to keep up with mutation. We will discover the marginal mutation rates at which self-organization manifests under the range of conditions we will explore, then divide that range of rates into 10 increments for exploration.

Empty space It was clear from our study of speciation in EVOSPACE that empty space can affect spatial evolutionary dynamics. Therefore, we plan to explore behavior of the model with the amount of empty space set to 0, 10%, etc., up to 60%. Population size will be held constant for these comparisons, while the size of the grid is varied.

Outbreeding depression There are two parameters to vary in our broken stick model of outbreeding depression: the degree of genetic difference at which outbreeding depression begins to appear and the degree of genetic difference at which reproductive compatibility is eliminated. We will set the former at 4%, 6%, 8%, and 10%. Previous observations suggest that this value determines the extent of genetic diversity allowed to accumulate within emergent subpopulations, so we expect it will also scale with the maximum size of subpopulations. The latter, the “speciation point”, will be set at 10%, 30%, and 50%. This will address the effect of the outbreeding depression slope and the importance of speciation speed (assuming the “Biological Species Concept”) on spatial evolutionary dynamics. Closely related work by Gavrillets (2004) has assumed a stepped outbreeding depression function (sudden and complete onset of outbreeding depression), so varying our outbreeding depression function as described should help connect our results with his.

Environmental Matrix

EVOSPACE has been studied so far under a “null” environmental matrix to investigate the dynamics of spatially extended populations in the absence of external constraints. However, real landscapes generally impose constraints of various kinds on evolutionary dynamics. These constraints can be roughly divided into two kinds, local obstruction of dispersal and ecological selection, which have been previously identified as potential external causes of population subdivision. There is no doubt that such external factors can impose spatial boundaries on subpopulations. The question raised by EVOSPACE is: how does pattern formation through self-organization interact with external constraints? For example, we will explore “edge effects” (e.g., Minor et al. 2008), i.e., reflective boundaries on the grid space, such as: hard edges, periodic boundaries, curved “river” boundary through the middle of the grid, etc.

Relevant Publications

Full Papers – Books, Journals, Conferences, Workshops, Reports

Hoelzer, G., Drewes, R., Meier, J. & Doursat, R. (2008) Isolation-by-distance and outbreeding depression are sufficient to drive parapatric speciation in the absence of environmental influences. *PLoS Computational Biology* 4(7): e1000126 [doi:10.1371/journal.pcbi.1000126].

Abstracts (for Presentations or Posters) – Conferences, Workshops

Hoelzer, G., Drewes, R. & Doursat, R. (2006) Temporal waves of genetic diversity in a spatially explicit model of evolution: Heaving toward speciation. *6th International Conference on Complex Systems (ICCS 2006)*, June 25-30, 2006, New England Complex Systems Institute (NECSI), Boston, MA (presenter: G. Hoelzer).
 Hoelzer, G., Drewes, R. & Doursat, R. (2008) Speciation through spatial self-organization of the gene pool. *12th Evolutionary Biology Meeting (EBM 2008)*, September 24-26, 2008, Université de Provence, Marseille, France (presenter: G. Hoelzer).

3. Neural Dynamics: Large-Scale Spiking Neural Networks

Mesoscopic emergence, interaction and composition of spatiotemporal patterns of activity and connectivity.

“How could you,” began Mackey, “how could you, a mathematician, a man devoted to reason and logical proof . . . how could you believe that extraterrestrials are sending you messages? How could you believe that you are being recruited by aliens from outer space to save the world?” ... “Because,” Nash said slowly in his soft, reasonable southern drawl, as if talking to himself, “the ideas I had about supernatural beings came to me the same way that my mathematical ideas did. So I took them seriously.”

—Sylvia Nasar, *A Beautiful Mind*

Toward a Mind-Brain “Modern Synthesis”, via Complex Systems

The foundational thesis of cognitive science is that the mind relies on internal dynamical “states”, “regimes” or “representations” that correspond to (or are triggered by) states of the external world. It operates by creating, assembling and transforming these states, both under the influence of external stimuli and the constraints and meanders of its own internal dynamics. The nature and structure of these brain states, however, is still an open question, in particular their embodiment in the *neural code*, i.e., the laws of organization of electrophysiological signals. When trying to bring an answer to this deep problem, however, the multidisciplinary nature of cognitive science appears to be more of an obstacle than an advantage. According to Bechtel & Graham (1998, p3): “Cognitive science is the multidisciplinary scientific study of cognition and its role in intelligent agency”, and the same authors ask: “Do [these disciplines] interact substantively—share theses, methods, views—or do they simply converse?”. Currently, this field can only be defined extensionally as a vast federation of disciplines (psychology, AI, linguistics, logic, neuroscience, neural modeling, robotics, etc.) with widely different viewpoints, but fundamentally lacking a “central theory” that would unify them around a common set of laws—as was the case, for example, when molecular biology provided the missing connection from physics and chemistry to genetics and evolution. In fact, in many languages cognitive science is designated in the plural, such as *sciences cognitives* in French.

Moreover, across these various cognitive disciplines, theoretical models are broadly divided between a logical paradigm, or “cognitivism”, and a dynamical paradigm, or “connectionism”. Similarly to the epistemological scale where physics, chemistry and biology occupy increasing levels of organization of the matter and emergent phenomena (particles → atoms → proteins → cells → organisms → ecosphere), cognitive science could also be viewed along a vertical axis, where dynamical systems occupy the lower levels (networks of neuronal activities) and formal systems, the higher emergent levels (psychological and linguistic entities). Toward the top of this axis, logical models define high-level symbols and formal grammars, but do not possess the microstructure needed to account for the fuzzy complexity of perception, memory or learning (Smolensky 1988). Conversely, toward the bottom, dynamical models define functionality as a product of neural networks and low-level activation equations, but lack the macroscopic level supporting the systematic symbol composition abilities of language and planning (Fodor & Pylyshyn 1988). In the middle, between symbol-based AI architectures and node-based neural computation, there is a lingering theoretical gap. Bridging this gap will require an intermediate, or *mesoscopic*, scale of description of cognitive functions, which must offer finer granularity than symbols but larger structural complexity than small artificial neural nets. This effort can be accomplished from two complementary directions:

Top-down approach: The underlying microstructure of symbolic systems When DNA, RNA, proteins and cell components were discovered, evolution and genetics became united into biology’s Modern Synthesis. In other terms, by elucidating the mesoscopic level of life’s complex self-organization (molecular and cell biology), macroscopic emergent phenomena (heredity, speciation) could be explained on the basis of microscopic elements (atoms and small molecules; Fig. 3.1a). By

contrast, the inner structure of the mind's representational states is not yet known. Psychology, AI or symbolic grammars do not yet possess the explanatory foundations that a truly dynamic level of cognition could offer. Therefore, a new discipline of “molecular cognition” (Bienenstock 1995, 1996; Fig. 3.1b) might be needed to provide the laws of perception and language on the basis of elementary neuronal dynamics. What could then be the candidate “molecules” of cognitive science's new Mind-Brain Modern Synthesis? In this sense, a discipline like *cognitive linguistics* (e.g., Talmy 2000, Langacker 1987, Lakoff 1987, Jackendoff 1983; see review in Croft & Cruse 2004) constitutes an original first top-down attempt at digging under the surface in the search of protosemantic elements. For example, a verbal schema like ‘to give’ involves three participants, subject, object, and recipient, that have the potential to interact and bind in a topological-temporal space (transfer between domains of ownership, etc.). It is therefore much more than a mere symbolic node in a syntactic parsing tree.

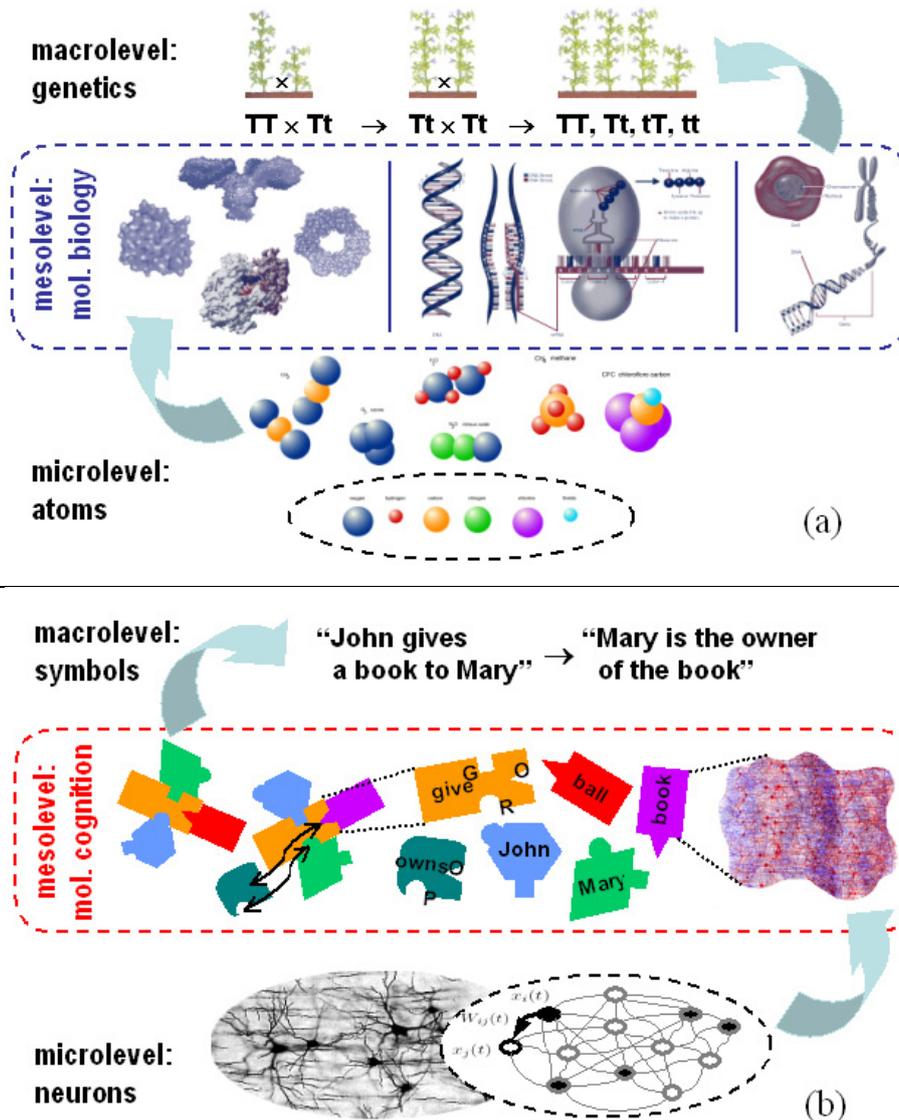


Figure 3.1: Metaphorically speaking, cognitive science in the 21st century (bottom) faces the same type of challenge as biology did in the 20th century (top). Between the microscopic level (atoms \leftrightarrow neurons) and the macroscopic level (genetics \leftrightarrow symbolic abilities), there remains to discover the central mechanisms and theory (DNA, RNA, proteins \leftrightarrow ???) at appropriate mesoscopic level(s) of description. This new kind of “Mind-Brain” Modern Synthesis needs to establish a proper “microstructure” for the symbolic level (top-down in (b)), while at the same time providing a complex systems perspective of the elementary components (bottom-up in (b)). It is suggested here that this endeavor could hinge on compositional “building blocks” made of spatiotemporal patterns of neural activity (red frame in (b); after Bienenstock 1996).

Bottom-up approach: Emergent macrostructures in complex dynamical systems At the lower end of the spectrum reside neuroscience and neurally inspired dynamical systems. These physicalist or “dynamicist” approaches, which bear no resemblance to logical-combinatorial systems (van Gelder & Port 1995), start with the neurons and attempt to derive their collective behavior analytically and numerically. Despite their relative success, however, they were criticized (Fodor & Pylyshyn 1988) for not explaining the higher properties of *constituency* and *compositionality* (Bienenstock 1996). For classical cognitivism and AI, intelligence relies on symbols (constituents) that can be assembled (composed) by syntactic rules in a systematic and generative way. Mainstream connectionism, however, has focused on memory, learning and perception, through chiefly *associationist* models (a group of cells activates another group of cells). An alternative and promising school of neural modeling has advocated *temporal correlations* between neural activities as the key to the “binding problem” (see review in Roskies 1999) and the basis of the brain’s code, both in theoretical and experimental studies. This hypothesis launched a new series of models looking at *synchronization* among coupled excitable units (e.g., oscillatory; König & Schillen 1991, Campbell & D. L. Wang 1996, Buzsáki & Draguhn 2004, D. L. Wang 2005). Such phenomena on the larger population scale hold a great potential for supporting the microstructure of symbolic and combinatorial systems.

The overall theoretical objective of my research in computational neuroscience is thus to span a bridge between these two opposite ramps, prepared by cognitive linguistics on the one side and temporally synchronized neural networks on the other side. Today’s machines, which surpass humans in computationally intensive tasks, are still surpassed by children in simple scene recognition, story understanding or interactive behavioral tasks. The reason for this persistent hiatus is that most artificial systems are engineered either directly as symbolic machines (macro levels) or as associationist/reactive systems (micro levels) but never rely on the same type of “building blocks” that the mind uses at the subsymbolic/supraneuronal meso levels. Yet, these blocks might be the key to a true *representational invariance*, i.e., schemas (cognitive, perceptual or motor), categories and constituents, which can only be addressed by complex, biologically inspired engineered systems.

From Rate Coding to Temporal Coding to Spatiotemporal Patterns

As mentioned above, there is yet a finer split within the connectionist/dynamicist framework. Traditionally, the great majority of neural models proposed by theoretical and computational neuroscience over the last decades have followed an overly literal “signal processing” paradigm originating from engineering thinking. In this (somewhat naive) perspective, pioneered by cybernetics and later reestablished by artificial neural networks in the 1980’s, a few coarse-grain units are able to perform high-level meaningful functions, such as feature or concept detection. These units are organized into hierarchical, multilayered architectures, in which activity is actually “flowing” from the input (i.e., the “problem” at sensory level) to the output (i.e., “the solution” at motor level) through successive transformations (e.g., in visual perception, Serre et al. 2007). It is also entirely stimulus-driven, i.e., in these architectures neural layers are initially silent and must wait to be activated.

Recently, however, entirely new ways of construing complex neural systems have been gaining ground, toward a more genuinely *complex emergent* view of neural activity. In particular, documentation of (a) pervasive lateral and *feedback connectivity* (e.g., Binguier et al. 1999) and (b) *persistent* (e.g., X.-J. Wang 2001, Y. Wang et al. 2006) or *ongoing activity* (e.g., Kenet et al. 2003, Fox & Raichle 2007) in the absence of explicit input or output both challenge the traditional view that “lower” areas are necessary to activate “higher” areas, or that there is a fixed hierarchy of “receptive fields”. Instead, the emphasis is now set on *myriads* of fine-grain neurons interacting through dense *recurrent* connections. In this new schema, external stimuli are no longer an essential driving force but only play a secondary role of “perturbation” or “influence” exerting itself on already active patterns (Llinas 2001, Harris 2005)—possibly poised at “criticality”, i.e., ready to switch quickly between states: evoked, bound/composed, unbound/competing, dismissed, etc. Shifting this paradigm even further, it is proposed here that these complex neuronal systems form the substrate of “excitable media” capable of producing endogenous activity in the form of dynamic, transient, *spatiotemporal patterns of activity* (Bienenstock 1995). In sum: it is not because the brain is an intricate network of microscopic causal signal transmission (a neuron activates/inhibits other neurons) that the appropriate functional description at the *mesoscopic* and macroscopic scales is indeed a flow of signal processing.

The importance of temporal coding The structure and properties of representational states has often been debated since the beginnings of modern neuroscience but it was generally admitted that the *average firing rate* of neurons constituted an important part of the neural code. In short, the classical view holds that mental entities are coded by cell assemblies (Hebb 1949), which are spatial patterns of average activity (see also Ermentrout 1998). By contrast, following Christoph von der Malsburg’s “Correlation theory of brain function” (1981) and the work of my thesis advisor Elie Bienenstock (see, e.g., von der Malsburg and Bienenstock 1986), I have defended another format of representation that involves higher-order moments or *temporal correlations* among neuronal activities. Here, mental representations are not exclusively based on individual mean activity rates $\langle x_i \rangle$, which are events of order 1, but more generally on order-N events $\langle x_{i1} x_{i2} \dots x_{iN} \rangle$ and, in particular, correlations between two neurons, $\langle x_i x_j \rangle$.

Naturally, the traditional order-1 code stems from classical observations in the primary sensory areas (e.g., visual cortex), in which cells seem to possess selective response properties. From these experiments, it was inferred that one such neuron, or a small cluster of neurons, could individually and independently represent one specific type of stimulus (e.g., the orientation of an edge). Then, to obtain the global representation of an object, these local features must be linked and integrated. The problem is that this integration is unlikely to be carried out by highly specialized cells at the top of a hierarchical processing chain (the conjectural “grand-mother” cells that fire only when you see your grand-mother). Equally unlikely would be for the assembly of feature-coding activity rates to be maintained in a distributed state because of the impossibility to overlap two such states without losing relational information (the so-called “binding problem”). If two cells coding for “red” and “circle” are active and two other cells coding for “green” and “triangle” also become active, then this global state of mean activation is unable to distinguish the original stimulus “red circle and green triangle” from an alternative stimulus “red triangle and green circle” (von der Malsburg 1987; Fig. 3.2b).

This is why we advocated the idea that feature integration required higher-order codes to be able to represent *relationships* between elementary components that are initially uncorrelated (in the above example the spike trains of “red” and “circle” would be synchronous, but out of phase with “green” and “triangle”, also in sync). These correlation events bring to the representation format a *structure* that is fundamentally missing from the mere feature lists of Hebbian cell assemblies. To continue the chemical metaphor, we could say that feature lists are to molecular formulas (e.g., C_3H_8O) what correlations are to structural line-bond diagrams (e.g., 1-propanol vs. 2-propanol; Fig. 3.2a).

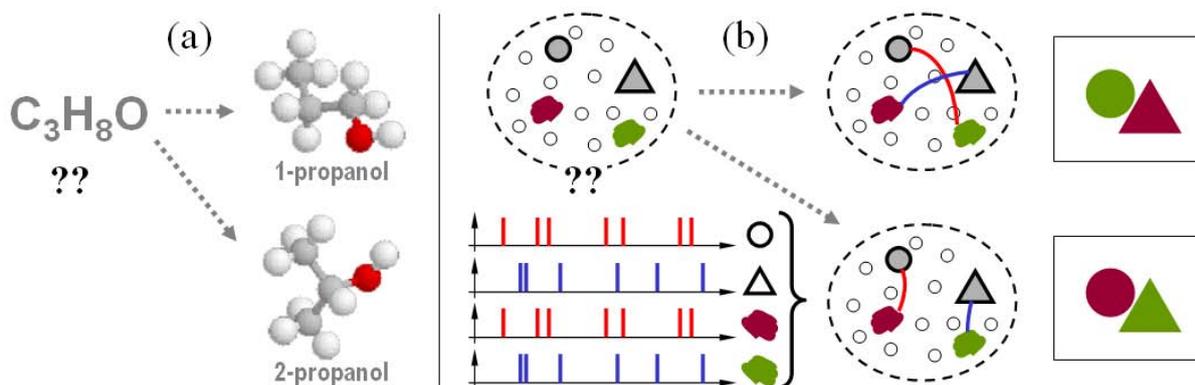


Figure 3.2: Solving the binding problem through temporal correlations. (a) An ambiguous molecular formula is resolved by revealing its internal bond structure. (b) In the same way, an ambiguous rate-coding representation (in which four feature detectors coding for “red”, “circle”, “green” and “triangle” are simultaneously active) can be resolved by revealing its internal spatiotemporal structure—e.g., in the bottom configuration, “red” and “circle” are bound by synchronization between their spike trains.

Complex spatiotemporal patterns Expanding upon these last remarks, it is also hypothesized that temporal coding is employed beyond the mere binding of two features to actually provide the generic “glue” for the microstructure of large objects. In the molecular metaphor, temporal binding and synaptic plasticity together play the role of elementary forces or “bonds”, which can have various amplitudes: strong “covalent” bonds maintain the cohesiveness and stability inside STPs, while

weaker “ionic” or “hydrogen” coupling quickly assemble and disassemble STPs on a larger scale (Bienenstock 1995). Formally: if $x_i(t)$ denotes the time-varying potential of neuron i , then the “cognitive molecules” postulated above could be implemented by dynamic cell assemblies made of large, coherent sets of neuronal activities $\{x_1(t), \dots, x_n(t)\}$. In particular, such a set can be described as a *spatiotemporal pattern* (STP), which is a complex series of spike timings $\{t_1^1, t_1^2, t_1^3, \dots, t_n^1, t_n^2, t_n^3, \dots\}$ containing many high-order statistical moments $\langle x_i(t) x_j(t - \tau_{ij}) x_k(t - \tau_{ik}) \dots \rangle$. These moments are typically combinations of synchronized groups (delays $\tau_{ij} = 0$) and waves or “rhythms” (delays $\tau_{ij} > 0$). They correspond to reproducible *temporal correlations* among electric signals, supported by underlying regular patterns of connectivity. Hence, similarly to proteins, STPs can interact in several ways and assemble at several levels, forming a hierarchy of complex structures from simpler ones in a modular fashion. Thus, by relying on temporal coding, STPs might constitute the building blocks of intelligent behavior.

Rebuilding Compositionality from the Ground Up

Complex spatiotemporal phenomena in large-scale neural populations have the potential to support the sought-after mesostructure of symbolic and combinatorial systems. Thus the theoretical proposal is that representations at the mesoscopic scale can be embodied in local but large-scale *dynamical states* or “mesoscopic patterns” of bioelectrical activity forming quasi-discrete entities. These mesoscopic patterns are (a) endogenously produced by the neuronal substrate, (b) exogenously perturbed under the influence of stimuli and (c) interactively binding to each other.

(a) Mesoscopic patterns are endogenously produced (Fig. 3.3a) Given a certain connectivity pattern, cell assemblies exhibit various possible *dynamical regimes* / modes / patterns of ongoing activity. The underlying connectivity is itself the product of *epigenetic* development and *Hebbian* learning, moulded by feedback from activity. The identity / specificity / stimulus-selectiveness, or in short the “*shape*”, of a mesoscopic entity is largely, but not exclusively, determined by its internal pattern of connections.

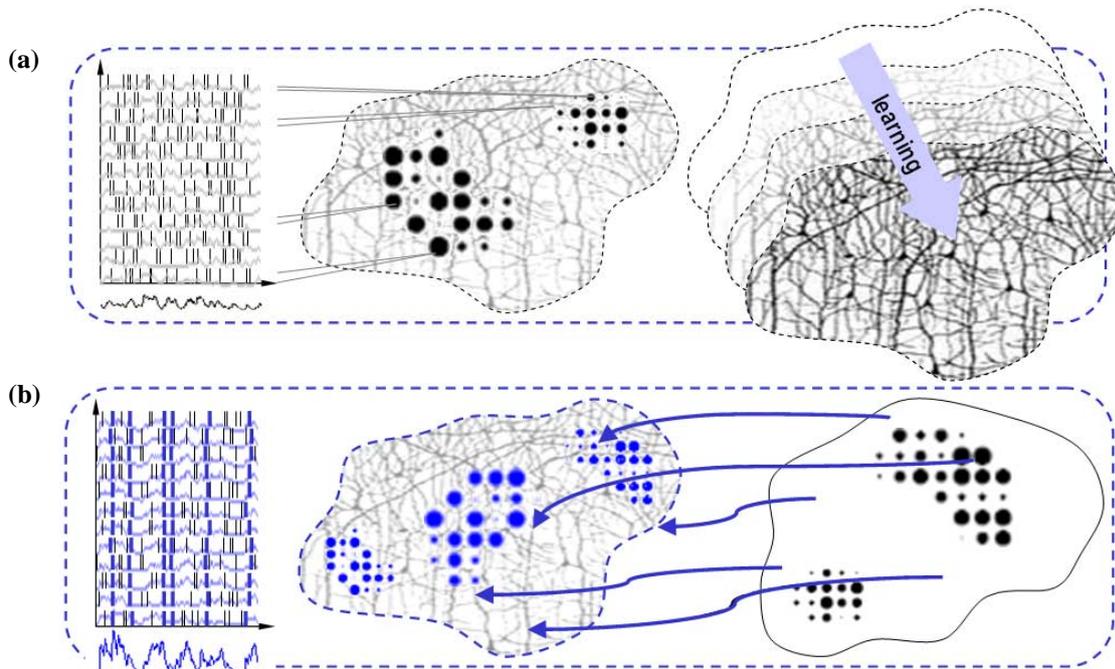


Figure 3.3: Schematic illustration of mesoscopic pattern dynamics. (a) Patterns are endogenously produced. Left: raster of spikes; center: evocation of a spatiotemporal pattern of neural activity; right: evolution of the underlying synaptic connectivity by learning. (b) Patterns are exogenously influenced. Right: stimulus pattern impinging on previous pattern; left: in this case, the effect was to enhance an alignment of spikes, revealed by a greater oscillatory amplitude of the mean field potential (bottom).

(b) Mesoscopic patterns are exogenously influenced (Fig. 3.3b) External stimuli (via other patterns) may *evoke and influence* the pre-existing dynamical patterns of a mesoscopic assembly. They constitute an indirect *perturbation* mechanism, not a direct activation mechanism (Harris 2005). Mesoscopic entities may have stimulus-specific *recognition or “representation”* abilities, without being “templates” or “attractors” (no resemblance to stimulus).

(c) Mesoscopic patterns interact with each other (Fig. 3.4b) Populations of mesoscopic entities can compete and differentiate from each other to create specialized recognition units (under an evolutionary population paradigm). Alternatively or concurrently, they can also bind to each other to create composite objects, via some form of temporal coherency based on synchronization, correlations and fast synaptic plasticity (under a molecular compositionality paradigm).

Understanding the laws of self-organization, and induced organization, of the neural signals supporting those entities should become the main topic of a new *mesoscopic neurodynamics* (Freeman 2000). In recent years, encouraged by multi-electrode recordings, brain imaging and increased computing power, this discipline has greatly progressed through the large-scale modeling and simulation of biologically realistic spiking neuron networks (see, e.g., review in Brette et al. 2007). Taking into account the fine timing of membrane potentials has revealed a great diversity of possible, and plausible, *spatiotemporal* regimes of cortical activity in large cell populations: synchronization and phase locking (e.g., Campbell & D. L. Wang 1996), delayed correlations and traveling waves (e.g., Diesmann et al. 1999), regular rhythms and chaos (e.g., Brunel 2000), etc. All these regimes are candidates for supporting the above-mentioned mesoscopic entities of cognition.

Populating the Mesoscopic Level with Models of Complex Neurodynamics

In summary, while individual firing rates $\langle x_i(t) \rangle$ have traditionally dominated neuroscience, alternative theories (von der Malsburg 1981, Abeles 1982) have long proposed temporal code and higher-order correlations as the basic code used by the brain to represent mental entities. Since the 1980's, the correlation hypothesis launched a series of experiments (e.g., Gray & Singer 1989) and models (e.g., König & Schillen 1991, D. L. Wang 2005) investigating synchronization and wave patterns among oscillatory or otherwise excitable units. This new field of neural dynamics is known today under the broad appellation of *spiking neural networks*.

Different spiking neural models have focused on different classes of neuronal dynamics at varying levels of biological detail: conductance-based, integrate & fire, pulsed, oscillatory, excitable, rate-coded, binary, etc. They have also explored different forms of temporal order binding these neurons together: synchronization, phase locking, delayed correlations, waves, rhythms, induction, resonance, etc. In recent years, several theoretical proposals, some of them to which I contributed, have started populating the mesoscopic level with STP-like molecular objects: synfire chains and braids (Abeles 1982, 1991, Doursat 1991, Bienenstock 1995, Doursat & Bienenstock 2006), polychronous groups (Izhikevich 2006), cortical columns (Markram 2006), traveling waves (Doursat et al. 1995, Doursat & Petitot 2005), subthreshold harmonics (Doursat & Goodman 2006), etc.

My own research aims to outline a new theoretical framework for mesoscopic neurodynamics with compositional properties. I have conducted different studies (see “Projects” section below) that all construe the cortical substrate of neuronal units and synaptic contacts as an *excitable medium* (Winfrey 1980) and have potential applications in the design of artificial systems for perceptual, linguistic or behavioral tasks.

Future Directions

In summary, my long-term aim is to go beyond classical thinking in neural modeling (Fig. 3.4a) and contribute to a new form of neurodynamics (Fig. 3.4b):

From coarse grain to fine grain Instead of a few units already capable of performing complex “functions” → myriads of neurons, substrate of “excitable media” that support mesoscopic patterns

From hierarchical, multilayered architectures to recurrent architectures Instead of an activity flow “moving” from input (problem) to output (solution) → distributed activity dynamically forming/erasing transient patterns

From input-driven activity to endogenous activity Instead of initially silent neural layers waiting to be “activated” → already active cell assemblies *under the influence* of external stimuli, and each other

From atomistic hierarchies to compositional hierarchies Instead of “grandmother cells” → modular assembly “flocking”

From statistical uniformity to heterogeneity Instead of global synchrony or chaos → heterogeneity and complex modes

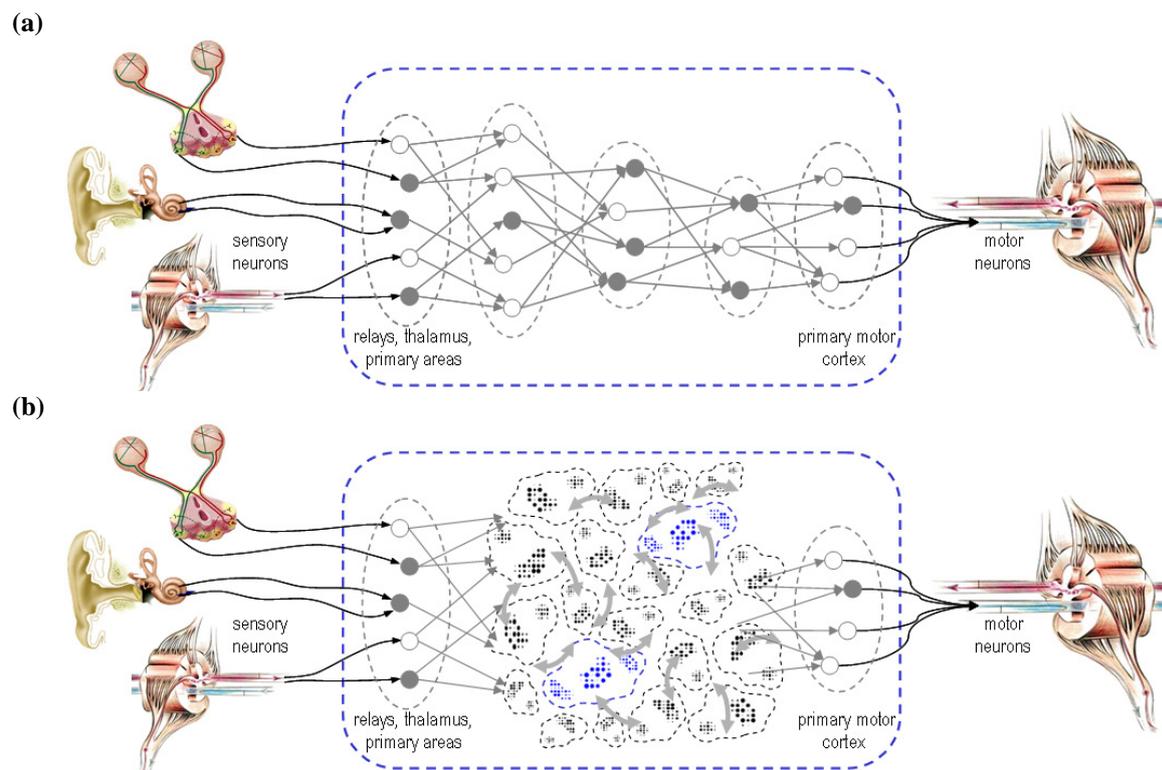


Figure 3.4: The paradigm shift from traditional neural networks to complex neurodynamics. (a) The (naive) “litteral informational” paradigm follows the engineering metaphor of signal processing. It relies on a feed-forward structure of a few “coarse-grain” units individually capable of performing high-level functions, in which passive layers are “switched on/off” by potentials transmitted from external stimuli and neural activity “flows” from sensory to motor areas. (b) By contrast, the “emergent dynamical” paradigm envisions a complex pool made of myriads of “fine-grain” neurons (without meaning in themselves) forming quasi-continuous “excitable media”. The network structure is fundamentally recurrent, scrambling the notion of activity “flow” but continuously forming multiple structured patterns on a fast time scale, which can bind to each other and create composite entities. These dynamical assemblies are endogenously active and only “perturbed” by external stimuli.

The resulting picture is a dynamic microstructure of compositional, “molecule-like” collective entities that can (a) represent “mental objects” (what underlying connectivity is needed? what are their dynamic modes of activity? what makes their identity/relative stability?), (b) interact with an external input (how are they recalled/evoked/deformed by stimuli?), (c) interact among each other (composition, modularity, creating higher structures, or competing), (d) be learned (how did their underlying connectivity form?)

Projects

My ambition is to continue deploying this paradigm across different mesoscopic-level studies. Each of the three projects presented in this section follows one of the mesoscopic paradigms described above, addressing different topics and challenges in robotics, machine vision, linguistic and pattern recognition: (1) *SynBlock*, a “self-made tapestry” of neocortex: a model of neural self-structuration into synfire motifs; (2) *CogniMorph*, a “morphodynamic pond” interface between perception and language: a model of traveling waves on lattices of quasi-oscillatory units; and (3) *NeuroForm*, a “lock-and-key” mechanism of spatiotemporal pattern recognition: a model of perturbation and coherence induction among Recurrent Asynchronous Irregular Networks (RAINs).

3.1. Project SYNBLOCK: Synfire Chains as the Building Blocks of Cognition

Parallel self-organization of connectivity and activity in an initially random spiking neural network, with the goal of supporting a hierarchy of structured mental representations in visual, auditory or linguistic tasks.

Abstract: Striking regularities in the connectivity structure of the visual system and other cortical areas account for their functional specialization. **Elie Bienenstock** (Department of Applied Mathematics and Department of Neuroscience, Brown University) and myself have designed a model that reproduces the development of such regularities as a phenomenon of *spatiotemporal pattern formation*. We show the spontaneous and simultaneous emergence of regular “synfire chains” (Abeles 1982, 1991) of synaptic connectivity together with a wave-like propagation of neural activity. Starting from an undifferentiated random state, our neural network transitions into a dual ordered regime, in which chains sustain and guide waves, while waves create and reinforce chains. We postulate that these patterns might constitute the elementary components or “molecular building blocks” at the mesoscopic level of the mind’s symbolic abilities, in particular the faculty of *compositionality* (Bienenstock 1996) at the core of linguistic and perceptual functions.

3.2. Project COGNIMORPH: The Morphodynamics of Cognitive Categorization

Bridging the gap between vision and language by importing complex systems into linguistics, in particular modeling categorization with traveling waves and dynamic singularities in coupled excitable units.

Abstract: I have proposed with **Jean Petitot** (Ecole Polytechnique, Paris) a novel dynamical system approach to cognitive linguistics based on the generation of traveling waves in cellular automata and spiking neural networks. Our objective is to categorize the infinite diversity of schematic visual scenes into a small set of grammatical elements and elucidate how language deals with space (Levinson 2003), or what is the *topology of language*. How can the same relationship ‘in’ apply to containers as different as ‘box’, ‘tree’ or ‘bowl’? We suggest that this invariance can be explained by introducing *morphodynamical transforms*, which erase image details and create virtual structures (boundaries, skeleton). This work addresses the crucial cognitive mechanisms of spatial *schematization* and *categorization* at the interface between vision and language and anchors them into expansion processes such as activity diffusion or wave propagation.

3.3. Project NEUROFORM: Cell Assembly Locks & Keys

A neural network model of associative learning by “lock and key” coherence induction between dynamic cell assemblies, where learning consists in tuning synaptic efficacies to a point of maximal response.

Abstract: Conducted at **Philip H. Goodman's** Brain Computation Laboratory (University of Nevada, Reno), as part of a “robotic sentry” project, this study focuses on the stimulus-behavior association area (AS), for which it proposes a pattern recognition model based on collective “resonant” dynamics between spiking neural assemblies. In this paradigm, a network possesses preferred endogenous modes of activity (whether overt patterns of spikes or covert fluctuations of subthreshold potentials) that can be *perturbed* through transient coupling, and learning consists in tuning synaptic efficacies to a point of maximal response of this perturbation. Stimulus-behavior association tasks can then be reformulated as processes of selection among several transients.

Publications (other than specific to the three projects; see more in sections below)

Full Papers – Books, Journals, Conferences, Workshops, Reports

- Bienenstock, E. & Doursat, R. (1989) Elastic matching and pattern recognition in neural networks. *nEuro'88 Conference*, June 6-9, 1988, Ecole Supérieure de Physique et Chimie Industrielles (ESPCI), Paris, France. In *Neural Networks: From Models to Applications*, L. Personnaz & G. Dreyfus, eds., pp. 472-482, IDSET, Paris.
- Bienenstock, E. & Doursat, R. (1990) Spatio-temporal coding and the compositionality of cognition. *Workshop on Temporal Correlations and Temporal Coding in the Brain*, April 25-27, 1990, Paris, France.
- Bienenstock, E. & Doursat, R. (1991) Issues of representation in neural networks. In *Representations of Vision: Trends and Tacit Assumptions in Vision Research*, A. Gorea, ed., pp. 47-67, Cambridge University Press.
- Bienenstock, E. & Doursat, R. (1994) A shape-recognition model using dynamical links. *Network: Computation in Neural Systems* 5(2): 241-258.
- Doursat, R., Konen, W., Lades, M., von der Malsburg, C., Vorbrüggen, J. C., Wiskott, L. & Würtz, R. P. (1993) Neural mechanisms of elastic pattern matching. Internal Report IRINI 93-01, Institut für Neuroinformatik, Ruhr-Universität Bochum, Germany.
- Doursat, R., von der Malsburg, C. & Bienenstock, E. (1995) Coding metric with delayed temporal correlations: An oscillator model of graph-matching. Technical Report, Institut für Neuroinformatik, Ruhr-Universität Bochum, Germany.
- Geman, S., Bienenstock, E. & Doursat, R. (1992) Neural networks and the bias/variance dilemma. *Neural Computation* 4: 1-58.

Abstracts (for Presentations or Posters) – Conferences, Workshops

- Bienenstock, E. & Doursat, R. (1988) Graph-matching and shape recognition in neural networks. *1st Conference on Image Recognition and Neural Networks: From Signal Processing to Representation (NEURO-IMAGE 1988)*, October 6-7, 1988, Université de Bordeaux II, France.
- Bienenstock, E. & Doursat, R. (1989) Of shapes, graphs and neural codes. *NATO Advanced Research Workshop on Neuro Computing: Algorithms, Architectures and Applications*, February 27-March 3, 1989, Les Arcs, France (presenter: E. Bienenstock).

Invited Keynote Presentations & Talks (with Abstracts) – Conferences, Workshops

- Doursat, R. (1995) The microdynamics of mental schemas. *Workshop on Morphodynamic Models for Language and Perception*, December 11-13, 1995, International Centre for Semiotic and Cognitive Studies (Umberto Eco & Patrizia Violi, dirs.), University of San Marino, Italy.
- Doursat, R. (2007d) Of tapestries, ponds and RAIN: Toward fine-grain mesoscopic neurodynamics in excitable media. *International Workshop on Nonlinear Brain Dynamics for Computational Intelligence*, at *10th Joint Conference of Information Systems (JCIS 2007)*, July 20, 2007, Salt Lake City, UT.
- Doursat, R. (2009i) Causing and influencing patterns by designing the agents: Complex systems made simpler. *4th Workshop on Causality in Complex Systems*, co-organized by DSTO, CSIRO (Australia), and ONR, AFRL (US), in association with the *Conference on Spatial Simulation for the Social Sciences (S4)*, November 25-27, 2009, Institut des Systèmes Complexes, Paris Ile-de-France.

3.1. Project SYNBLOCK: Synfire Chains as the Building Blocks of Cognition

Parallel self-organization of connectivity and activity in an initially random spiking neural network, with the goal of supporting a hierarchy of structured mental representations in visual, auditory or linguistic tasks.

Striking regularities in the connectivity structure of the visual system and other cortical areas account for their functional specialization. **Elie Bienenstock** (Department of Applied Mathematics and Department of Neuroscience, Brown University) and myself have designed a model that reproduces the development of such regularities as a phenomenon of *spatiotemporal pattern formation*. We show the spontaneous and simultaneous emergence of regular “synfire chains” (Abeles 1982, 1991) of synaptic connectivity together with a wave-like propagation of neural activity. Starting from an undifferentiated random state, our neural network transitions into a dual ordered regime, in which chains sustain and guide waves, while waves create and reinforce chains. We postulate that these patterns might constitute the elementary components or “molecular building blocks” at the mesoscopic level of the mind’s symbolic abilities, in particular the faculty of *compositionality* (Bienenstock 1996) at the core of linguistic and perceptual functions.

Rationale: The compositionality of Cognition

In this work, we address on a general level the *compositionality* of cognitive processes, i.e., the faculty of assembling elementary constituent features into complex representations. Answering to Fodor and Pylyshyn’s (1988) influential criticism about the lack of structured representations in neural networks, our goal is to show that compositionality can arise from the simultaneous self-organization of connectivity and activity in an initially random cortical network.

Already apparent in invariant perceptual tasks, where objects are categorized according to the relationships among their parts, compositionality is particularly striking in *language*, where it is also referred to as *constituency*. Language can be therefore described as a “building block” system, in which the operative objects are symbols endowed with an internal combinatorial structure. This structure allows elementary symbols to be assembled in many different ways into *complex symbols*, whose meaning is sensitive to their internal arrangement. Here again, chemistry provides a useful metaphor if we compare symbols with molecules and symbolic composition with the various possible reactions and products that depend on the geometrical structure of molecules. In this context, the issue of an appropriate format of representation of mental entities is of particular importance and our proposal is that the nervous system uses a higher-order temporal code to represent linguistic entities.

The present neural model proposes that compositionality might arise from the gradual ontogenetic development of the nervous system during the early stages of synaptogenesis. By this, we adhere to Chomsky’s conception that language actually “grows” and matures in children’s brain like a limb or an organ (e.g., Chomsky 1986). This claim might sound surprising at first but is in accordance with well-known observations and general principles of neural development. Indeed, the visual system and many other cortical areas display strong regularities in their connectivity, which self-organize during fetal and postnatal development (with or without input from external stimuli) and account for their functional specialization. Similarly, it is postulated here that the *faculty* of language (as opposed to any specific language) is supported by specialized neural pathways that develop through a feedback interaction between neuronal activities and synaptic efficacies.

Self-Organized Growth of One Synfire Pattern

Starting from an initially disordered network characterized by broad diffuse contacts and low stochastic firing, an ordered “synfire-chain” structure of connections and wave-like correlated activation can emerge simultaneously. In their simplest implementation, these linear structures consist of a sequence of synchronous groups $P_0 \rightarrow P_1 \rightarrow P_2 \rightarrow \dots$ connected by feed-forward synaptic contacts (Fig. 3.1.1a). Experiments in mammalian neocortex have gathered some evidence for these patterns, which were hypothetically named “synfire chains” (Abeles 1982, 1991) when based on uniform

connection delays, or “synfire braids” if they contained unequal delays (Bienenstock 1995; Fig. 3.1.1b). It is postulated here that synfire chains could explain the preservation of accurately synchronized action potentials even in the presence of noise (e.g., Diesmann et al. 1999, Ikegaya et al. 2004). Note that this type of structures at a fine-grain microscopic level should not be confused with the macroscopic signal processing paradigm of Fig. 3.4a (Section 3 above). Neurons in a synfire chains or braids do not carry out any specific feature detection task, or transform any “input” into an “output”. Their main purpose is to collaborate to create emergent patterns of temporal correlations, which can then serve as elementary bricks of a higher compositional system (see below).

During synfire chain growth, certain connections are gradually selected and strengthened to the detriment of others. This *focusing* of the connectivity is also accompanied by a gradual increase and durability of correlated firing. Connections and correlations reinforce each other through heterosynaptic *cooperation*, while the global stability of the network is maintained through a constraint of *competition*.

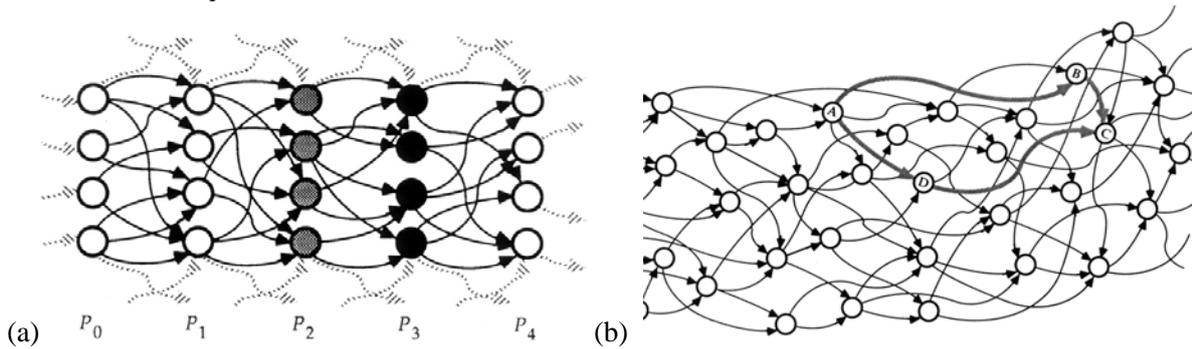


Figure 3.1.1: Schematic illustration of (a) segments of synfire chain (at a microscopic scale; not to be confused with the macroscopic signal processing paradigm of Fig. 3.4a) and (b) a synfire braid. In both cases, the geometry of the network has been unfolded along a temporal axis to make these linear structures appear clearly. A transitive pathway $A \rightarrow (B, D) \rightarrow C$ is highlighted in the synfire braid (from Doursat 1991, Doursat & Bienenstock 2006).

Summary of the model’s rules We consider a network of N excitatory neurons with binary values x_i representing spikes on the ms time scale. Synaptic weights w_{ij} vary by small increments on the same time scale as x_i . Time is discrete, in steps of roughly 1 ms, and connections have fixed transmission delays τ_{ij} . At each time t , the state of the network consists of action potentials $\mathbf{x}(t) = \{x_i(t)\}_{i=1\dots N}$ and synaptic weights $\mathbf{w}(t) = \{w_{ij}(t)\}_{i,j=1\dots N}$. This state evolves according to three laws: (a) neuronal activation, (b) synaptic plasticity and (c) intersynaptic competition.

(a) Neurons obey a simple linear-nonlinear Poisson (LNP) dynamics, equivalent to the McCulloch & Pitts mean rate model, but transposed here to the 1-ms timescale. The probability of activation of neuron j is given by $P[x_j(t) = 1] = \sigma_T(V_j(t) - \theta_j)$, where $V_j(t) = \sum_i w_{ij}(t) x_i(t - \tau_{ij})$ is the membrane potential of j at time t , θ_j its firing threshold and $\sigma_T(v) = 1 / (1 + \exp(-v/T))$, a sigmoidal step function. “Temperature” T controls the slope of the logistic function σ_T , i.e., the amount of noise in the system.

(b) The variation of connection weights depends on the fine temporal correlation between pre- and postsynaptic neurons. It is given by $w_{ij}(t) = w_{ij}(t-1) + b_{ij}(t)$, with $b_{ij}(t) = +\alpha$ for each $j \neq i$ such that $x_i(t - \tau_{ij}) = x_j(t) = 1$, and $b_{ij}(t) = -\beta$ if $x_i(t - \tau_{ij}) \neq x_j(t)$, where α and β are small positive numbers, typically of the order of .1 and .01, respectively. Thus, the effective rate of synaptic modification is much slower than that of the neuronal dynamics. The α term is a schematic model of synaptic potentiation whereas the β term represents synaptic depression. Presynaptic neurons must cooperate to increase the likelihood of successful transmission and receive synaptic reward. This fast synaptic plasticity is a form of Hebbian learning on the 1-ms time scale, and can also be viewed as a simplification of STDP, replacing the exponential curves with fixed increments.

(c) The first two rules create a positive feedback in the network, whereby correlations and connections reinforce each other. To counterbalance this effect and prevent epilepsy, we introduce a third mechanism in the form of *competition* among synapses—a schematic formulation of otherwise complex synaptic homeostasis mechanisms (Frégnac 1998). We impose that all outgoing (“efferent”)

and incoming (“afferent”) weight sums be conserved at all times: $\sum_{j'} w_{ij'}(t) = \sum_i w_{ij}(t) = s_0$. Under such a constraint, the evolution of synaptic connections is better described as a *redistribution* rather than a creation of new contacts. For ease of calculation, we make this constraint a cost function $H(\mathbf{w}) = \gamma \sum_i [s_i^{\text{out}}(\mathbf{w}(t)) - s_0]^2 + \gamma \sum_j [s_j^{\text{in}}(\mathbf{w}(t)) - s_0]^2$, where $s_i^{\text{out}}(\mathbf{w}(t)) = \sum_{j'} w_{ij'}(t)$, $s_j^{\text{in}}(\mathbf{w}(t)) = \sum_i w_{ij}(t)$ and γ is of the order of .005. The synaptic rule thus becomes $w_{ij}(t) = w_{ij}(t-1) + b_{ij}(t) + c_{ij}(t)$, with $c_{ij}(t) = -(\partial H / \partial w_{ij})(\mathbf{w}(t-1) + \mathbf{b}(t))$. Finally, weights are clipped to stay inside $[0, 1]$.

In summary, the network is driven by two major forces: a positive feedback in the form of cooperation between (a) activity and (b) Hebbian connectivity, and a corrective negative feedback in the form of (c) competition among connections (Fig. 3.1.2a-b).

Preliminary stability analysis We briefly analyze the behavior of the above model under simplified conditions, setting all delays τ_{ij} to a constant τ_0 . Our first goal is tuning the network to a random activity mode with low average firing rate. Connectivity is broad and diffuse, with $w_{ij} \approx w_0 = s_0 / N$ (for example, $N = 100$, $s_0 = 10$, $w_0 = .1$). Denoting by n^* the average of $\langle n(t) \rangle$ over time, our goal is to obtain $0 < n^* \ll N$ to prepare conditions favorable to synfire growth. A mean field approximation yields: $\langle n(t) \rangle \approx \zeta(\langle n(t - \tau_0) \rangle)$, where ζ is an offset and rescaled version of σ_T , based on N , w_0 and θ_0 , thus the average firing rate is a fixed point $n^* = \zeta(n^*)$. A graphical analysis (Fig. 3.1.2c) reveals the existence of 1, 2 or 3 such points depending on the position of the sigmoidal curve’s center $\Omega = (\theta_0 / w_0, N / 2)$ and its slope at that point $\zeta'_{\Omega} = Nw_0 / 4T$. Placing Ω to the left of the diagonal, it means that ζ'_{Ω} must be steeper than the line from 0 to Ω to create two stable points, n_1^* near 0 and n_3^* near N . The corresponding conditions translate to $\theta_0 < s_0 / 2$ and $T < \theta_0 / 2$, for example: $\theta_0 = 3$ and $T = .5$ yielding $n_1^* \approx .25$ and ensuring a quick convergence to a stable low activity rate $\langle n(t) \rangle = n_1^*$ from a silent network $n(0) = 0$.

Interestingly, the same parameters allowing stable random activity in an unstructured network also allow the stable propagation of a wave in a future synfire chain of width n_c (average size of the pools). Reasoning is the same as above, leading to a sigmoidal fixed-point study this time under a rescaling factor n_c / N . In this domain of parameters, the critical number of active P_0 neurons necessary and sufficient to reliably trigger a wave on the rest of the chain is given by $n_2^* \approx n_c (\theta_0 / s_0)$.

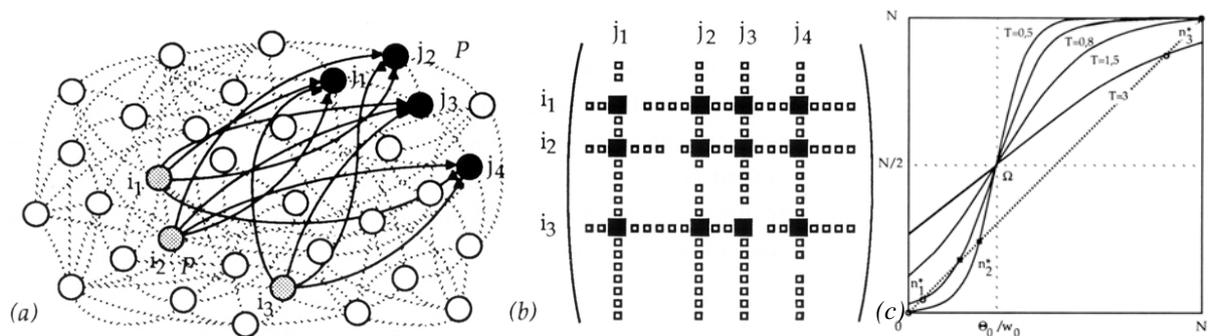


Figure 3.1.2: (a)-(b) Variation of connectivity caused by activity. If pool P' (three units) was active at $t - \tau_0$ and P (four units) was active at t , then $P' \rightarrow P$ weights are reinforced but other $P' \rightarrow \text{out}$ and $\text{in} \rightarrow P$ weights are weakened. With $N = 100$, $n' = 3$, $n = 4$, $\alpha = .1$, $\beta = 0$ and $\gamma = 1/2N = .005$, the three weight changes are $+0.093$, -0.004 , -0.003 . (a) Network view of $\Delta w(t)$. (b) Matrix view of $\Delta w(t)$. (c) Graphical study of mean activity in a random diffuse network, showing sigmoid curves ζ under different values of T (with $N = 100$, $w_0 = .1$ and $\theta_0 = 3$). For $T \leq .8$, there are 3 fixed points: n_1^* (near 0, stable), n_2^* (near θ_0 / w_0 , unstable) and n_3^* (near N , stable). Our double goal is to maintain background activity at n_1^* while synfire chains sustain $n_3^*(n_c / N)$ [←rescaling factor] (from Doursat & Bienenstock 2006).

Creation of the first synchronous pool After preparing the appropriate parametric conditions, we now examine the growth of a synfire chain. To this aim, we introduce a new singularity into the network—a special “seed” group of n_0 neurons, noted Q . These seed neurons tend to fire synchronously at a low average frequency, typically once every 10 or 20 τ_0 , although not necessarily regularly. Through its repeated activation, Q will become the root of a new synfire chain that develops

by aggregating new pools of synchronous neurons recursively.

During the first steps of a chain's growth, Q 's pulses create gradual differentiation in the landscape of activation probabilities. At first, potentials are near 0 in all neurons and activation probabilities are uniformly low at $n_1^*/N = .25\%$ (with the above-mentioned numerical values). When Q fires for the first time at t_0 , it injects a potential $n_0 w_0$ in the network and raises firing probabilities to $\sigma_T(w_0 n_0 - \theta_0) = 1.8\%$. Consequently, an average of 2 neurons (denoted P_1) fire at $t_0 + \tau_0$, provoking a $Q \rightarrow P_1$ weight increase to $w_0 + \alpha = .2$, hence a future P_1 's activation probability of $\sigma_T((w_0 + \alpha)n_0 - \theta_0) = 12\%$. For the next few Q pulses, P_1 will continue collecting neurons characterized by an increased post- Q firing probability of 12%. Then, inevitably one or more neurons from P_1 will fire a *second* time after Q . This differentiates them further from the other neurons by bumping up their next activation probability to $\sigma_T((w_0 + 2\alpha)n_0 - \theta_0) = 50\%$. The probability landscape is now partitioned into three groups: P_1 neurons that fired after Q twice, once, or never, and respectively have 50%, 12% or 1.8% chance of firing again after Q .

Neurons therefore differentiate on the basis of how many times they fired after Q . The fate of each neuron depends on its current degree of correlation with the seed group, i.e., the number of past $1 \rightarrow 1$ events. This is the core of the positive feedback loop: correlations increase connections, which encourage correlations. Once neuron j reaches probability 50%, it is very likely to be activated a 4th time by Q and move up to $\sigma_T((w_0 + 3\alpha)n_0 - \theta_0) = 88\%$ soon. From this point on, j becomes a permanent member of P_1 : $Q \rightarrow j$ connections reach the maximum $w_+ = s_0 / n_0$ and j is systematically triggered by Q , which maintains these connections. The $Q \rightarrow j$ connection pattern is extremely robust.

Negligible in the beginning, competition then becomes predominant in the later phase of P_1 's formation. In the first phase, undifferentiated neurons become candidates to P_1 's membership by firing once after Q . Then, in a second phase, these candidates compete to be recruited. Due to the sum rule, Q 's efferent connections cannot afford to sustain all candidates, so neurons that fire again earlier "drag" synaptic contacts towards them, to the detriment of undecided neurons. In sum, the aggregation of pool P_1 is evolutionary: it first expands by *diversification* (driven by T) then shrinks and rounds up a final set of n_1 winners through *selection* (driven by s_0).

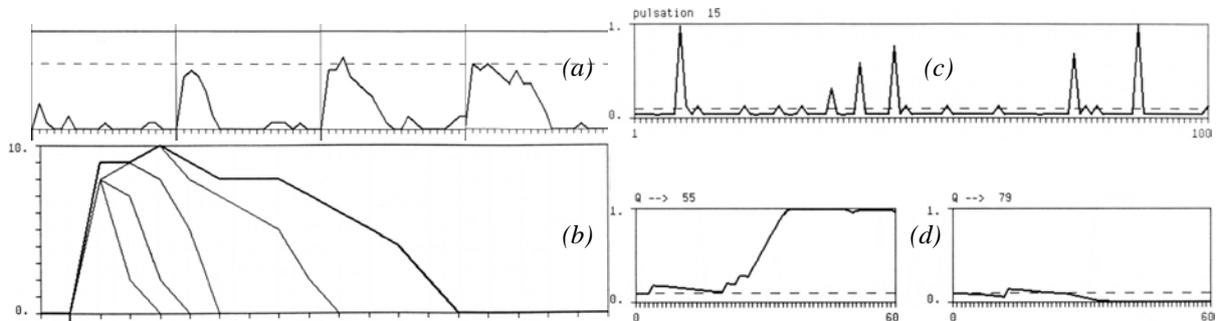


Figure 3.1.3: A growing synfire chain ($N = 100$, $n_0 = 10$, $w_0 = .1$, $\theta_0 = 3$, $T = .5$, $\alpha = .1$, $s_0 = 10$). The firing period of the seed group is about 20 time steps. (a) Four snapshots of the network's total activity following seed activations sampled at different times. (b) Five other snapshots, superimposed in this view, revealing the growing profile of the chain (respectively at seed activations 10, 30, 50, 100, 200). (c)-(d) Evolution of seed group Q 's outgoing connections during the recruitment process of the first pool P_1 . (c) Snapshot (slice in space) of the landscape of weight values going from Q to the network, at the 15th seed activation (horizontal axis: receiving neurons from #1 to #100). (d) Fate (slice in time) of two sets of connections, $Q \rightarrow \#55$ and $Q \rightarrow \#79$ (horizontal axis: temporal sequence of seed activations). The discrete jumps of $\alpha = .1$ caused by the neuron's activation are separated by periods of silence where weights slowly decrease again because of competition (from Doursat & Bienenstock 2006).

Recursive aggregation of a synfire chain Clearly, the same process from Q to P_1 then repeats itself with P_1 now playing the role of the seed and recruiting a new group P_2 . The growth of synfire chain $Q \rightarrow P_1 \rightarrow P_2 \rightarrow \dots$ is recursive and akin to the *growth by accretion of a crystal*—which also requires the presence of a singularity, acting as a seed. This accretion process is also not strictly iterative. The full period of P_1 's development covers several of Q 's firing events t_0, t_1, \dots, t_q (typically about 100), as

neurons are recruited at different times and connections grow unequally on a first-come-first-served basis. Thus, P_1 does not wait for completion to start recruiting P_2 : as soon as P_1 reaches a critical mass θ_0 , it is able to activate in turn new neurons downstream. The recruitment period of $Q \rightarrow P_1$ therefore greatly overlaps that of $P_1 \rightarrow P_2$, and so on. A growing chain typically lengthens before it widens, which gives it the aspect of a beveled head at the end of a mature trunk (if neurons' positions are rearranged in 2-D to make the chain appear visually; Fig. 3.1.4a). Several generations of immature groups along the growing tip of the chain compete to recruit neurons from the rest of the network. By recursive reasoning, P_{k-1} is always created before P_k , hence is larger and will be completed first. In the recruitment competition, older groups upstream maintain their advantage over younger groups downstream by instilling larger potentials into candidate neurons.

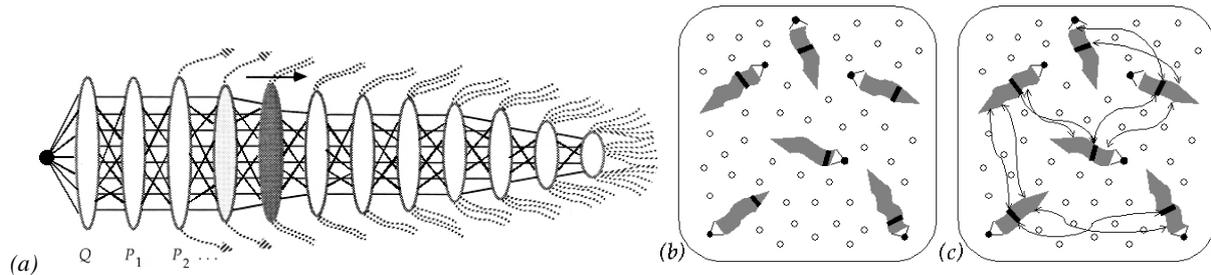


Figure 3.1.4: (a) Typical beveled profile of a growing synfire chain. The elongated ovals schematize synchronous pools in formation (height proportional to number of neurons) and the edges, $P_{k-1} \rightarrow P_k$ connections. A wave is currently propagating from P_3 to P_4 . A mature “trunk” of constant width (here including P_2) ends in a “searching head” of decreasing width, due to largely overlapping periods of pool development. Immature efferent links (dashed lines) from unfinished pools compete to recruit new neurons from the network. (b)-(c) Idealized sketch of a “self-made tapestry” of synfire chains. (b) Multiple chains simultaneously develop from independent seed groups, then (c) they synchronize and bind. The wavy pointed rectangles represent growing synfire chains or braids in a rearranged view (not showing the fact that chains may also overlap and share neurons). The black stripes illustrate the current position of the waves of activation and the curvy arrows in (c) symbolize weak coupling connections between chains (from Doursat & Bienenstock 2006).

A Self-Made Tapestry of Multiple Interacting Synfire Patterns

Finally, we suggest that synfire growth could be the first step in an infinitely productive “network of networks” hierarchy. The *concurrent growth of multiple chains* can define a *mesoscopic* scale of neural organization, in which synfire patterns have the required combinatorial structure to assemble in various ways through wave synchronization and fast synaptic binding (Fig. 3.1.4b-c). Synfire-chain binding is comparable to oscillator phase locking: the closer the frequencies, the weaker the coupling required to maintain a stable phase relationship between them. We posit that weak excitatory synaptic interactions induce coupling between chains, in the sense that it stabilizes the timing relationships across the chains. Such connections do not actually activate silent chains, but only ensure synchronization between already active chains. Under the influence of external stimuli, chain motifs dynamically bind into higher structural compositions characterized by complex modes of activity. This model suggests that the ontogenetic development of the nervous system could be another instance of a “self-made tapestry” (Ball 1999) that exhibit pattern formation, as do many natural complex systems.

Future Directions

Robustness and biological realism Although we chose a simplified set of equations and parameters, it is readily seen that the basic principles—the interplay of coincidence detection and synaptic reinforcement—are quite general, and neocortical structuration is a robust self-organization process. Following the initial presentation of this work in my PhD thesis (1991), a few other proposals based on more biologically detailed models of the cortex, using integrate-and-fire dynamics (e.g., Hertz &

Prügel-Bennett 1996), spike-timing dependent plasticity (STDP) and complex “small-world” networks (Izhikevich et al. 2004), have also demonstrated the spontaneous formation of time-locked neuronal groups, with the difference that the produced patterns are locally bounded and more unstable or rapidly transient compared to the iteratively long and persistent synfire structures that we obtained. We will use more realistic spiking and synaptic dynamics, too, in the next versions of this study.

Inhibition as a stabilizing and coupling mechanism Recurrent connectivity and Hebbian plasticity create a mutual reinforcement of excitatory activity and connectivity that could lead to a trivial and unrealistic run-away situation. In addition to (or replacement of) competition, we will also investigate *inhibition* as another negative feedback mechanism to keep this situation under control. Inhibition directly controls the global activity level in the network in a rather accurate way and on a faster time scale than synaptic competition. Much interest has been devoted in recent years to the study of “balanced networks”, where the mean inhibitory input to a neuron cancels the mean excitatory input. In particular, it was suggested (Aviel et al. 2004) that the propagation of a synchronous wave on the background of asynchronous activity can be achieved in a synfire chain containing inhibitory “shadow” pools to the excitatory ones. Moreover, global inhibition can also play an important role in controlling the dynamic coupling and uncoupling of grown chains (Abeles et al. 2004).

Multiple synfire-chain composition At the core of perception and language is the capacity for handling (producing or interpreting) composite entities never seen or heard before. Although new, each such entity bears many different relationships (traditionally termed “syntactic”, “semantic”, “pragmatic”) to previously experienced material. The proposal that synfire chains can be used as a substrate for compositional cognitive functions is based on their ability to *bind* with each other whenever induced by synaptic interactions. Our ultimate goal is to simulate the binding, unbinding and rebinding of multiple chains to each other in non-random ways, and into various composite structures, and relate these complex spatiotemporal objects to perceptual and linguistic tasks.

Spinoff Projects

Project SYNBLOCK-DEVO

Characterizing the “shape of mental states”: morphogenesis and structure of complex, heterogeneous neural activity.

Possible collaborators: Yves Frégnac, Unité de Neurosciences Intégratives et Computationnelles (UNIC), CNRS Gif-sur-Yvette, France – Elie Bienenstock, Department of Applied Mathematics and Department of Neuroscience, Brown University

Abstract: Generalizing synfire growth and composition, it would be of great importance to be able to characterize and simulate *intrinsically heterogeneous*, i.e., structurally and spatially complex, spiking dynamics. On the one hand, models of recurrent spiking networks in statistical physics exhibit homogeneous “flat” dynamical regimes (whether ir/regular, a/synchronous, etc.; e.g., Brunel 2000, Vogels & Abbott 2005). On the other hand, content-addressable memory models involve heterogeneous attractors, but these are based on mean-rate coding (e.g., Amit & Brunel 1997). Rarely are heterogeneity *and* complex spatiotemporal dynamics combined. This project will draw its inspiration from collective phenomena of complex systems, such as pattern formation, swarm motion and structured morphogenesis (see Part 2) and transfer them to computational neuroscience with the goal of producing non-trivial, endogenous states of neural activity. But instead of grains of sand, birds of a flock, or cells of an embryo, its elementary components will be the membrane and action potentials of large neural assemblies. I want to show how all these electrical contributions can self-assemble in a *non-random, reproducible fashion*. My goal is to “grow *specific shapes*” in a recurrent network or, switching from a geometric to an auditory metaphor, “learn *specific tunes*”, which the network can play back later *without explicit stimulus*. It is conjectured that these heterogeneous, spatially extended dynamic assemblies could be the fundamental substrate of *mental representations*.

Project SYNBLOCK-WAVEMATCHING

Coding visual metric with spatiotemporal patterns of activity: An oscillator-network model of graph matching.

Possible collaborators: **Elie Bienenstock**, Department of Applied Mathematics and Department of Neuroscience, Brown University – **Christoph von der Malsburg**, Frankfurt Institute for Advanced Studies (FIAS), Johann Wolfgang Goethe-Universität Frankfurt am Main, Germany

Abstract: Visual perception simultaneously involves low-level processing, in which elementary features group together spontaneously according to purely local information (Gestalt), and high-level processing, in which global patterns stored in memory intervene to guide overall segmentation and shape recognition. I proposed a model of template-matching based on an analogy between waves and elastic deformations (Bienenstock & Doursat 1994, Doursat et al. 1995). The key idea is that *spatial distances are coded by temporal delays*. In wave-like spiking activity, if *phases are interpreted as coordinates* then two such waves can code for a 2-D visual pattern. Consequently, the interaction between input pattern and schema pattern, formally interpreted as a graph-matching process, corresponds to the growth of dynamical links from one pair of waves to another pair of waves (Fig. 3.1.5). For example, this concept can be implemented in networks of coupled oscillators or excitable units.

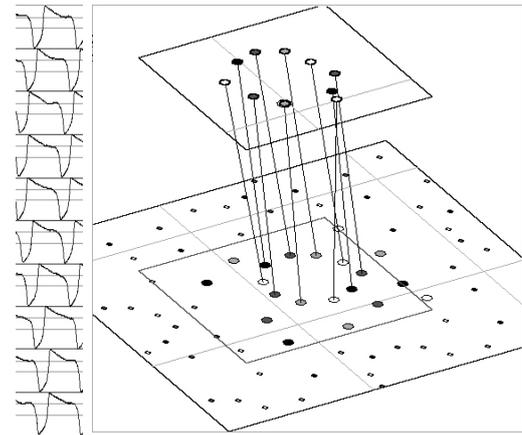


Figure 3.1.5: Schematic view of a wave-matching process, where spike timings (detailed left) code for coordinates and connection weights increase between synchronous units (from Doursat et al. 1995).

Relevant Publications

Full Papers – Books, Journals, Conferences, Workshops, Reports

Doursat, R. & Bienenstock, E. (2006b) Neocortical self-structuration as a basis for learning. *5th International Conference on Development and Learning (ICDL 2006)*, May 31-June 3, 2006, Indiana University, Bloomington, IN.

Doursat, R., von der Malsburg, C. & Bienenstock, E. (1995) Coding metric with delayed temporal correlations: An oscillator model of graph-matching. Technical Report, Institut für Neuroinformatik, Ruhr-Universität Bochum, Germany.

Abstracts (for Presentations or Posters) – Conferences, Workshops

Doursat, R. & Bienenstock, E. (2006a) The self-organized growth of synfire patterns. *10th International Conference on Cognitive and Neural Systems (ICCN 2006)*, May 17-20, 2006, Boston University, MA.

Doursat, R. & Bienenstock, E. (2006c) How activity regulates connectivity: A self-organizing complex neural network. *6th International Conference on Complex Systems (ICCS 2006)*, June 25-30, 2006, New England Complex Systems Institute (NECSI), Boston, MA.

Doursat, R. & Bienenstock, E. (2007) How activity regulates connectivity: A self-organizing complex neural network. *Ladislav Tauc Conference in Neurobiology 2007: Complexity in Neural Network Dynamics (Tauc 2007)*, December 13-14, 2007, Institut de Neurobiologie Alfred Fessard (INAF), CNRS, Gif-sur-Yvette, France.

3.2. Project COGNIMORPH: The Morphodynamics of Cognitive Categorization

Bridging the gap between vision and language by importing complex systems into linguistics, in particular modeling categorization with traveling waves and dynamic singularities in coupled excitable units.

I have proposed with **Jean Petitot** (Ecole Polytechnique, Paris) a novel dynamical system approach to cognitive linguistics based on the generation of traveling waves in cellular automata and spiking neural networks. Our objective is to categorize the infinite diversity of schematic visual scenes into a small set of grammatical elements and elucidate how language deals with space (Levinson 2003), or what is the *topology of language*. How can the same relationship ‘in’ apply to containers as different as ‘box’, ‘tree’ or ‘bowl’? We suggest that this invariance can be explained by introducing *morphodynamical transforms*, which erase image details and create virtual structures (boundaries, skeleton). This work addresses the crucial cognitive mechanisms of spatial *schematization* and *categorization* at the interface between vision and language and anchors them into expansion processes such as activity diffusion or wave propagation.

The Invariants of Spatial Linguistics

How can the same English relationship ‘in’ apply to scenes as different as “the shoe in the box” (small, hollow, closed volume), “the bird in the tree” (large, dense, open volume) or “the fruit in the bowl” (curved surface)? What is the common ‘across’ invariant behind “he swam across the lake” (smooth trajectory, irregular shape) and “the fly zigzagged across the hall” (jagged trajectory, regular volume)? How can language, especially its spatial elements, be so insensitive to wide topological and morphological differences among visual percepts? In short, how does language drastically simplify information and *categorize*? This core invariance of spatial semantics, referred to as the “linguistic form of topology” (Talmy 2000) or “cognitive topology” (Lakoff 1988), is at the same time more flexible (e.g., allowing holes) and more metrically constrained (e.g., limiting distortions) than mathematical topology.

Contemporary theories of semantics, such as cognitive linguistics (e.g., Talmy 2000, Langacker 1987, Lakoff 1987, Jackendoff 1983; see review in Croft & Cruse 2004), have shown that terms with spatiotemporal content are highly polysemous. For example, different uses of ‘in’ relate to qualitatively different spatial situations (Herskovits 1986): “the cat in₁ the house”, “the bird in₂ the tree”, “the flower in₃ the vase”, “the crack in₄ the vase”, etc. This study examines the link between the spatial structure of visual scenes and their linguistic descriptions. Its goal is to understand and reproduce how our cognitive system creates schemas and categories at the interface between vision and language, in particular its ability to effortlessly map an infinite diversity of visual scenes onto a small set of grammatical elements (Fig. 3.2.1a). Our suggestion is that spatial and grammatical structures are related to each other through image transformations that may rely on diffusion processes and wavelike neural activity.

Numerous examples collected by Talmy (2000) show that grammatical elements are largely indifferent to the morphological details of objects or trajectories. Typical cases are scale invariance (“this speck/planet is smaller than that speck/planet”), bulk invariance (“the caterpillar crawled up along the filament/flagpole/redwood tree”), continuity invariance, translation invariance (see examples below), shape invariance (“I zigzagged/circled/dashed through the woods”), and so on.

Uncovering Basic Morphodynamical Routines

All these invariants of meaning point to underlying visual-semantic routines that perform a *drastic but targeted simplification* of the geometrical data. They correspond to various types of data-reduction transforms essential to scene categorization. We describe two of them in greater detail here.

Continuity invariance Sentences such as “the ball/fruit/bird is in the box/bowl/cage” are good examples of the neutrality of the preposition ‘in’ with respect to the morphological details of the

container. To explain this effect, we propose that the active semantic effect of ‘in’ is to trigger routines that transform a scene by making its participants expand simultaneously (through some contour diffusion process) until they reach each other’s boundaries. Denoting the figure and ground of the semantic relationship by, respectively, *trajector* (*TR*) and *landmark* (*LM*) (Langacker 1987), an active-semantic definition of the prototypical ‘containment’ schema can exploit the fact that no *TR*-induced activity is detected on the borders of the visual field because it is blocked by *LM*. This can be easily implemented in a 2-D square lattice, three-state CA (empty cell, *TR* cell, *LM* cell; Fig. 3.2.1b). Note that the final boundary line between the domains is approximately equal to the skeleton of the complementary space between the objects, also called *skeleton by influence zones* or *SKIZ*. In the case of the containment schema, the *SKIZ* surrounds *TR* and no cell on the borders is in *TR*’s state. It is a robust feature that contributes to categorize the scene as ‘in’.

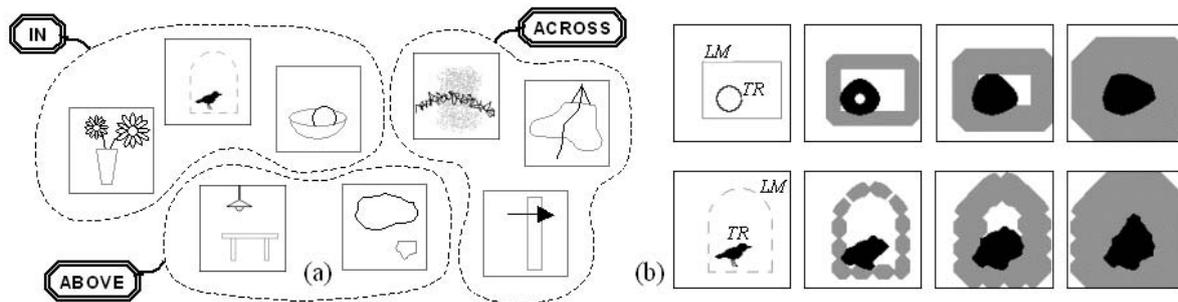


Figure 3.2.1: (a) Our cognitive abilities can effortlessly categorize an infinite diversity of visual scenes into a small set of spatial grammatical elements. (b) Expansion-based detection of an ‘in’ schema. We use a 100x100, 3-state, 2-D CA: 1 for *TR* (black), 2 for *LM* (gray) and 0 for the ambient space (white). A simple diffusion rule requires that a 0 cell adopt the state of any non-0 nearest neighbor, if it exists. Starting with any two initial *TR* and *LM* domains and stopping when the total *TR* activity is constant, the lattice quickly converges to an attractor characterized by two contiguous domains of 1’s and 2’s. *TR*’s expansion is blocked by *LM*’s expansion from reaching the borders despite discontinuities in *LM*. Top: “The ball in the box” converges in 21 steps. Bottom: “The bird in the cage,” in 27 steps.

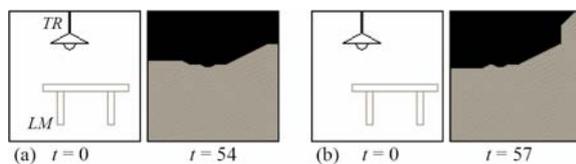


Figure 3.2.2: Detection of an ‘above’ schema in a 2-D cellular automata. We use the same 100x100 lattice as Fig. 3.2.1b. (a) *LM*’s expansion prevents *TR*’s expansion from reaching the bottom border. (b) Same effect when *LM* and *TR* are not vertically aligned, so that part of *TR* is directly facing the bottom border.

Translation invariance Another example, “the lamp is above the table”, can be processed in the same way: the simultaneous expansion of *TR* and *LM* creates a roughly horizontal *SKIZ* line in the center of the image (Fig. 3.2.2). This time, the key classification feature is the absence of *TR* activity on the *bottom* border of the field. This property is conserved by translation of *TR* in a broad region of space. This prototypical case of ‘above’ is one example of the generic ‘partition’ schema that includes elements such as ‘below’, ‘beside’, ‘behind’ and ‘in front of’ (viewed in 3-D).

Therefore, the double expansion process that we propose for the ‘containment’ and ‘partition’ schemas (and other) leads us to introduce the following general principles of active semantic morphodynamics: (i) objects have a tendency to occupy the whole space; (ii) objects are obstacles to each other’s expansion. Through the action of structuring routines the common space shared by the objects is divided into influence zones. These routines are similar to the basic operators of *dilation* and *erosion* defined in “mathematical morphology” (Serra, 1982). Image elements cooperate to propagate activity across the field and inhibit activity from other sources. A key idea is that singularities encode a lot of the image’s geometrical information in an extremely compact and localized manner and constitute a characteristic “signature” of the spatial relationship (Petitot 1995, 2003). After the morphodynamical routines have transformed the scene according to the expansion principles (i) and (ii), several types of characteristic features can be detected to contribute to the final

categorization: (iii) presence or absence of activity on the borders; (iv) intersection of skeletons; and (v) singularities in the SKIZ boundary line.

Like multiscale analysis, skeleton transforms are widely used in machine vision and implemented using various algorithms. Studied by Blum (1973) under the name “medial axis transform” and by others as “cut locus”, “stick figures”, “shock graphs” or “Voronoi diagrams” (Marr 1982, Siddiqi et al. 1999, Zhu & Yuille 1996), morphological symmetry plays a crucial role in theories of perception and is even considered a fundamental structuring principle of cognition (Leyton 1992). Skeletons indeed conveniently simplify and schematize shapes by getting rid of unnecessary details, while at the same time conserving their most important structural features. There is also experimental evidence that the visual system effectively constructs the symmetry axis of shapes (Kimia 2003, Lee 2003).

Morphodynamical Waves in Spiking Neural Networks

Elaborating upon this first abstract morphodynamical model, we now establish a parallel with neural modeling. Our main hypothesis is that the transition from analog to symbolic representations of space could be neurally implemented by *traveling waves in a large-scale network of coupled spiking units*, via the expansion processes discussed above. There is a vast cross-disciplinary literature, revived by Winfree (1980, 2001), on the emergence of ordered patterns in *excitable media* and coupled oscillators. Traveling or kinematic waves are a frequent phenomenon in nonlinear chemical reactions or multicellular structures (e.g., Swinney & Krinsky 1991, Cladis & Palffy-Muhoray 1995), such as slime mold aggregation, heart tissue activity, or embryonic pattern formation. Across various dynamics and architectures, these systems have in common the ability to be pushed (or to self-organize) into a state of criticality, from which they can rapidly bifurcate between randomness or chaos and ordered activity (Kauffman 1993). To this extent, they can be compared to “sensitive plates”, as certain external patterns of initial conditions (whether chemical concentrations, food, or electrical stimuli) can quickly trigger internal patterns of collective response from the units.

Excitable media made of coupled units We explore the same idea in the case of an input image impinging on a layer of neurons and draw a link between the produced response and categorical invariance. In the framework proposed here, a visual input is classified by the qualitative behavior of the system, i.e., the presence or absence of certain singularities in the response patterns. A possible neural implementation of the morphodynamical engine at the core of our model relies on a network of individual spiking neurons, or local groups of spiking neurons (e.g., columns), arranged in a 2-D lattice similar to topographic cortical areas, with nearest-neighbor coupling. Each unit obeys a system of differential equations that exhibit regular oscillatory behavior in a certain region of parameter space. Various combinations of oscillatory dynamics (relaxation, stochastic, reaction-diffusion, pulse-coupled, etc.) and parameters (frequency distribution, coupling strength, etc.) are able to produce waveform activity, however we want here to point out the generality of the wave propagation phenomenon, rather than its dependence on a specific model.

For practical purposes, we use here the Bonhoeffer-van der Pol (BvP) relaxation oscillator (FitzHugh 1961; Fig. 3.2.3). Each unit i is located on a lattice point x_i and described by a pair of variables (u_i, v_i) . Unit i is locally coupled to neighbor units j within a small radius r with Gaussian noise η and can also receive an input $I_i = 0$ or constant I . Parameters are tuned so that individual units are close to a bifurcation in phase space between a fixed point and a limit cycle, i.e., one spike emission. They are *excitable* in the sense that a small stimulus causes them to jump out of the fixed point and orbit the limit cycle, during which they cannot be disturbed.

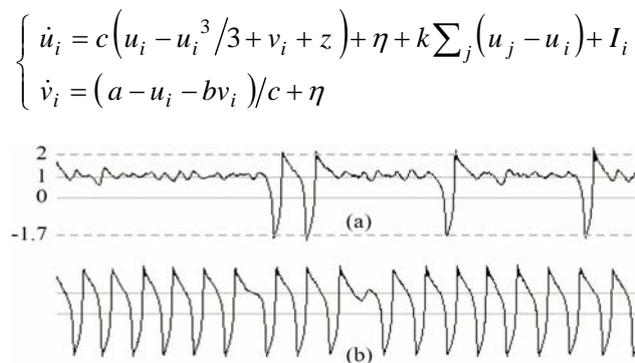


Figure 3.2.3: Firing modes $u(t)$ of a stochastic BvP relaxation oscillator ($a = .7$, $b = .8$, $c = 3$, $\eta > 0$, $k = 0$, $I = 0$). (a) Sparse random firing at $z = -.2$ (spikes are upside-down). (b) Quasi-periodic firing at $z = -.4$. At critical value $z_c = -.3465$ and zero noise, there is a bifurcation from a fixed point $u \approx 1$ to a limit cycle.

Wave categorization models Based on such lattices of weakly coupled excitable units, we propose a family of models that exploit wave dynamics to support the categorization of spatial schemas. Waves implement the expansion-based transformations stated in principles (i)-(ii), then the detection of global activity or singularities created by wave collisions follows principles (iii)-(v). Simpler models implement the border detection principle (iii) used in the ‘containment’ (Fig. 3.2.1b) and ‘partition’ (Fig. 3.2.2) schemas, while more elaborate models focus on the SKIZ singularities and “signature” detection principle (v), which can be used as a complement or alternative to border detection.

Figure 3.2.4 shows the typical waves of excitation created in a network of coupled BvP units at the basis of all these models—here in a schematic spatial scene representing “a small blob above a large blob”. Block impulses of spikes trigger wave fronts of activity that propagate away from the object contours and collide at the SKIZ boundary between the objects. These fronts are “grass-fire” traveling waves, i.e., single-spike bands followed by refraction and reproducing only as long as the input is applied. Under the nonlinear dynamics, waves annihilate when they meet, instead of adding up. Again, there is convincing perceptual and neural evidence for the significant role played by this virtual SKIZ structure and propagation in vision (Kimia 2003).

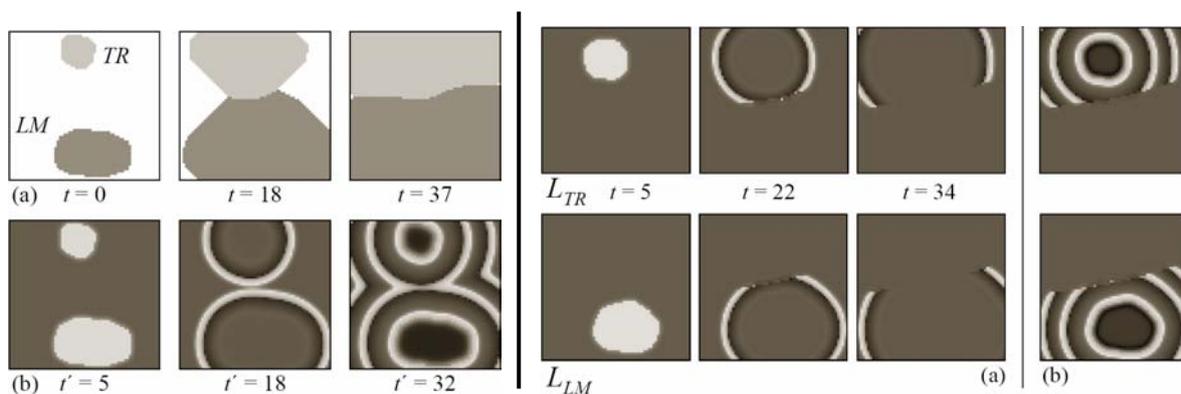


Figure 3.2.4: Running morphodynamical routines with spiking units. LEFT: (a) SKIZ obtained by simple diffusion in a 64×64 3-state CA, as in **Error! Reference source not found.** (b) Same SKIZ obtained by traveling waves on a 64×64 lattice of coupled BvP oscillators in the regime of Fig. 3.2.3a. Activity u is shown in gray levels, brighter for lower values, i.e., spikes $u < 0$. Starting with weak stochastic firing ($\eta > 0$), an input image is continuously applied with amplitude $I = -.44$ in both TR and LM domains. This amounts to shifting z to a subcritical value $z < z_c$, thus throwing the BvP oscillators into periodic firing mode (Fig. 3.2.3b). This in turn creates traveling waves in the rest of the network. RIGHT: Detection of the ‘above’ schema by mutually inhibiting waves: an alternative setup where two separate lattices of BvP units, L_{TR} and L_{LM} , are cross-coupled. (a) Single wave fronts obtained by injecting a pulse input $I = -.44$ in TR and LM for $0 \leq t < 2$ (10 time steps $dt = .2$). (b) Multiple wave fronts obtained by applying the same input amplitude indefinitely. In both cases, no spike reaches the bottom of L_{TR} .

Original Points of this Proposal

Bringing large-scale dynamical systems to cognitive linguistics Despite their deep insights into the conceptual and spatial organization of language, cognitive grammars still lack mathematical and computational foundations. Our project is among few attempts to import spatiotemporal connectionist models into linguistics and spatial cognition. Other authors (e.g. Regier 1996, Shastri & Ajjanagadde 1993) have pursued the same objectives, but using small “hybrid” artificial neural networks, where nodes already carry geometrical or symbolic features. We work at the fine-grained level of numerous spatially arranged units.

Addressing semantics in CA and neural networks Conversely, our work is also an original proposal to apply large-scale lattices of cellular automata or neurons to high-level semantic feature extraction. These bottom-up systems are usually exploited for low-level image processing applications (e.g., D. L. Wang 2005) or visual cortical modeling (e.g., König & Schillen 1991), or both—see, e.g., Pulse-Coupled Neural Networks (Johnson 1994) or Cellular Neural Networks (Chua

& Roska 1998). Shock graphs and medial axes are also used in computer vision models of object recognition (Siddiqi et al. 1999, Zhu & Yuille 1996), but with the concern to preserve and match object shapes, not erase them. Adamatzky (2002) also envisions collision-based wave dynamics in excitable media, but as a mechanism of universal computing based on logic gates.

Advocating pattern formation in neural modeling Self-organized, emergent processes of pattern formation or *morphogenesis* are ubiquitous in nature (stripes, spots, branches, etc.; see Ball 1999, Bourgin & Lesne 2006). As a complex system, the brain produces “cognitive forms”, too, but instead of spatial arrangements of molecules or cells, these forms are made of *spatiotemporal patterns* of neural activities (synchronization, correlations, waves, etc.). In contrast to other biological domains, however, pattern formation in large-scale neural networks has attracted only few authors (e.g., Milton et al. 1993, Ermentrout 1998). This is probably because precise rhythms involving a large number of neurons are still experimentally difficult to detect, hence not yet proven to play a central role.

Future Directions: Toward a Perceptual-Semantic Machine

The overall theoretical objective of this project is to show how semantic categorization can be supported by a dynamical network system performing morphological image processing. Figure 3.2.5 gives an overview of our system’s architecture.

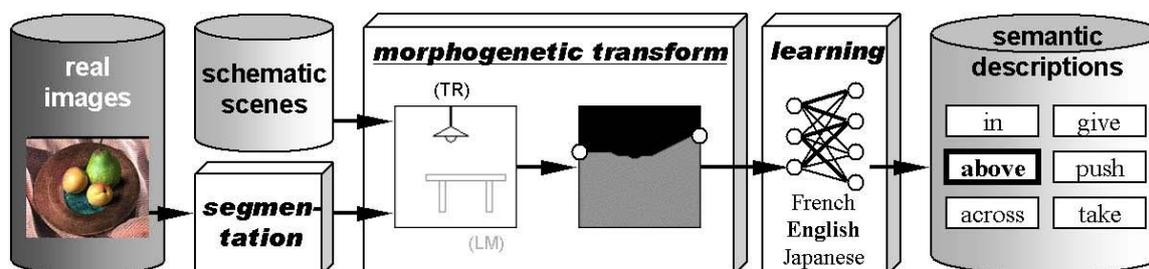


Figure 3.2.5: The perceptual-semantic system comprises: (center) a core “morphogenetic transform” engine, the bridge between vision and language and the main focus of our research: its function is motivated by cognitive linguistic observations and its mechanisms by complex neurodynamics; (left) in input, a database of prelabeled schematic scenes or, equivalently, segmented real images; (right) in output, a linguistic classification module relying on the features produced by the transforms.

By developing this mathematical and computational model of cognitive linguistics, our goal is to (i) demonstrate fundamental principles of neural dynamics underlying semantic categorization and (ii) create a software system leading to software and robotics applications. The basic methodology consists in presenting image/response pairs to the system and adjusting the model to fit known experimental psychological data on semantic classification. Starting with preliminary experiments, the project can progress on five major fronts:

Wave dynamics and scene database We want to conduct a more systematic investigation of the morphodynamical routines and their link with protosemantic classes. Similarly to Regier (1996), a database of schematic image/label pairs representing a broad cross-linguistic variety of spatial elements could be used to assess the level of invariance of the singularities and their robustness to noise.

Real images and low-level vision Currently, our primary material consists of presegmented schematic images. It could be extended to real-world examples by using low-level image processing techniques based on edge contiguity and texture. Segmentation models such as nonlinear diffusion (Whitaker 1993), variational boundary/domain optimization (Mumford & Shah 1989) or temporal phase tagging (D. L. Wang 2005) have proven that shapes can be separated from the background in a bottom-up way without prior knowledge, if the scene is not too cluttered.

Learning semantics from protosemantics Semantic classes are intrinsically fuzzy: as *TR* moves around *LM* and their *SKIZ* rotates, when is *TR* no longer ‘above’ but ‘beside’ or ‘below’ *LM*? Different languages also divide space differently: for example, ‘on’ translates in German either as ‘auf’ (top contact) or as ‘an’ (side contact). Intra- and cross-linguistic boundaries could be learned using known image/response pairs. Our morphodynamical routines already considerably reduce the dimensionality of the input space by mapping images to a few singularities. In a final step, the same universal pool of protosemantic features could be combined in various ways to form full-fledged semantic classes using statistical estimation methods.

Verb processes and bifurcation events Another important challenge is the temporal processes and events of verbal scenarios. The singularities created by fast wave activity can themselves evolve on a slower timescale. Landmark psychophysical experiments on the perception of causality and animacy (see review in Scholl & Tremoulet 2000) have shown that movies involving simple geometrical figures were spontaneously interpreted by human subjects as intentional actions. For example, a few triangles and circles moving around a square strongly tend to elicit verbal statements such as ‘chase’, ‘hide’, ‘attack’, ‘protect’, etc. In our system, too, short animated clips of moving *TR*’s and *LM*’s could be categorized into archetypal verbs, e.g., ‘give’ or ‘push’.

Complex scenes After treating single schemas separately, we also want to show how multiple schemas can be evoked simultaneously and assembled to form complex scenarios. This addresses the *compositionality* of semantic concepts (Bienenstock 1996), or “binding problem” (von der Malsburg 1999, Roskies 1999). Our ultimate goal is to explain mental imagery (Kosslyn 1994) in terms of structured compositions of morphodynamical routines.

Relevant Publications

Full Papers – Books, Journals, Conferences, Workshops, Reports

- Doursat, R. & Petitot, J. (1997) Modèles dynamiques et linguistique cognitive: vers une sémantique morphologique active. *6ème École d’été de l’Association pour la Recherche Cognitive (ARCo)*, July 5-13, 1997, Formation du CNRS, Bonas (Toulouse), France.
- Doursat, R. & Petitot, J. (2005a) Bridging the gap between vision and language: A morphodynamical model of spatial categories. *International Joint Conference on Neural Networks (IJCNN 2005)*, July 31-August 4, 2005, Montréal, QC, Canada.
- Doursat, R. & Petitot, J. (2005b) Dynamical systems and cognitive linguistics: Toward an active morphodynamical semantics. *Neural Networks* 18: 628-638. **Selected for this special issue among less than 10% of the papers accepted at the IJCNN 2005 conference.**
- Petitot, J. & Doursat, R. (1998) Modèles dynamiques et linguistique cognitive: vers une sémantique morphologique active. Technical Report 9809, in *Rapports et documents du CREA*, Ecole Polytechnique, Paris.
- Petitot, J. & Doursat, R. (2010) *Cognitive Morphodynamics: Dynamical Morphological Models for Constituency in Perception and Syntax*, Peter Lang. **To appear.**

Invited Keynote Presentations & Talks (with Abstracts) – Conferences, Workshops

- Doursat, R. & Petitot, J. (2005c) Notes on the possibility of embodied computation based on the emergence of singularities in a large-scale complex dynamical system. *Workshop on Neurodynamics and Intentional Dynamic Systems*, at *International Joint Conference on Neural Networks (IJCNN 2005)*, August 5, 2005, Montréal, QC, Canada.
- Doursat, R. & Petitot, J. (2010a) [TBA]. *2nd Symposium on Language and Robots (LangRo 2010)*, June 2010 [TBA], Intelligent Systems and Robotics Institute (ISIR), Université Pierre et Marie Curie (Paris 6), France.
- Doursat, R. & Petitot, J. (2010b) [TBA]. *Symposium on Structured Flows on Manifolds: A General Dynamical Framework to Cognition*, at the “*Cognition, Emotions and Society*” *Conference of the French Psychology Society (SFP)*, September 7-9, 2010, Université Charles-de-Gaulle Lille 3, France.

3.3. Project NEUROFORM: Cell Assembly Locks & Keys

A neural network model of associative learning by “lock and key” coherence induction between dynamic cell assemblies, where learning consists in tuning synaptic efficacies to a point of maximal response.

Conducted at **Philip H. Goodman’s** Brain Computation Laboratory (University of Nevada, Reno), as part of a “robotic sentry” project, this study focuses on the stimulus-behavior association area (AS), for which it proposes a pattern recognition model based on collective “resonant” dynamics between spiking neural assemblies. In this paradigm, a network possesses preferred endogenous modes of activity (whether overt patterns of spikes or covert fluctuations of subthreshold potentials) that can be *perturbed* through transient coupling, and learning consists in tuning synaptic efficacies to a point of maximal response of this perturbation. Stimulus-behavior association tasks can then be reformulated as processes of selection among several transients.

Spatiotemporal Pattern Resonance

Modern physiological recordings have revealed precise and reproducible complex temporal order in neural signals related to behavior (e.g., Abeles 1982, O’Keefe & Recce 1993, Bialek et al. 1991). *Temporal coding* (von der Malsburg 1981) is now recognized as a major mode of neural activity. In particular, quick onsets of transitory correlations among firing patterns have been shown to play an important role in the communication between neurons engaged collectively in a perceptual or associative task (e.g., Gray et al. 1989). Moreover, neocortical regions are also characterized by a considerable amount of lateral and feedback connectivity (e.g., Bringuier et al. 1999). Consequently, instead of the traditional feed-forward view, where a “lower” area literally activates a “higher” area (otherwise silent), new experiments and models of mesoscopic neural dynamics involve “persistent” (e.g., X.-J. Wang 2001, Brunel 2000, Y. Wang et al. 2006) or “ongoing” activity (e.g., Kenet et al. 2003, Fox & Raichle 2007).

All these observations have set the stage for an important paradigm shift in cortical dynamics focused on synchronization and temporal correlations. In particular, the present study investigates *coherence induction* or *resonance* among pre-active subnetworks—starting from premises similar to Liquid State Machines (Maass et al. 2002), but without the goal of computing mathematical functions. The main idea is that, in the absence of stimulus, local groups of neurons already possess spontaneous modes of activity that interact and influence each other in various ways. These preferred modes can be construed as instances of *spatiotemporal patterns* (STPs; also musically termed “rhythms” or “cortical songs”; Ikegaya et al. 2004) taking the form of constellations of action potentials or, more generally, covert subthreshold potentials that can be revealed by interference with matching input. In this context, it becomes especially interesting to reformulate tasks such as the recognition of a stimulus or the association between a stimulus and a behavior as a process of *selection* among several alternative STPs. If a neural group K (as in “key”) stimulates another group L (as in “lock”), one of the modes intrinsically generated by L might resonate more strongly with K than other L modes. Thus, the idea is that STP_K would *elicit*—but not create—one of several possible STP_L response states.

A Simple Sine Wave Model

We propose a first model of “STP resonance” along these lines. It contains a network of N neurons whose membrane potentials $\{V_i(t)\}_{i=1\dots N}$ are typically fluctuating in quasi-periodic patterns, consistent with subthreshold patterns recorded *in vivo* (Fig. 3.3.1a) At any given moment, we assume that the potentials of highly recurrently connected neurons can be pulled into *relative* coherence at a characteristic frequency f , so that each neuron is characterized by a phase $\varphi_i \in [0, 2\pi)$. As a simplified example, potentials can be single sine waves $V_i(t) = V_0 + V_m \sin(2\pi ft + \varphi_i)$. The set of phases $\{\varphi_i\}_{i=1\dots N}$, or rather phase shifts $\{\varphi_i - \varphi_1\}_{i=2\dots N}$, describes an attractor mode of activity STP_L reproducibly generated by the network. When an external stimulus is applied then removed, the network consistently relaxes back to STP_L . Several factors could support this slow dynamic “memory”: for

example, remote sources of periodic background activity (Destexhe & Paré 2000) from thousands of apical synapses contributing to the potentials V_i through combinations of weights determining the phase shifts; or, alternatively, recurrent network connections with transmission delays and inhibitory pathways, similar to synfire chains.

We define the order parameter of the network as the mean field potential or “interference sum” $V_L(t) = \sum_i V_i(t)$ and look at its patterning and peak magnitudes when perturbing the neurons with specific patterns of external spiking signal. We propose that this parameter may represent the real *propensity* of a subnetwork to respond instantaneously as a population code to external perturbation. In the simple sine wave version, $V_L(t)$ is itself a sine wave and the effect of the perturbation can be measured by amplitude $|V_L|$. In the relaxed state, $V_L(t)$ is stationary near the resting level V_0 (i.e., $|V_L| \approx 0$), as scattered phases mutually cancel. In a perturbed state, phases are pulled toward each other and form transient, history-dependent coherent clusters, increasing $|V_L|$ in an irregular pattern. The essential point is that the degree of network response $|V_L|$ depends on the precise temporal structure of the input stimulus and the spectral composition and instantaneous phase distribution among the V_i of the neurons in the subnetwork.

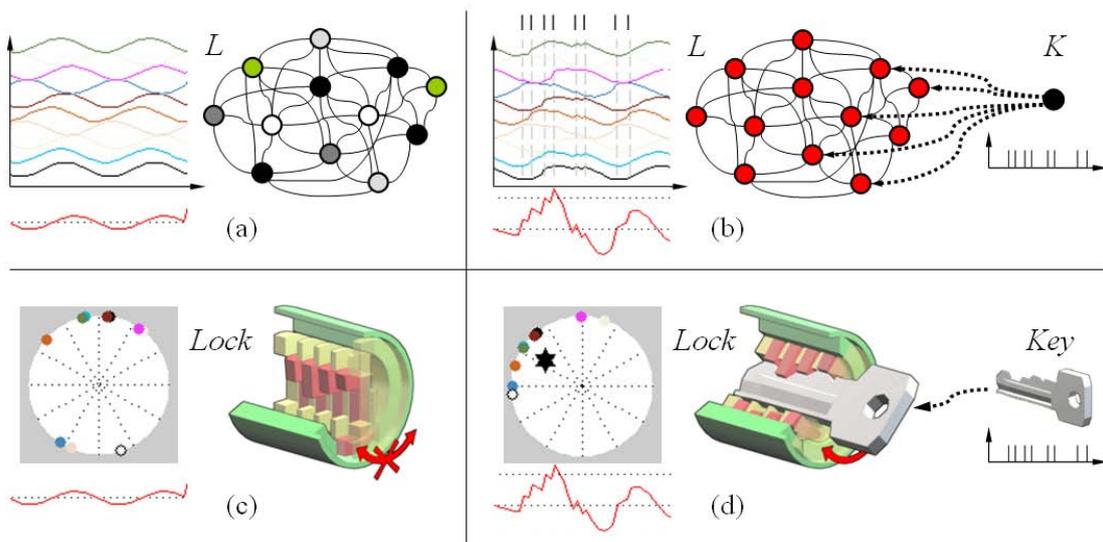


Figure 3.3.1: Simplified model & simulation of coherence induction between assemblies with ongoing activity. (a) L 's autonomous modes are characterized by sinusoidal subthreshold membrane potentials at specific phases (circle view in (c)). (b) L is stimulated by spike trains coming from another assembly K of synchronous units. The effect of K is to pull L 's phases together, thus increase L 's mean field potential V_L (bottom curve). (c)-(d) Locksmith metaphor of the same phenomenon: Tumbler *Lock* is a set of discs at varying heights (= phases), *Key* is a series of notches (= spikes). *Key*'s notches raise *Lock*'s discs (= align phases) enough to release them and open *Lock* (from Doursat & Goodman 2006).

Let this input be another pattern STP_K made of a spike train with a variable firing rate: $V_K(t) = \delta[\sin(2\pi f_K(t).t)]$, where δ is a spike shape centered in 0 (Fig. 3.3.1b). This signal can be equivalently formulated as the sum of multiple contributions from fixed-rate spiking units with variable phases: $V_K(t) = \sum_j \delta[\sin(2\pi f t + \psi_j(t))]$. The core influence of STP_K on STP_L is then the following: when spike j from STP_K arrives shortly after neuron i in STP_L has reached its peak potential, then i will peak slightly longer, i.e., φ_i will decrease. Conversely, if a spike arrives shortly before a wave's peak, then this peak is reached earlier and φ_i increases. *In all cases, spike j attracts phases φ_i towards its own phase ψ_j .* We model the amount of this phase displacement $\Delta\varphi_i$ as a *decreasing* function of phase difference applied at each cycle (e.g., a cosine function). This mirrors the physiological nonlinearity that a cell is *less* likely to be brought to fire by incoming post-synaptic potentials the further it lies below firing threshold.

Viewed on the phase circle, STP_L is originally a scattered pattern of dots $\{\varphi_i\}_{i=1..N}$ (Fig. 3.3.1c). The net effect of the arrival of one spike j on this circle is a sudden jerk of all the dots, to varying degrees, towards the spike's phase ψ_j . If the spike is repeatedly applied at each period $1/f$, the dots coalesce into clumps and eventually fuse together in the limit of a long stimulus period (Fig. 3.3.1d).

Two spikes with opposite phases interfere to form two opposite clumps of dots and perpetuate the cancellation. More spikes elicit more complex responses. When the stimulus is removed, the dots relax back to their original STP_L phase distribution constrained by the ongoing activity (with a possible global shift). The bottom row of Fig. 3.3.2 presents snapshots of L 's phases: before stimulation, at different spike times (stars), and after stimulation.

Preliminary numerical results under simplified assumptions show (a) the remarkable uniqueness of the transient response of a specific phase distribution STP_K to a specific incoming spike pattern STP_L , despite identical mean rates, (b) the reproducibility of this unique response and (c) its sensitivity to variations in either pattern, K or L . Thus there is evidence for unique and distinct “key and lock” relationships, provided sufficient variability in the lock combinations (analogous to the complexity of the tumbler of a safe). These first observations based on a phase-space dynamics offer a promising approach to models of pattern recognition and stimulus-response association based on a spiking neuron dynamics.

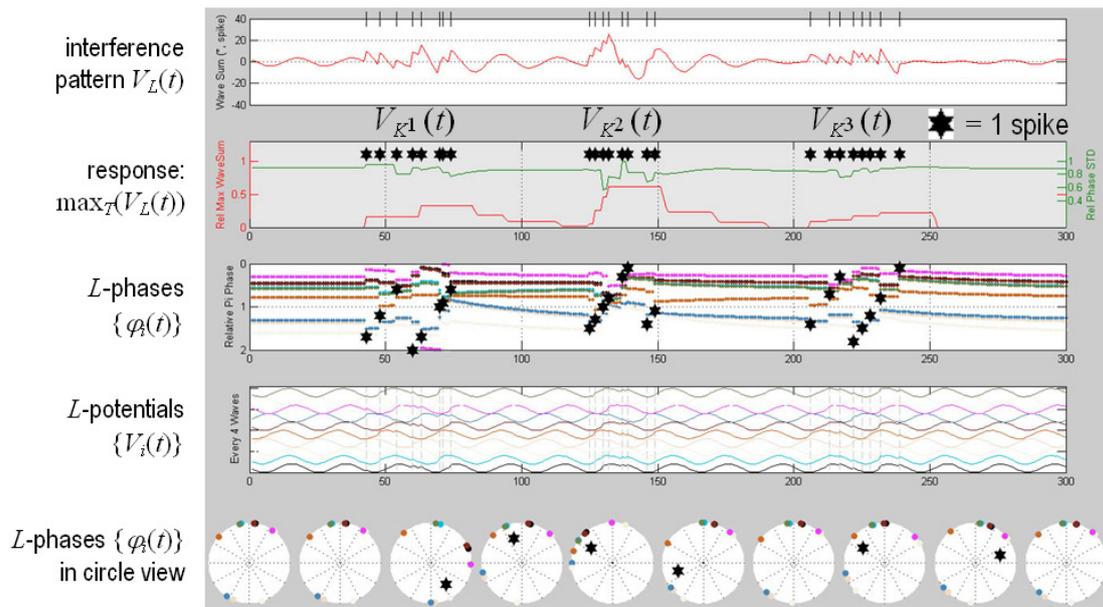


Figure 3.3.2: Specificity of key-lock interactions. The amplitude of L 's response depends on the match between the spectral composition φ_i of the potentials $V_i(t)$ in L and the fine temporal structure of K 's spike trains. We observe a uniqueness of the transient response of a specific phase distribution L to specific incoming patterns K_1, K_2, K_3 , despite identical mean rates (here max. for K_2). This response is both reproducible and sensitive to variations in K or L . Thus there is evidence for distinct key-lock engagement, provided sufficient diversity of lock combinations. This constitutes a promising approach for real-time pattern recognition and stimulus-response learning (from Doursat & Goodman 2006).

Future Directions

In the preliminary model above, the dynamics of a simplified network of quasi-periodic units was described on a phase circle by the collective coalesce-and-scatter motion of dots. In a second model, we have also started investigating the regimes and phase transitions of *Recurrent Asynchronous Irregular Networks* (RAINs), named after one of the possible combinations of (A)Synchronous and/or (Ir)Regular dynamical regimes of a dual excitatory-inhibitory system—a recurrent excitatory spiking network E connected to a recurrent inhibitory spiking network I , parametrized by four types of connections: $E \rightarrow E$, $E \rightarrow I$, $I \rightarrow E$, and $I \rightarrow I$ (Fig. 3.3.3; see, e.g., Brunel 2000, Vogels & Abbott 2005, Brette et al. 2007). We have examined the performance and sensitivity of dynamically igniting-and-quenching RAINs and explored their regimes and phase transitions under conditions of calibrated voltage-sensitive ionic membrane channels, synaptic facilitation and depression, and Hebbian spike-timing dependent plasticity (STDP). We have also shown the possibility of recognition and discrimination among RAIN activity patterns in a learning task based on Hebbian/STDP synaptic dynamics (Fig. 3.3.4).

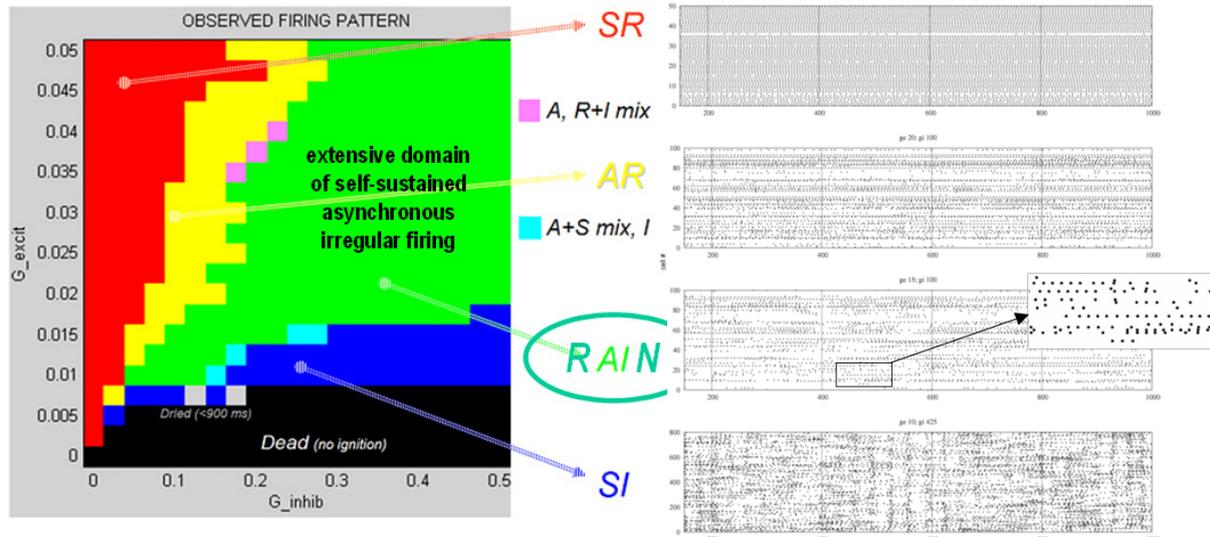


Figure 3.3.3: Firing phase diagram of the ongoing activity of a dual excitatory/inhibitory system (Fig. 3.3.4 below, inset). Based on a combination of firing statistics, four consistent domains combining two types of spatial order (A/Synchronous) and two types of temporal order (Ir/Regular) are discovered as excitatory and inhibitory conductances G_{exc} and G_{inh} are covaried in separate experiments (Brunel 2000). The A-I combination is termed RAIN and contain unique patterns of spikes that can be used in lock-key coherence induction experiments, such as Fig. 3.3.4 (from Goodman et al. 2007).

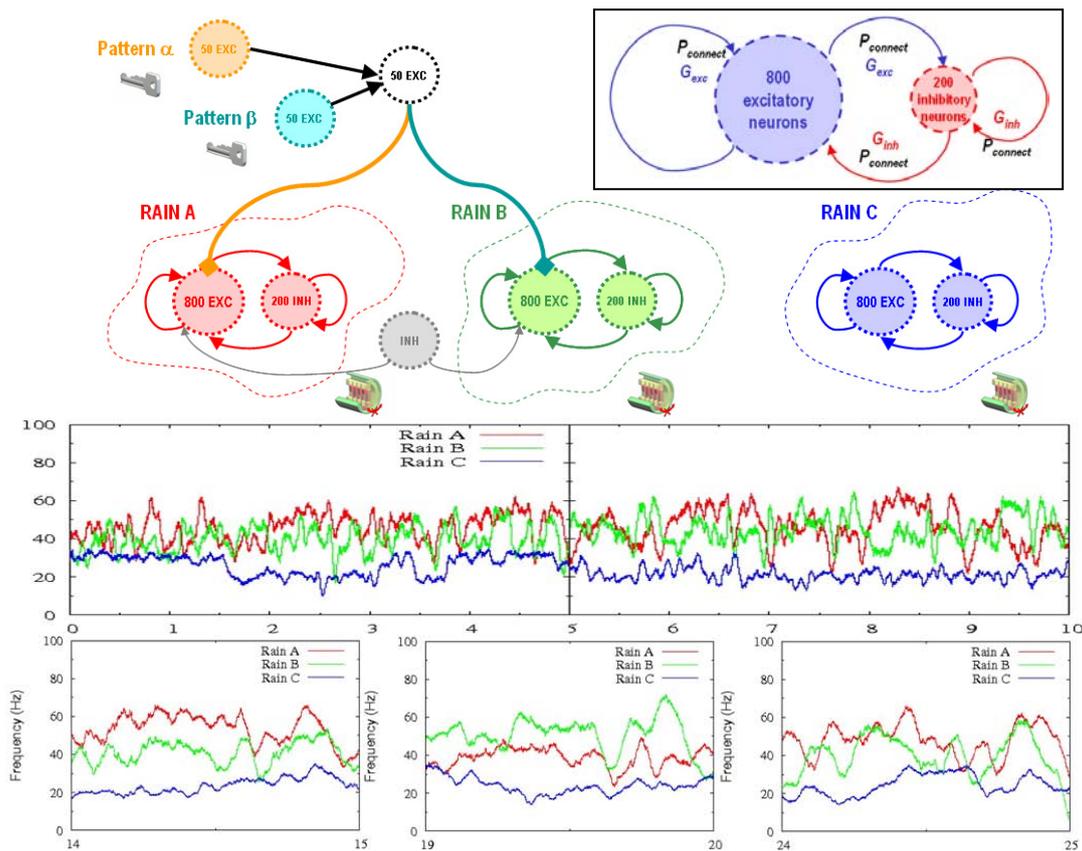


Figure 3.3.4: Multi-RAIN discriminate Hebbian/STDP learning. **Top:** Experimental setup involving 2 RAINs A and B stimulated by 2 patterns α and β (RAIN extracts, as in inset of Fig. 3.3.3), 1 control RAIN C (not stimulated), 1 control pattern γ (not learned), and 1 inhibitory pool common to A and B. Hebbian learning affects $\alpha \rightarrow A$ and $\beta \rightarrow B$ connections. **Middle:** Training phase alternating α -learning on A and β -learning on B (showing the 3 RAINs' global potentials). **Bottom:** Test phase: A's response (red) is higher for a stimulation by α (left) than β (center); and conversely for B. Untrained assembly C does not distinguish α from β (from Goodman et al. 2007).

In both cases, whether simplified oscillatory units or complex RAIN activity, our goal is to explore “lock and key” principles, proposing that pattern recognition and nondiscrete memory storage are based on a dynamics of *coherence induction* triggered by input stimuli (the “keys”). Here, learning a pattern (a “lock”) means tuning synaptic efficacies of the receiving lock patterns are tuned to a point of maximal postsynaptic response. They represent another form of neocortical *pattern formation*, i.e., the emergence of structurally complex, spiking neurodynamic “shapes”.

Spinoff Projects

Project NEUROFORM-AIBO

An integrated, modular brain architecture of spiking neural networks that emulate learning in a hybrid neuromorphic/AI socially interactive robot

Collaborator: Philip H. Goodman, Brain Computation Laboratory, University of Nevada, Reno

Abstract: This project is an original attempt to implement a complete information processing loop between a neural network simulator running on a computer cluster (Fig. 3.3.5a) and a real-time embedded robot (Fig. 3.3.5c) learning to interact socially with humans (e.g., robotic sentry, industrial assistant). The system must (i) collect disparate signal patterns from multiple sensory modalities coming from the robot, (ii) process these signals by interaction with perceptual, associative, memory and motor systems and (iii) send actuator commands back to the robot. To this aim, we plan to complete the design of an anatomically realistic, albeit simplified, brain architecture inspired comprising interconnected auditory/visual (AV), associative (AS) and motor (MC) cortical areas, modulated by prefrontal cortex (PFC) and subcortical structures (SC) (Fig. 3.3.5a). These areas are modeled with spiking neural networks in various dynamical regimes, under Hebbian synaptic redistribution. The functional systems we plan to implement are multimodal processing, working memory, and executive behavior, with the inclusion of attentional and reward signals from subcortical networks. At the core of the architecture lies the stimulus-behavior association area (AS), which is based on “coherence induction” between spiking and subthreshold STPs. Our approach is to develop the different areas as independent modules, then combine them to obtain a global stimulus-response learning. We hope to demonstrate the ability of a remote-brained robot to navigate in a realistic terrain, through real-time recognition and strategic planning, while learning to respond appropriately to surrounding humans via reward and punishment.

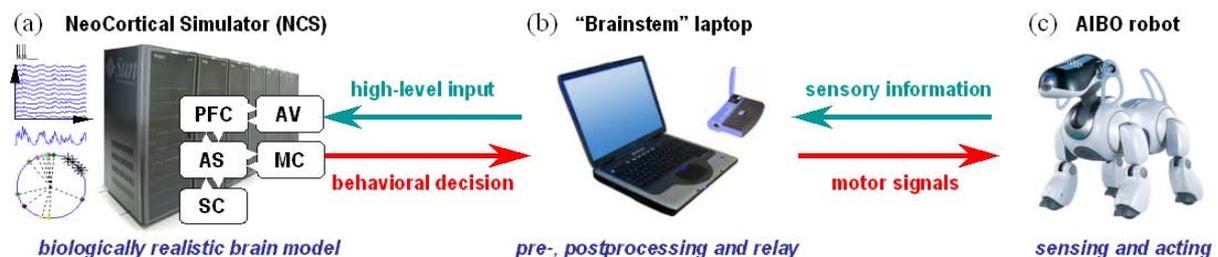
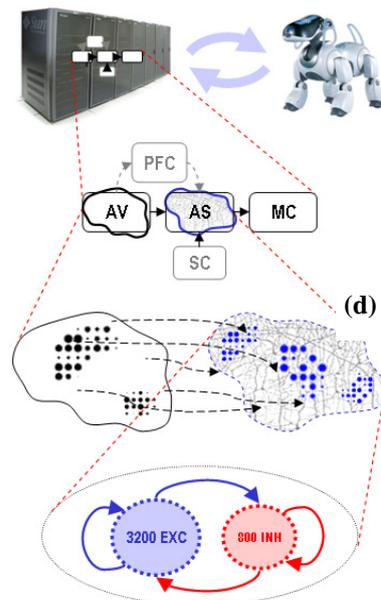


Figure 3.3.5: A complete sensorimotor loop between cluster and robot. (c) Robot (e.g., Sony Aibo) interacts with environment and humans via sensors & actuators. (a) Neural network simulator software (e.g., NCS developed at U. of Nevada) runs on computer cluster: it contains the brain architecture for decision-making and learning. (c) “Brainstem” laptop brokers WiFi connection: it transmits multimodal sensory signals to simulator and sends actuator commands to robot. (d) Multiscale schema showing link from RAINs to robot (from Doursat & Goodman 2006, Goodman et al. 2007).

Relevant Publications

Full Papers – Books, Journals, Conferences, Workshops, Reports

Zou, Q., Doursat, R. & Goodman, P. H. (2010) The role of spatiotemporal correlations in the encoding and retrieval of synaptic patterns by STDP in recurrent spiking neural networks. *In Preparation*.

Abstracts (for Presentations or Posters) – Conferences, Workshops

Doursat, R. & Goodman, P. H. (2006) Neocortical keys and locks: A neural model of associative learning by coherence induction between spike patterns and ongoing membrane potentials. *10th International Conference on Cognitive and Neural Systems (ICCNS 2006)*, May 17-20, 2006, Boston University, MA.

Doursat, R., Goodman, P. H. & Zou, Q. (2007) Neocortical locks and keys: Coherence induction among complex, heterogeneous neuronal patterns. *Ladislav Tauc Conference in Neurobiology 2007: Complexity in Neural Network Dynamics (Tauc 2007)*, December 13-14, 2007, Institut de Neurobiologie Alfred Fessard (INAF), CNRS, Gif-sur-Yvette, France.

Goodman, P. H., Doursat, R., Zou, Q., Zirpe, M. & Sessions, O. (2007) RAIN brains: Mammalian neocortex as a hybrid analog-digital computer. *Unconventional Computation Conference (UC 2007)*, March 21-23, 2007, Los Alamos National Laboratory (LANL) and Santa Fe Institute (SFI), Santa Fe, NM.

Invited Keynote Presentations & Talks (with Abstracts) – Conferences, Workshops

Goodman, P. H. & Doursat, R. (2007) Large-scale biologically realistic models of cortical mesocircuit dynamics. *Computational Neuroscience, Sensory Augmentation, and Brain-Machine Interface*, April 25-26, 2007, Office of Naval Research (ONR), Arlington, VA.

References (other than my own publications)

- Abeles, M. (1982) *Local Cortical Circuits*, Berlin: Springer-Verlag.
- Abeles, M. (1991) *Corticonics*. Cambridge University Press.
- Abeles, M., Hayon, G. and Lehmann, D. (2004) Modeling compositionality by dynamic binding of synfire chains. *J. Comput. Neurosci.* 17: 179-201.
- Abelson, H., Allen, D., Coore, D., Hanson, C., Homsy, G., Knight, Jr., T., Nagpal, R., Rauch, E., Sussman, G. and Weiss, R. (1999) *Amorphous Computing*. MIT Artificial Intelligence Lab memo no. 1665.
- Adamatzky, A., Ed. (2002) *Collision-based computing*. Springer-Verlag.
- Amit, D. J. and Brunel, N. (1997) Model of global spontaneous activity and local structured activity during delay periods in the cerebral cortex. *Cerebral Cortex* 7:237-252.
- Aviel, Y., Horn, D. and Abeles, M. (2004) Synfire waves in a small balanced network. *Neurocomputing* 58-60: 123-127.
- Ball, P. (1999) *The Self-Made Tapestry*. Oxford University Press.
- Barabási, A.-L. and Albert, R. (1999) Emergence of scaling in random networks. *Science* 286: 509-512.
- Barrat, A., Barthélémy, M. and Vespignani, A. (2008) *Dynamical Processes on Complex Networks*. Cambridge University Press.
- Bechtel, W. and Graham, G. (1998) *A Companion to Cognitive Science*. Wiley-Blackwell.
- Beal, J. and Bachrach, J. (2006) Infrastructure for engineered emergence on sensor/actuator networks. *IEEE Intell. Sys.* 21(2): 10-19.
- Bentley, P. and Kumar, S. (1999) Three ways to grow designs: A comparison of embryogenies for an evolutionary design problem. In *Proceedings of the Genetic and Evolutionary Computation Conference* (Orlando, Florida), W. Banzhaf et al., Eds. Morgan Kaufmann, vol. 1, pp. 35-43.
- Bialek, W., Rieke, F., de Ruyter van Steveninck, R., & Warland, D. (1991) Reading a neural code. *Science* 252: 1854-1857.
- Bienenstock, E. (1995) A model of neocortex. *Network* 6: 179-224.
- Bienenstock, E. (1996) Composition. In *Brain Theory*, A. Aertsens and V. Braitenberg, Eds. Elsevier, pp. 269-300.
- Blum, H. (1973) Biological shape and visual science. *Journal of Theoretical Biology* 38: 205-287.
- Boardman, J. and Sauser, B. (2007) *Systems Thinking: Coping with 21st Century Problems*. CRC Press.
- Bonabeau, E., Dorigo, M. and Theraulaz, G. (1999) *Swarm Intelligence: From Natural to Artificial Systems*. Oxford University Press.
- Bourgine, P., Dutreix, M., Mikula, K., Peyriéras, N., Sarti, A., Snyers, D. and Vico, F. (2006) *BioEmergences: "In What" and "How Much" are Individuals Similar and Different? Towards the Measurement of the Individual Susceptibility to Diseases or Response to Treatments*. NEST Grant, European Union, €1.7M, 6/2006-5/2009.
- Bourgine, P. and Lesne, A., eds. (2006) *Morphogenèse : l'Origine des formes*. Editions Belin, Paris.
- Braha, D., Bar-Yam, Y. and Minai, A. A., eds. (2006) *Complex Engineered Systems: Science Meets Technology*, Springer Verlag.
- Brette, R. et al. (2007) Simulation of networks of spiking neurons: A review of tools and strategies. *Journal of Computational Neuroscience* 23(3): 349-398.
- Bringuier, V., Chavane, F., Glaeser, L. and Frégnac, Y. (1999) Horizontal propagation of visual activity in the synaptic integration field of area 17 neurons. *Science* 283: 695-699.
- Brooks, R. A. (1985) *A Robust Layered Control System For a Mobile Robot*. Technical Report: AIM-864, MIT.
- Brunel, N. (2000) Dynamics of networks of randomly connected excitatory and inhibitory spiking neurons. *J. Physiol. (Paris)* 94: 445-463
- Buzsáki, G. and Draguhn, A. (2004) Neuronal oscillations in cortical networks. *Science* 304: 1926-1929.
- Callebaut, W. and Rasskin-Gutman, D., eds. (2005) *Modularity: Understanding the Development and Evolution of Natural Complex Systems*. The MIT Press, Cambridge, MA.
- Campbell, S., & Wang, D. (1996) Synchronization and desynchronization in a network of locally coupled Wilson-Cowan oscillators. *IEEE Transactions on Neural Networks* 7: 541-554.
- Carreras, I., Miorandi, D. and Chlamtac, I. (2007) From biology to evolve-able ICT systems. *1st International Workshop on eNetworks Cyberengineering, IEEE Systems Man and Cybernetics Conference* (Montreal, Canada, October 7-10, 2007). IEEE SMC'07.
- Carreras, I., Miorandi, D., Saint-Paul, R. and Chlamtac, I. (2009) Bottom-up design patterns and the Energy Web. *IEEE Transactions on Systems, Man and Cybernetics, Part A*, Special issue on *Engineering Cyber-Physical Ecosystems*, July 2009.
- Carroll, S. B. (2005) *Endless Forms Most Beautiful: The New Science of Evo Devo and the Making of the Animal Kingdom*. W. W. Norton & Company.
- Carroll, S. B., Grenier, J. K. and Weatherbee, S. D. (2001) *From DNA to Diversity*. Blackwell Scientific.

- Chomsky, N. (1986) *Knowledge of Language: Its Nature, Origin, and Use*. Praeger, New York.
- Christensen, A., O'Grady, R. and Dorigo, M. (2007) Morphology control in a self-assembling multi-robot system. *IEEE Robotics & Automation Magazine* 14(4): 18-25.
- Chua, L., & Roska, T. (1998) *Cellular neural networks and visual computing*. Cambridge, UK: Cambridge University Press.
- Cladis, P. E. and Palfy-Muhoray, P., eds. (1995) *Spatio-Temporal Patterns in Nonequilibrium Complex Systems*. Addison-Wesley.
- Coen, E. (2000) *The Art of Genes*. Oxford University Press, UK.
- Coen, E., Rolland-Lagan, A.-G., Matthews, M., Bangham, J. A. and Prusinkiewicz, P. (2004) The genetics of geometry. *PNAS* 101(14): 4728-4735.
- Coore, D. (1999) *Botanical Computing: A Developmental Approach to Generating Interconnect Topologies on an Amorphous Computer*, Ph. D. thesis, Dept. of Elec. Eng. & Computer Science, MIT.
- Croft, W., and Cruse, D. A. (2004) *Cognitive Linguistics*. Cambridge University Press.
- Dawkins, R. (1996) *Climbing Mount Improbable*. W. W. Norton & Company.
- Destexhe, A. and Paré, D. (2000) A combined computational and intracellular study of correlated synaptic bombardment in neocortical pyramidal neurons in vivo. *Neurocomputing* 32-33: 113-119.
- Dieckmann, U., Doebeli, M., Metz, J. A. J. and Tautz, D., eds. (2004) *Adaptive speciation*. Cambridge University Press.
- Diesmann, M., Gewaltig, M.-O. and Aertsen A. (1999) Stable propagation of synchronous spiking in cortical neural networks. *Nature* 402: 529-533.
- Dorigo, M. and Stützle, T. (2004) *Ant Colony Optimization*. The MIT Press.
- Dressler, F. (2007) *Self-Organization in Sensor and Actor Networks*. Wiley, NY.
- Edelman, G. M. (1988) *Topobiology*. Basic Books.
- Eggenberger, P. (1997) Evolving morphologies of simulated 3-D organisms based on differential gene expression. In P. Husbands and I. Harvey, eds., *4th European Conference on Artificial Life*, pp. 205-213. The MIT Press.
- Endy, D. (2005) Foundations for engineering biology. *Nature* 438: 449-453.
- Ermentrout, B. (1998) Neural networks as spatio-temporal pattern-forming systems. *Reports on Progress in Physics* 61: 353-430.
- FitzHugh, R. A. (1961) Impulses and physiological states in theoretical models of nerve membrane. *Biophysical Journal* 1: 445-466.
- Floreano, D. and Mattiussi, C. (2008) *Bio-Inspired Artificial Intelligence: Theories, Methods, and Technologies*. The MIT Press.
- Fodor, J. A. & Pylyshyn, Z. (1988) Connectionism and cognitive architecture: a critical analysis. *Cognition* 28(1/2): 3-71.
- Fox, M. D. and Raichle, M. E. (2007) Spontaneous fluctuations in brain activity observed with functional magnetic resonance imaging. *Nature Rev. Neurosci.* 8: 700-711.
- Freeman, W. J. (2000) *Neurodynamics: An Exploration in Mesoscopic Brain Dynamics*. Springer.
- Frégnac, Y. (1998) Homeostasis or synaptic plasticity. *Nature* 391: 845-846.
- Fruchterman, T. M. J. and Reingold, E. M. (1991) Graph drawing by force-directed placement. *Software—Practice and Experience* 21(11): 1129-1164.
- Gavrilets, S. (2004) *Fitness Landscapes and the Origin of Species*. Princeton University Press.
- Giavitto, J.-L. and Michel, O. (2002) The topological structures of membrane computing. *Fundamenta Informaticae* 49:107-129.
- Giavitto, J.-L. and Spicher, A. (2008) Topological rewriting and the geometrization of programming. *Physica D* 237(9): 1302-1314.
- Gierer, A. and Meinhardt, H. (1972) A theory of biological pattern formation, *Kybernetik* 12: 30-39.
- Goldstein, S. C., Campbell, J. D. and Mowry, T. C. (2005) Programmable matter. *IEEE Comp.* 38(6): 99-101.
- Goodwin, B. (1994) *How the Leopard Changed Its Spots: Evolution of Complexity*. Weidenfeld Nicolson Illustrated
- Grant, P. R. and Grant, B. R. (1997) Genetics and the origin of bird species. *Proc. Natl. Acad. Sci. USA* 94: 7768-7775.
- Gray, C. M., König, P., Engel, A. K., & Singer, W. (1989) Oscillatory responses in cat visual cortex exhibit intercolumnar synchronization which reflects global stimulus properties. *Nature* 338: 334-337.
- Grégoire, G. and Chaté, H. (2004) Onset of collective and cohesive motion. *Physical Rev Letters* 92: 025702.
- Grobbelaar, S. and Ulieru, M. (2006) Self-organizing cyber-systems as infrastructure for optimizing power distribution networks. *Annual Conference of the South African Institute of Computer Scientists and Information Technologists* (Capewineland, South Africa, October 9-11, 2006). SAICSIT'06.
- Grobbelaar, S. and Ulieru, M. (2007) Complex networks as control paradigm for complex systems. *1st International Workshop on eNetworks Cyberengineering, IEEE Systems Man and Cybernetics Conference*

- (Montreal, Canada, October 7-10, 2007). IEEE SMC'07.
- Gross, R., Bonani, M., Mondada, F. and Dorigo, M. (2006) Autonomous self-assembly in swarm-bots. *IEEE Transactions on Robotics* 22(6): 1115-1130.
- Harris, K. D. (2005) Neural signatures of cell assembly organization. *Nature Rev. Neurosci.* 6: 399-407.
- Hebb, D. O. (1949) *The organization of behavior*. John Wiley & Sons, New York.
- Herskovits, A. (1986) *Language and spatial cognition: An interdisciplinary study of the prepositions in English*. Cambridge University Press.
- Hertz, J. and Prügel-Bennett, A. (1996) Learning short synfire chains by self-organization. *Network* 7: 357-363.
- Hoelzer, G. (2001) The self-organization of population substructure in biological systems. *InterJ Genet* 345.
- Hofmeyr, S. A. and Forrest, S. (2000) Architecture for an artificial immune system. *Evolutionary Computation* 8(4): 443-473.
- Hogeweg, P. (2000) Evolving mechanisms of morphogenesis: On the interplay between differential adhesion and cell differentiation. *Journal of Theoretical Biology* 203: 317-333.
- Hogeweg, P. and Takeuchi, N. (2003) Multilevel selection in models of prebiotic evolution: compartments and spatial self-organization. *Orig Life Evol Biosphere* 33: 375-403.
- Holland, J. (1992) *Adaptation in Natural and Artificial Systems*. The MIT Press.
- Holland, J. (1996) *Hidden Order: How Adaptation Builds Complexity*. Basic Books.
- Holland, J. (1998) *Emergence: From Chaos to Order*. Addison-Wesley, Redwood City, CA.
- Hornby, G. S. and Pollack, J. B. (2002) Creating high-level components with a generative representation for body-brain evolution. *Artificial Life* 8(3): 223-246.
- Ikegaya, Y., Aaron, G., Cossart, R., Aronov, D., Lampl, I., Ferster, D., & Yuste, R. (2004) Synfire chains and cortical songs: temporal modules of cortical activity. *Science* 304: 559-564.
- Irwin, D. E., Bensch, S. and Price, T. D. (2001) Speciation in a ring. *Nature* 409: 333-337.
- Isermann, R. (1981) *Digital Control Systems*. Springer-Verlag, New York.
- Izhikevich, E. M. (2006) Polychronization: Computation with spikes. *Neural Computation* 18: 245-282.
- Izhikevich, E. M., Gally, J. A. and Edelman, G. M. (2004) Spike-timing dynamics of neuronal groups. *Cereb. Cortex* 14: 933-944.
- Jackendoff, R. (1983) *Semantics and cognition*. The MIT Press.
- Johnson, J. L. (1994) Pulse-coupled neural nets: translation, rotation, scale, distortion and intensity signal invariance for images. *Applied Optics* 33(26): 6239-6253.
- Jukes, T. H. and Cantor, C. R. (1969) Evolution of proteins molecules. In: *Mammalian protein metabolism*, H. N. Munro, ed. Academic Press. pp. 21-132.
- Kauffman, S. A. (1969) Metabolic stability and epigenesis in randomly constructed genetic nets, *Journal of Theoretical Biology* 22: 437-467.
- Kauffman, S. A. (1993) *The Origins of Order: Self-Organization and Selection in Evolution*. Oxford University Press.
- Kauffman, S. A. (2008) *Reinventing the Sacred*. Basic Books.
- Kenet, T., Bibitchkov, D., Tsodyks, M., Grinvald, A. and Arieli, A. (2003) Spontaneously emerging cortical representations of visual attributes. *Nature* 425: 954-956.
- Kennedy, J. and Eberhart, R. C. (1995) Particle swarm optimization. In *Proceedings of the IEEE 1995 International Conference on Neural Networks*, pp. 1942-1948.
- Kephart, J. O. and Chess, D. M. (2003) The vision of autonomic computing. *Computer* 36(1): 41-50.
- Kimia, B. B. (2003) On the role of medial geometry in human vision. *Journal of Physiology Paris* 97(2/3): 155-190.
- Kirschner, M. W. and Gerhart, J. C. (2005) *The Plausibility of Life: Resolving Darwin's Dilemma*. Yale University Press, New Haven.
- Knight, T.F. (2003) *Idempotent Vector Design for Standard Assembly of Biobricks*. Tech. Rep., MIT Synthetic Biology Working Group.
- Komosiński, M. and Rotaru-Varga, A. (2001) Comparison of different genotype encodings for simulated three-dimensional agents. *Artificial Life* 7(4): 395-418.
- Komosiński, M. and Ulatowski, S. (1999) Framsticks: Towards a simulation of a nature-like world, creatures and evolution. In D. Floreano, J. -D. Nicoud and F. Mondada, eds., *5th European Conference on Advances in Artificial Life (ECAL-99)*, pp261-265, Lausanne, Sept. 13-17, 1999. Springer.
- Kondo, S. and Asai, R. (1995) A reaction-diffusion wave on the skin of the marine angelfish *Pomacanthus*. *Nature* 376: 765-768.
- König, P., & Schillen, T. B. (1991) Stimulus-dependent assembly formation of oscillatory responses. *Neural Computation* 3: 155-166.
- Kosslyn, S. M. (1994) *Image and Brain: The Resolution of the Imagery Debate*. The MIT Press.
- Lakoff, G. (1987) *Women, fire, and dangerous things*. Chicago, IL: University of Chicago Press.
- Lakoff, G. (1988) A suggestion for a linguistics with connectionist foundations. In *Proceedings of the 1988*

- Connectionist Models Summer School*. Morgan Kaufman.
- Langacker, R. (1987) *Foundations of cognitive grammar*. Palo Alto, CA: Stanford University Press.
- Lee, T. S. (2003) Computations in the early visual cortex. In J. Petitot & J. Lorenceau (Eds.), *Journal of Physiology Paris* 97(2/3): 121-139.
- Lenski, R. E., Ofria, C., Pennock, R. T. and Adami, C. (2003) The evolutionary origin of complex features. *Nature* 423: 139-144.
- Levinson, S. C. (2003) *Space in Language and Cognition: Explorations in Cognitive Diversity*. Cambridge University Press.
- Leyton, M. (1992) *Symmetry, causality, mind*. The MIT Press.
- Lipson, H. and Pollack, J. B. (2000) Automatic design and manufacture of robotic lifeforms. *Nature* 406: 974-978.
- Llinas, R. (2001) *I of the Vortex: From Neurons to Self*. The MIT Press, Cambridge, MA.
- Lombardot, B., Luengo-Oroz, M. A., Melani, C., Faure, E., Santos, A., Peyrieras, N., Ledesma-Carbayo, M. and Bourguine, P. (2008) Evaluation of four 3-D non-rigid registration methods applied to early zebrafish development sequences. *3rd International Workshop on Microscopic Image Analysis with Applications in Biology (MIAAB 2008)*, September 5-6, 2008, New York, NY.
- Maass, W., Natschläger, T. and Markram, H. (2002) Real-time computing without stable states: a new framework for neural computation based on perturbations. *Neural Computation* 14: 2531-2560
- Macal, C. M. and North, M. J. (2006) Tutorial on agent-based modeling and simulation, Part 2: How to model with agents. In *Proceedings of the 2006 Winter Simulation Conference*. L. F. Perrone et al., Eds., 73-83.
- Marée, A. F. M. and Hogeweg, P. (2001) How amoeboids self-organize into a fruiting body: Multicellular coordination in *Dictyostelium discoideum*. *PNAS* 98(7): 3879-3883.
- Markram, H. (2006) The BlueBrain project. *Nature Reviews Neuroscience* 7(2): 153-160.
- Marr, D. (1982) *Vision*. San Francisco, CA: Freeman Publishers.
- Marzano, S. and Aarts, E. (2003) *The New Everyday: Views on Ambient Intelligence*. Uitgeverij 010 Publishers.
- Mayr, E. (1942) *Systematics and the Origin of Species*. Columbia University Press.
- McMillin, B., Gill, C., Crow, M. L., Liu, F., Niehaus, D., Potthast, A. and Tauritz, D. (2006) Cyber-physical systems engineering: The advanced power grid. In *Proc. of NSF Workshop on CyberPhysical Systems*.
- Meinhardt, H. (1998) *The Algorithmic Beauty of Sea Shells*. Springer-Verlag.
- Miller, J. F. and Banzhaf, W. (2003) Evolving the Program for a Cell: From French Flags to Boolean Circuits. In *On Growth, Form and Computers*, S. Kumar and P. Bentley, Eds., Elsevier Acad. Press.
- Milton, J. G., Chu, P. H., & Cowan, J. D. (1993) Spiral waves in integrate-and-fire neural networks. In *Advances in Neural Information Processing Systems, Vol. 5* (pp. 1001-1007). Morgan Kaufmann.
- Minai, A. A., Braha, D. and Bar-Yam, Y. (2006) Complex engineered systems. In D. Braha, Y. Bar-Yam and A. A. Minai, eds., *Complex Engineered Systems: Science Meets Technology*. Springer Verlag.
- Minor, E.S., McDonald, R.I., Treml, E. A. and Urban, D.L. (2008) Uncertainty in spatially explicit population models. *Biol Conserv* 141: 956-970.
- Mjolsness, E., Sharp D. H. and Reintz, J. (1991) A connectionist model of development, *Journal of Theoretical Biology* 152: 429-453.
- Müller, G. B. and Newman, S. A., eds. (2003) *Origination of Organismal Form: Beyond the Gene in Developmental and Evolutionary Biology*. The MIT Press.
- Müller-Schloer, C. and Sick, B. (2008) Controlled emergence and self-organization. In *Organic Computing*, R. P. Würtz, ed. Springer-Verlag, pp. 81-104.
- Mumford D., & Shah, J. (1989) Optimal approximations by piecewise smooth functions and associated variational problems. *Communications on Pure and Applied Mathematics* 42: 577-685.
- Nagpal, R. (2002) Programmable self-assembly using biologically-inspired multi-agent control. *First International Conference on Autonomous Agents*, Bologna, July 15-19.
- Newman, M. E. J. (2006) Modularity and community structure in networks. *Proc. Natl. Acad. Sci.* 103(23): 8577-8582.
- Nijhout, H. F. (1990) A comprehensive model for colour pattern formation in butterflies. *Proc. R. Soc. Lond. B* 239: 81-113.
- Nilsson, D. E. and Pelger, S. (1994) A pessimistic estimate of the time required for an eye to evolve. *Proceedings of the Royal Society of London B* 256: 53-58.
- Nunes de Castro, L. (2006) *Fundamentals of Natural Computing: Basic Concepts, Algorithms, and Applications*. Chapman & Hall/Crc Computer and Information Sciences.
- O'Keefe, J., & Recce, M. L. (1993) Phase relationship between hippocampal place units and the EEG θ rhythm. *Hippocampus* 3: 317-330.
- Pearson, J. E. (1993) Complex patterns in a simple system. *Science* 261: 189-192.
- Petitot, J. (1995) Morphodynamics and attractor syntax. In T. van Gelder & R. Port (Eds.), *Mind as Motion* (pp. 227-281). The MIT Press.

- Petitot, J. (2003) *Morphogenesis of Meaning*. Peter Lang, Bern.
- Peyri ras, N. (PI), Bourguine, P., Hirsinger, E., Mikula, K. & Sarti, A. (2005) *Embryomics: Reconstructing in Space and Time the Cell Lineage Tree*. NEST Grant, European Union,  1.45M, 11/2005-10/2008.
- Pfeifer, R. and Bongard, J. C. (2006) *How the Body Shapes the Way We Think: A New View of Intelligence*. The MIT Press.
- Prusinkiewicz P. and Lindenmayer A. (1990) *The Algorithmic Beauty of Plants*. Springer-Verlag NY.
- Regier, T. (1996) *The Human Semantic Potential*. The MIT Press, Cambridge, MA.
- Rauch, E. M., Sayama, H. and Bar-Yam, Y. (2003) Dynamics and genealogy of strains in spatially extended host-pathogen models. *J Theor Biol* 221: 655-664.
- Rogers, A. R. and Harpending, H. (1992) Population growth makes waves in the distribution of pairwise genetic differences. *Mol. Biol. Evol.* 9: 552-569.
- Roskies, A. L. (1999) The binding problem. *Neuron* 24: 7-9.
- Rothmund, P. W. K. (2006) Folding DNA to create nanoscale shapes and patterns. *Nature* 440: 297-302.
- Salazar-Ciudad, I., Garcia-Fern andez, J. and Sol , R. (2000) Gene networks capable of pattern formation, *Journal of Theoretical Biology* 205: 587-603.
- Salazar-Ciudad, I. and Jernvall, J. (2002) A gene network model accounting for development and evolution of mammalian teeth. *PNAS* 99(12): 8116-8120.
- Sayama, H. (2007) Decentralized control and interactive design methods for large-scale heterogeneous self-organizing swarms. *Advances in Artificial Life: Proceedings of the 9th ECAL*.
- Sayama H., Kaufman L. and Bar-Yam, Y. (2000) Symmetry breaking and coarsening in spatially distributed evolutionary processes including sexual reproduction and disruptive selection. *Phys Rev E* 62: 7065-7069.
- Schlosser, G. and Wagner, G. P., eds. (2004) *Modularity in Development and Evolution*, The University of Chicago Press.
- Scholl, B. J., & Tremoulet, P. D. (2000) Perceptual causality and animacy. *Trends in Cognitive Science* 4(8): 299-309.
- Serra, J. (1982) *Image analysis and mathematical morphology*. New York: Academic Press.
- Serre, T., Wolf, L., Bileschi, S., Riesenhuber, M. and Poggio, T. (2007) Robust object recognition with cortex-like mechanisms. *IEEE Trans. on Pattern Analysis and Machine Intelligence* 29(3): 411-426.
- Shapiro, B. E., Levchenko, A., Meyerowitz, E. M., Wold, B. J. and Mjolsness, E. D. (2003) Cellerator: Extending a computer algebra system to include biochemical arrows for signal transduction simulations. *Bioinformatics* 19(5): 677-678.
- Sharp, D. H. and Reinitz, J. (1998) Prediction of mutant expression patterns using gene circuits. *BioSystems* 47: 79-90
- Shastri, L., & Ajjanagadde, V. (1993) From simple associations to systematic reasoning. *Behavioral and Brain Sciences* 16(3): 417-451.
- Siddiqi, K., Shokoufandeh, A., Dickinson, S. J., & Zucker, S. W. (1999) Shock graphs and shape matching. *International Journal of Computer Vision* 35(1), 13-32.
- Siero, P., Rozenberg, G. and Lindenmayer, A. (1982) Cell division patterns: syntactical description and implementation. *Comp Graph Image Proc* 18:329-346.
- Silberman, S. (2001) The energy web. *Wired Magazine* 9.07.
- Silvertown, J. and Antonovics, J., eds. (2001) *Integrating Ecology and Evolution in a Spatial Context*. Cambridge University Press.
- Sims, K. (1994) Evolving 3D morphology and behavior by competition. *Artificial Life IV: 4th Int'l Workshop on the Synthesis and Simulation of Living Systems*, R. A. Brooks and P. Maes, eds. The MIT Press.
- Slatkin, M. (1993) Isolation by distance in equilibrium and non-equilibrium populations. *Evolution* 47: 264-279.
- Smolensky, P. (1988) On the proper treatment of connectionism. *Behavioral and Brain Sciences* 11: 1-74.
- Stanley, K., Bryant, B. and Miikkulainen, R. (2005) Real-time evolution in the NERO video game. *IEEE Symposium on Computational Intelligence and Games*, pp182-189, Essex University, Colchester, UK, April 4-6, 2005.
- Stanley, K. O. and Miikkulainen, R. (2003) A taxonomy for artificial embryogeny. *Artificial Life* 9(2): 93-130.
- Swinney, H. L. and Krinsky, V. I., eds. (1991) *Waves and Patterns in Chemical and Biological Media*. The MIT Press.
- Talmy, L. (2000) *Toward a Cognitive Semantics*. The MIT Press, Cambridge. (Original work published 1972-1996)
- Tanenbaum, A. S. and van Steen, M. (2002) *Distributed Systems: Principles and Paradigms*. Prentice Hall.
- Treuil, J. P., Drogoul, A. and Zucker, J. D. (2008) *Mod lisation et simulation   base d'agents*. Dunod, Paris.
- Turing, A. M. (1952) The chemical basis of morphogenesis. *Phil. Trans. R. Soc. London B* 237: 37-72.
- Ulieru, M. (2007) Evolving the "DNA blueprint" of eNetwork middleware to control resilient and efficient cyber-physical ecosystems. *2nd International Conference on Bio-Inspired Models of Network, Information, and Computing Systems* (Budapest, Hungary, December 10-14, 2007). BIONETICS'07.

- Ulieru, M. (2008) Enabling the SOS network, *Proceedings of the IEEE Systems, Man and Cybernetics Conference (SMC 2008)*, October 12-15, 2008, Singapore.
- Ulieru, M., Brennan, R. and Walker, S. (2002) The holonic enterprise: A model for Internet-enabled global supply chain and workflow management. *Int'l J. of Integrated Manufacturing Systems* 13(8): 538-550.
- Ulieru, M. and Unland, R. (2004) Emergent e-Logistics infrastructure for timely emergency response management. In *Engineering Self-Organising Systems: Nature Inspired Approaches to Software Engineering*, G. Di Marzo Serugendo et al., Eds. Springer-Verlag, Berlin, 139-156.
- van Gelder, T., and Port, R. F. (1995) It's about time: an overview of the dynamical approach to cognition. In *Mind as Motion: Explorations in the Dynamics of Cognition*. The MIT Press.
- Vicsek, T., Czirók, A., Ben-Jacob, E., Cohen, I. and Shochet, O. (1995) Novel type of phase transition in a system of self-driven particles. *Physical Review Letters* 75: 1226-1229.
- Vogels, T. P. and Abbott, L. F. (2005) Signal propagation and logic gating in networks of integrate-and-fire neurons. *Journal of Neuroscience* 25: 10786-10795.
- von Dassow, G., Meir, E., Munro, E. M. and Odell, G. M. (2000) The segment polarity network is a robust developmental module, *Nature* 406: 188-192.
- von der Malsburg, C. (1981) *The Correlation Theory of Brain Function*. Internal Report 81-2, Max Planck Institute for Biophysical Chemistry, Department of Neurobiology, Göttingen, Germany.
- von der Malsburg, C. (1987) Synaptic plasticity as basis of brain organization. In *The neural and molecular bases of learning*, J.-P. Changeux and M. Komishi, eds., pp. 411-432. John Wiley & Sons, New York.
- von der Malsburg, C. (1999) The what and why of binding: The modeler's perspective. *Neuron* 24: 95-104.
- von der Malsburg, C. & Bienenstock, E. (1986) Statistical coding and short-term synaptic plasticity: A scheme for knowledge representation in the brain. In *Disordered systems and biological organization*, E. Bienenstock, F. Fogelman and G. Weisbuch, eds., pp. 247-272. Springer-Verlag, Berlin.
- von der Malsburg, C., Würtz, R. and Schäfer A. (2006) *The Organic Computing Group*, <http://www.organic-computing.org>.
- Wang, D. L. (2005) The time dimension for scene analysis. *IEEE Trans. Neural Networks* 16(6): 1401-1426.
- Wang, X. J. (2001) Synaptic reverberation underlying mnemonic persistent activity. *Trends in Neurosciences* 24(8): 455-463.
- Wang Y., Markram H., Goodman P. H., Berger T., Ma J. & Goldman-Rakic P. S. (2006) Heterogeneity in the pyramidal network of the medial prefrontal cortex. *Nature Neuroscience* 9(4): 534-542.
- Watson, R. A. and Pollack, J. B. (2005) Modular interdependency in complex dynamical systems. *Artificial Life* 11(4): 445-458.
- Webster, G. and Goodwin, B. (1996) *Form and Transformation: Generative and Relational Principles in Biology*. Cambridge University Press.
- Weiser, M. (1993) Some computer science issues in ubiquitous computing. *Commun. of the ACM* 36: 75-84.
- Werfel, J. and Nagpal, R. (2006) Extended stigmergy in collective construction. *IEEE Intelligent Systems* 21(2): 20-28.
- Whitaker, R. (1993) Geometry-limited diffusion in the characterization of geometric patches in images. *Computer Vision, Graphics, and Image Processing: Image Understanding* 57(1): 111-120.
- Whitesides, G. M. and Grzybowski, B. (2002) Self-assembly at all scales. *Science* 295: 2418-2421.
- Willinger W. and Doyle J. (2002) Robustness and the Internet. Design and evolution. In *Robust Design: A Repertoire of Biological, Ecological, and Engineering Case Studies*, E. Jen, Ed. Oxford University Press, pp. 231-272.
- Winfield, A. F. T., Harper, C. and Nembrini, J. (2005) Towards dependable swarms and a new discipline of swarm engineering. In *Swarm Robotics*, LNICST, Springer-Verlag Berlin, pp126-142.
- Winfree, A. (1980, 2001) *The Geometry of Biological Time*. Springer-Verlag.
- Wolpert, L. (1969) Positional information and the spatial pattern of cellular differentiation development. *J. Theoret. Biology* 25: 1-47.
- Wolpert, L., Smith, J., Jessell, T., Lawrence, P., Robertson, E. and Meyerowitz, E. (2006) *Principles of Development*. Oxford University Press.
- Wooldridge, M. (2002) *An Introduction to Multiagent Systems*. John Wiley and Sons Ltd.
- Wright, S. (1943) Isolation by distance. *Genetics* 28: 114-138.
- Würtz, R. P., ed. (2008) *Organic Computing*. Series: *Understanding Complex Systems*. Springer-Verlag.
- Young, D. (1984) A local activator-inhibitor model of vertebrate skin patterns. *Mathematical Biosciences* 72: 51-58.
- Zanella, C., Rizzi, B., Melani, C., Campana, M., Bourguin, P., Mikula, K., Peyriéras, N. and Sarti, A. (2007) Segmentation of cells from 3-D confocal images of live zebrafish embryo. *29th Annual Int'l Conference of the IEEE Engineering in Medicine and Biology Society (EMBS 2007)*, Aug 22-26, 2007, Lyon.
- Zhu, S. C., & Yuille, A. L. (1996) FORMS: A flexible object recognition and modeling system. *Int. Journal of Computer Vision* 20(3): 187-212.

Curriculum Vitæ (Revision April 12, 2010)

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SUMMARY

Institut des Systèmes Complexes, CNRS, Paris Ile-de-France

- *Director*, 1/2009–Present
- *Guest Researcher*, 9/2007–Present
- *Research Engineer*, 11/2006–8/2007

University of Nevada, Reno, USA

- *Visiting Assistant Professor, Department of Computer Science*, 7/2005–6/2006
- *Research Assistant Professor, Brain Computation Laboratory*, 8/2004–6/2005

Akheron Technologies, Palo Alto, California

- *Chief Engineer*, 3/2002–8/2004

BIOwulf Genomics, Berkeley, California

- *Senior Software Architect*, 11/2000–2/2002

RedCart.com, San Francisco, California

- *Senior Software Engineer & Architect*, 7/1999–11/2000

Neuron Data, Mountain View, California, and Paris, France

- *Senior Software Engineer*, 8/1998–7/1999
- *Software Engineer, Research & Development*, 4/1995–7/1998

CREA, Ecole Polytechnique & CNRS, Paris, France

- *Research Associate*, 10/1996–9/1997
- *Associate Member*, then *Foreign Correspondent*, then *Full Member*, 10/1995–Present

Institut für Neuroinformatik, Ruhr-Universität Bochum, Germany

- *Postdoctoral Assistant*, 10/1991–12/1994

Université Pierre et Marie Curie (Paris 6), France

- *Ph.D. in applied mathematics / computational physics*, 5/1991

Laboratoire d'Electronique, ESPCI, Paris, France

- *Doctoral Fellow*, 10/1987–9/1991 (aged 25)

Ecole Normale Supérieure (ENS), Paris, France

- *M.S. in theoretical physics*, 9/1987

EDUCATION

Ph.D., applied maths / computational physics, Université Pierre et Marie Curie (Paris 6), France, 5/1991

- Fields: computational neuroscience, neural networks, machine learning, computer vision, biological modeling, complex systems, cognitive science
- Title: *A Contribution to the Study of Representations in the Nervous System and in Artificial Neural Networks* (dissertation in French)
- Advisor: Elie Bienenstock, CNRS (currently Associate Professor, Department of Neuroscience and Division of Applied Mathematics, Brown University, Providence, Rhode Island)

M.S., theoretical physics, Ecole Normale Supérieure (ENS), Paris, France, 9/1987

ENS and Ecole Polytechnique are the two most selective and prestigious graduate schools in France.

Lead graduate candidate, “Grandes Ecoles”, Paris, France, 7/1985 (aged 19)

Single-digit ranks at several competitive entrance exams to the best science & engineering graduate schools:

- Ranked 1st of 2,818 candidates at the Ecole Centrale league examination (group of four schools)
- Ranked 5th of 2,239 candidates at the Ecole des Mines league examination (group of eight schools)
- Ranked 9th of 222 candidates (physics section) at the Ecole Normale Supérieure (ENS), Paris
- Ranked 7th at the written examination (physics section) of the Ecole Normale Supérieure de St-Cloud

High-school & undergrad student, Lycée Louis-le-Grand, Paris, 1979–1985

Lycée Louis-le-Grand is ranked Nr. 1 high school/college in France.

Born in 1966.

ACADEMIC POSITIONS

Director, Institut des Systèmes Complexes, CNRS, Paris Ile-de-France, 1/2009–Present

The Complex Systems Institute, Paris Ile-de-France (ISC-PIF; founded by Paul Bourguine) is a multidisciplinary research center and network (GIS = Groupement d'Intérêt Scientifique) sponsored by the Paris Region (Ile-de-France; DIM = Domaine d'Intérêt Majeur) and 15 French academic partners—graduate schools, universities, and national institutions (Ecole Polytechnique, Ecole Normale Supérieure, Université Pierre et Marie Curie, CNRS, INRIA, CEA, INSERM, et al.). Its mission is to create a community of research in “complex systems”—viewed as large sets of elements interacting locally and producing collective behavior—that studies common questions (self-organization, emergence, autonomy, adaptation, etc.) across many domains (molecular, cellular, cognitive, social, economic, technological, environmental).

Beside my research activities (see below), I am in charge of managing the institute, together with a monthly Steering Committee (12 external advisors), in particular leading the renewal of ISC's mandate and funding for the next four-year period 2010-2013. I report twice a year to an Executive Board (composed of our supporting partners) about the institute's program, activities and budget use (capital and operating budget totaling about €1M/year). Scientific orientations are overseen by a Scientific Council of foreign scholars. Capital budget is used to create ISC “branches” hosted by its different academic partners, i.e., build/renovate and equip office space to become complex systems research labs. Another part is invested in a large computing grid (already 1600 cores, soon 2400) dedicated to complex systems modeling and numerical simulations. Operating budget supports ISC's activities, including scientific events (conferences, workshops, seminars) and educational programs (summer school, thematic institutes, Master's curriculum), and the resident staff of 8 researchers, 3 engineers, 3 admins, who coordinate them.

Researcher, Institut des Systèmes Complexes, CNRS, Paris Ile-de-France, 9/2007–Present

Research Engineer, Institut des Systèmes Complexes, CNRS, Paris Ile-de-France, 11/2006–8/2007

Active in several collaborations with colleagues in Europe, United States and Canada on the modeling and simulation of complex multi-agent systems, in particular biological and techno-social, which can also inspire novel principles in intelligent systems design. My research topics belong to Artificial Life (biologically inspired engineering) and Computational Neuroscience (dynamics of large-scale spiking neural networks). Especially interested in the self-organization of complex, articulated morphologies from a swarm of heterogeneous agents, through dynamical, developmental, and evolutionary processes (see Research Activities below). Also worked on and co-managed with Paul Bourguine (founder and former head of ISC and the Complex Systems Society) on the *Embryomics* and *Bioemergences* projects toward the spatiotemporal reconstruction of the cell lineage tree underlying animal embryogenesis.

Visiting Assistant Professor, Dept. of Computer Science, University of Nevada, Reno, 7/2005–6/2006

Research Assistant Professor, Brain Computation Lab., University of Nevada, Reno, 8/2004–6/2005

The UNR Brain Computation Laboratory (“Brain Lab”) is an interdisciplinary research group studying large-scale spiking neuronal models of the cortex. Its core technology is the NeoCortical Simulator (NCS), a biologically detailed software model running on a massively parallel 220-CPU Beowulf computer cluster.

Co-PI in the “Neuromorphic Mesocircuits” project led by Philip H. Goodman (Professor & Lab Director, School of Medicine). It constitutes an original attempt to design a modular brain architecture of spiking neural networks that emulate robotic behavior learning. We model pattern recognition and association by “lock-and-key” coherence induction between dynamic cell assemblies. Also further developed the research on spatial categorization started at CREA, Paris (emergence of symbolic language from visual scenes; see below) and became actively involved in several other complex systems projects (see above). Additionally, as a visiting faculty in the Department of Computer Science and Engineering, taught two to three classes per semester, organized & co-managed student projects, and assisted supervising M.S. and Ph.D. works.

Research Associate, CREA, Ecole Polytechnique & CNRS, Paris, France, 10/1996–9/1997

Associate Member, then Foreign Correspondent, then Full Member, 10/1995–Present

The Centre de Recherche en Epistémologie Appliquée (CREA) is an interdisciplinary theoretical research center in cognitive and social sciences. Its activities range from neuroscience to linguistics and economics, focusing on the mathematical and computational modeling of complex, self-organizing systems.

Worked with Jean Petitot (Professor & Chair; also at EHESS—School for Advanced Studies in Social Sciences, Paris) on dynamic models of semantics based on cognitive linguistics (in contrast to logical models of syntax based on generative grammar). Specifically examined spatial categorization, i.e., how the mind is able to map an infinite variety of visual scenes to only a few prepositions ('in', 'over', 'across', etc.). This study addressed central theoretical questions such as the interface between physicalist and symbolic representations and the existence of a “cognitive topology” in perception (less metric than vector spaces, yet more metric than topological spaces). Created an image-processing application to illustrate the schematization pathways underlying spatial categorization.

Postdoctoral Assistant, Inst. für Neuroinformatik, Ruhr-Universität Bochum, Germany, 10/1991–12/1994

The Institut für Neuroinformatik (INI) is a research institute in neural networks, computer vision, neurobiological models and robotics.

Worked under the supervision of Christoph von der Malsburg (Professor & Chair; also at the University of Southern California) on theoretical aspects of pattern recognition, specifically the ability of the visual system to segment and regroup image domains under the influence of previously learned shapes. Focused on the study of networks of coupled oscillating units and their properties of emergent collective behavior, such as phase-locking synchronization or traveling waves of activity. Designed models showing that shape extraction can arise from such networks and created network simulator applications with high-end graphical user interfaces to support these models. Also taught two original seminars in cognitive science for graduate students.

Doctoral Fellow, Laboratoire d'Electronique, ESPCI, Paris, France, 10/1987–9/1991

The Laboratoire d'Electronique at the Ecole Supérieure de Physique et Chimie Industrielles (ESPCI) is an engineering research lab in machine learning, neural networks and biological system modeling, led by Gérard Dreyfus, Professor & Chair.

Under the direction of Elie Bienenstock, CNRS (currently Associate Professor at Brown University, Providence), elaborated a criticism of the traditional activity-rate code in neural models and advocated temporal correlations as the basis of brain function (after von der Malsburg, 1981). Illustrated this question by three mathematical and numerical studies:

1. a critical review of “learning” in neural networks as a nonparametric statistical estimation method
2. an algorithm of handwritten character recognition using 2-D “elastic” lattices (instead of pixel lists)
3. a model of synaptic self-organization in the cortex based on an activity/connectivity feedback loop

Designed the models, created visualization tools and carried out numerical simulations for all three parts.

RESEARCH ACTIVITIES & INTERESTS

The main theme of my research is the computational modeling and simulation of complex multi-agent systems, in particular biological and techno-social, which can also inspire novel principles in intelligent systems design. I am especially interested in “self-made puzzles”, i.e., the self-organization of complex, articulated morphologies from a swarm of heterogeneous agents, through dynamical, developmental, and evolutionary processes. For example, these emergent patterns can be innovative structures in multicellular organisms, autonomic networks of computing devices, or “mental representations” and imagery made of correlated spiking neurons.

Artificial Life – Biologically Inspired Engineering “Meta-designing” the development, function and evolution of self-organized complex systems that do not use a symbolic level. *Keywords:* *artificial development, self-assembly, pattern formation, spatial computing, evolutionary computation*

- multi-agent and cellular automata models of morphogenesis, based on gene regulation networks
- decentralized but programmable pattern formation, network self-assembly and shape development
- spatially extended cellular automata models of population genetics, evolution and ecology

Neural Dynamics – Large-Scale Spiking Neural Networks Understanding and reconstructing the emergence of a symbolic level from a complex dynamical system. *Keywords:* *mesoscopic level, segmentation, schematization, categorization, perception, language, ontology*

- mesoscopic emergence and interaction of spatiotemporal patterns of activity and connectivity
- based on: stochastic-firing, excitable, oscillatory and subthreshold neuron models
- creating: synchronization, traveling waves, coherence induction, synfire chains, compositionality
- for: segmentation, schematization, pattern recognition & categorization in perception and language

TEACHING EXPERIENCE

Lecturer of graduate seminars in Cognitive Science, Ecole Polytechnique, Paris, France, Fall 2009

- “Brain and Cognition”: Co-organized, with Prof. Yves Frégnac, a series of 12 seminars by prominent invited speakers (e.g., Jean-Pierre Changeux), including paper review presentations by students, on the multiscale neural basis of cognition: From the microscopic level (molecular, genetic and cellular foundations, individual neuron physiology) and mesoscopic level (computational neuroscience, electrophysiology, complex neural dynamics, network modeling) to the macroscopic level (cognitive neuroscience, functional imaging, phenomenology, epistemology) and social cognition.

Annual French Complex Systems Summer School, Institut des Systèmes Complexes, Paris & Lyon Principal Organizer, 2009 – Principal Organizer & Instructor, 2008 – Coordinator & Instructor, 2007

- “Complex Systems Made Simple: A Hands-On Exploration of Agent-Based Modeling” (2007, 2008): Modeling and simulation of canonical exs. of complex systems (cellular automata, pattern formation, swarm intelligence, complex networks, spatial communities) using the NetLogo programming platform.
- “Toward a Fine-Grain Mesoscopic Neurodynamics” (2007): An overview of spiking neural network models, introducing temporal coding and the “binding problem”, and describing various studies of emergent spatiotemporal order of neural activity/connectivity at the mesoscopic level of cognition.
- “From Embryogenesis to Embryomorphic Architectures” (2007): Example of a computational model of biological organism development based on intercellular coupling among gene regulatory networks.

Adjunct & Visiting Assistant Professor of Computer Science, University of Nevada, Reno, 2004–2006

- Created over 1,000 original PowerPoint slides, many of which are now used by other instructors.
- CS 790R: “Computational Models of Complex Systems”: Designed from scratch, fully developed and taught this original, cross-disciplinary 3-credit seminar for graduate students, including lectures, paper reviews, programming assignments and term projects. We examined self-organized systems and emergence based on myriads of simple agents, across a variety of topics: cellular automata, pattern formation, insect colonies, spatial ecology, neural networks, complex networks, etc. (2 semesters).
- CS 446/646: “Principles of Operating Systems”: The principles, components, and design of modern operating systems, focusing on the UNIX platform. Topics include: concurrent processes, inter-process communication, processor management, virtual and real memory management, deadlock, file systems, disk management, performance issues, case studies, etc. (2 semesters).
- CS 135: “Computer Science I”: An introduction to modern problem solving and programming methods in C++, with emphasis on algorithm development. Also, an introduction to procedural and data abstraction, design, testing, and documentation (2 semesters).

Co-supervision of Postdocs, Ph.D and M.S. students, 1993, 2004–Present

Adv = main advisor: I proposed the research topic and supervised the work

Co-Adv = co-advisor: I contributed to an existing topic and co-supervised the work

- **Postdocs**
 - Quan Zou, University of Nevada, Reno: *Adv*, 2006–2007 (Co-Adv: Philip H. Goodman)
- **Ph.D. students**
 - Julien Delile, Université Paris 5: *Adv*, 2008–Present (Co-Adv: Nadine Peyriéras)
 - Emmanuel Faure, Ecole Polytechnique: Co-Adv, 2006–07, Jury Exam, 2009 (Adv: Paul Bourguine)
 - Rich Drewes, University of Nevada, Reno: Co-Adv, 2004–2005 (Adv: Philip H. Goodman)
 - Christine Wilson, University of Nevada, Reno: Co-Adv, 2004–2005 (Adv: Philip H. Goodman)
- *Juries & committees only:*
 - Sylvain Cussat-Blanc, Univ. de Toulouse 1: Jury Examiner and Chair, 2009 (Adv: Yves Duthen)
 - Heike Sichtig, Binghamton Univ. SUNY: Committee & Jury Examiner, 2009 (Adv: Craig Laramee)
- **M.S. students**
 - Adam MacDonald, Univ. of New Brunswick, Fredericton: *Adv*, 2008–09 (Co-Adv: Mihaela Ulieru)
 - Oscar Sessions, University of Nevada, Reno: *Adv*, 2006–2007 (Co-Adv: Philip H. Goodman)
 - Milind Zirpe, University of Nevada, Reno: Co-Adv, 2006–2007 (Adv: Philip H. Goodman)
 - James King, University of Nevada, Reno: Co-Adv, 2004–2005 (Adv: Philip H. Goodman)
 - Andreas Schwarz, Ruhr-Universität Bochum: *Adv*, 1993–94 (Co-Adv: Christoph von der Malsburg)

Winner candidate of a Math Instructor position, Truckee Meadows Community College, Reno, 5/2005

The thorough interview process for this position was conducted by a committee of 6 faculty members and consisted of one hour of questions and 30 minutes of a teaching demonstration on a topic given two days ahead. I was selected first among 6 interviewees. (I later declined the position in favor of UNR.)

Guest Instructor of M.S. in Software Engineering, Golden Gate University, San Francisco, 3/2003

CIS 386: Advanced Enterprise Java Programming: Invited by the instructor to teach a few classes about Enterprise JavaBeans.

Lecturer of graduate seminars in Cognitive Science, Ruhr-Universität Bochum, Germany, 1992, 1993

Organized and conducted credit seminar courses for graduate students (in German), including lectures and student presentations. Developed courses, selected literature, facilitated discussions:

- Language and connectionism (Spring 1993): Analysis of the formal vs. dynamical systems debate in cognitive science (rule-based AI vs. example-based neural networks) from a linguistic perspective.
- Learning in artificial and natural systems (Spring 1992; co-organizer): Overview of learning processes, theories and methods in psychology, animal behavior, neurophysiology and neural networks.

Instructor of training seminars in Neural Networks for engineers & researchers, ESPCI, Paris, 1989, 1990

TEACHING COMPETENCIES & INTERESTS

Computer science (open-ended list of domains I have taught or can teach)

- **Core topics**: theory and practice of programming languages (object-oriented, procedural, declarative; Java, C/C++, etc.), data structures, algorithms, automata, compilers, operating systems, GUIs, etc.
- **Distributed systems**: object distribution and component/middleware frameworks (J2EE, CORBA, Messaging, etc.), Web technologies, application servers, TCP/IP networking, database systems
- **Software engineering**: object-oriented methodology, design patterns, software architecture

Research & seminar topics (see also Research Activities & Interests above)

- **Complex systems, biological modeling & bio-inspired engineering**: multi-agent modeling, cellular automata, artificial life, pattern formation, morphogenesis, swarm intelligence, genetic algorithms, complex networks
- **Cognitive science**: computational neuroscience, artificial & spiking neural networks, neurobiological modeling, cognitive linguistics, pattern recognition, machine learning, computer vision

Undergraduate mathematics & physics

- **Mathematics**: logic, sets, groups, algebra, linear algebra, geometry, trigonometry, topology, calculus, integrals, differential equations, functional analysis, probability, statistics, etc.

INDUSTRIAL RESEARCH & DEVELOPMENT

Chief Engineer, Akheron Technologies, Palo Alto, California, 3/2002–8/2004

Akheron (early-stage start-up) built innovative network security technology extending traditional firewall protection (traffic analysis & filtering) to the application layer, e.g. instant messaging (IM) and peer-to-peer.

Designed and developed a suite of Java applications to monitor, archive and display IM traffic, based on a complex thread-pooled, multi-client architecture using the Jabber protocol (40,000 lines of code). Also contributed to Akheron's proprietary High-Bandwidth Transparent Vectoring (HBTV) technology. Co-authored or assisted writing four provisional patents.

Senior Software Architect, BIOwulf Genomics, Berkeley, California, 11/2000–2/2002

BIOwulf (early-stage start-up, ended 2/2002) focused on machine learning methods, especially support vector machines (SVMs), for genomic, proteomic and medical data analysis.

At the company's start, was hired to integrate math and engineering by designing a system to deliver productized SVM algorithmic methods. Created an online application service provider (ASP), the "Discovery Platform", to centralize and streamline multiple data processing chains: (a) users upload raw input data; (b) math analysts custom-tailor optimal classification methods and deploy them as "numerical engines" (componentware of the system); (c) users download output results. Single-handedly designed and built the entire J2EE-based system, including a back-end numerical computation server (JNI over Matlab). Collaborated with SVM co-inventor Isabelle Guyon. Co-authored one patent.

Senior Software Engineer & Architect, RedCart.com, San Francisco, California, 7/1999–11/2000

RedCart (early/mid-stage start-up, ended in 12/2000) provided e-commerce technology as an application service provider (ASP) to consumer web portal sites. Its "Universal Shopping" technology enabled transactions across multiple online merchants through a single virtual shopping cart account.

Joined at an early stage and played a major role in the design and development of the system. Single-handedly created and implemented the automatic checkout functionality across two coupled servers:

- A J2EE front-end: Wrote a multi-tier, multi-threaded checkout engine in Java (EJB, Servlets, JSP).
- An Apache-based proxy: Wrote an HTTP "bot" (agent) module in C automating the navigation of merchant sites through pluggable "wrappers" (merchant-specialized software components analogous to drivers). To streamline the massive development of wrapper code, created an original macro script in C containing 120 bot navigation commands and trained groups of programmers in its use.

Helped supervise and provide technical leadership to the engineering team, in collaboration with the CTO and VP of Engineering. Led or contributed to code reviews for most of the system.

Senior Software Engineer, Neuron Data, Mountain View, California, 8/1998–7/1999**Software Engineer, Research & Development, Neuron Data France, Paris, France, 4/1995–7/1998**

Neuron Data (founded in 1985, IPO in 2000 as Blaze Software, followed by several buyouts and mergers) built market-leading high-end application development tools for Fortune 500 customers.

Hired to work directly with the Chief Software Architect on new projects. Created major new features, core modules and prototypes of products from scratch. For the "Advisor" product, a suite of tools for business rules management (business rules are componentware expert systems based on English-like scripts):

- Developed the first prototype of Advisor's rules engine, based on the RETE search algorithm.
- Coded various lexical and syntactical parsers for an English-like 4GL script compiler.
- Created the complete initial GUI which was further developed by the whole engineering team.
- Wrote multiple client/server demos using CORBA, RMI, HTTP, and MQSeries.

For "Open Interface", a cross-platform GUI builder (precursor of IDE tools like Visual Basic or Delphi):

- Created a C/C++ code generation engine, automatically resynchronizing GUI and text modifications. Invented a set of "annotations" (special comments) inserted in the code. Wrote the user manual.

COMMITTEES & REVIEWS

Organizing committees (preparation of events & books)Book editing

- Chief Editor, *Morphogenetic Engineering: Toward Programmable Complex Systems*, R. Doursat, H. Sayama, & O. Michel, eds., in *NECSI "Studies on Complexity" Series*, Springer-Verlag. **In Preparation.**
- Co-Editor, *IT Revolutions: 1st International ICST Conference, Venice, Italy, December 17-19, 2008, Revised Selected Papers*, M. Uliuru, P. Palensky, R. Doursat, eds., LNICST 11, Springer-Verlag.

Conferences & workshops

- Co-Chair, *11th European Conference on Artificial Life (ECAL)*, August 8-12, 2011, Cité Universitaire, Paris, France. **Upcoming.**
- Chair, *Special Session on Morphogenetic Engineering*, at the *7th International Conference on Swarm Intelligence (ANTS)*, September 8-10, 2010, IRIDIA, Université Libre de Bruxelles, Belgium. **Upcoming.**
- Principal Organizer, *1st International Workshop on the Shapes of Brain Dynamics (SBD 2010)*, June 18, 2010, Institut des Systèmes Complexes, Paris Ile-de-France (ISC-PIF). [Keynote: Walter Freeman, UC Berkeley.]

- Panel Discussion Chair, *Ladislav Tauc Conference in Neurobiology 2010: Multiscale Analysis of Neural Systems*, February 15-16, 2010, Institut de Neurobiologie Alfred Fessard (INAF), CNRS, Gif-sur-Yvette, France.
- General Chair, *3rd French Conference on Complex Systems Science & Engineering*, organized by the National Network of Complex Systems (RNSC), November 25-27, 2009, CNRS, Paris, France.
- Co-Chair, *International Symposium on Complex Systems*, organized by the National Network of Complex Systems (RNSC), September 17-18, 2009, Institut Henri Poincaré (IHP), Paris, France.
- Principal Organizer, *1st International Workshop on Morphogenetic Engineering (MEW 2009)*, June 19, 2009, Institut des Systèmes Complexes, Paris Ile-de-France (ISC-PIF). [Keynote: Marco Dorigo, ULB, Bruxelles.]
- Technical Program Chair, *IT Revolutions 2008 Conference* (co-sponsored by ICST, IEEE, Create-Net), and Co-Chair, "Approaching Complexity" Theme, December 17-19, 2008, Venice, Italy.
- Co-Organizer, *Workshop on Spatial Evolutionary Dynamics (SED 2008)*, October 17, 2008, Institut des Systèmes Complexes, Paris Ile-de-France (ISC-PIF). [Keynote: Paulien Hogeweg, Utrecht University.]

Summer schools

- Principal Organizer, *3rd Annual French Complex Systems Summer School*, July 20-August 14, 2009.
- Principal Organizer & Instructor, *2nd Annual French Complex Systems Summer School*, July 15-August 9, 2008.
- Coordinator & Instructor, *1st Annual French Complex Systems Summer School*, July 30-August 26, 2007.

Program committees & reviews (review of submissions)

Journals

- Associate Editor, *IEEE Transactions on Neural Networks (TNN)*, 2009
- Advisory Board Member, *Embedded Self-organising Systems*, 2009
- Reviewer, *ACM Transactions on Autonomous Adaptive Systems (TAAS)*, 2007
- Reviewer, *Advances in Complex Systems*, 2008
- Reviewer, *IEEE Transactions on Neural Networks (TNN)*, 1994, 2008
- Reviewer, *Neural Computation*, 1993, 1994
- Reviewer, *Neural Networks*, 1992
- Reviewer, *Technique et Science Informatiques (TSI)*, 2010

Conferences & workshops

- Reviewer, Program Committee, *3rd IEEE Symposium on Artificial Life (IEEE ALIFE 2011)*, at *IEEE Symposium Series on Computational Intelligence (SSCI 2011)*, April 11-15, 2011, Paris, France.
- Reviewer, Program Committee, *Special Track on State-Topology Coevolution in Adaptive Networks (STCAN 2010)*, at *5th International Conference on Bio-Inspired Models of Network, Information, and Computing Systems (BIONETICS 2010)*, December 1-3, 2010, Boston, MA.
- Reviewer, Program Committee, *Spatial Computing Workshop (SCW 2010)*, at *4th IEEE International Conference on Self-Adaptive and Self-Organizing Systems (SASO 2010)*, Sept. 27-Oct. 1, 2010, Budapest, Hungary.
- Reviewer, Program Committee, *Swarm, Amorphous, Spatial, and Complex Systems Track*, at *12th Int'l Symposium on Stabilization, Safety, & Security of Distributed Systems (SSS 2010)*, Sept. 20-22, 2010, New York.
- Reviewer, Program Committee, *12th International Conference on the Simulation and Synthesis of Living Systems (ALIFE 12)*, August 19-23, 2010, University of Southern Denmark, Odense, Denmark.
- Reviewer, Program Committee, *Special Session on Organic Computing (OC 2010)*, at *IEEE World Congress on Computational Intelligence (WCCI 2010)*, July 18-23, 2010, Barcelona, Spain.
- Reviewer, Program Committee, *Spatial Computing Workshop (SCW 2009)*, at *3rd IEEE International Conference on Self-Adaptive and Self-Organizing Systems (SASO 2009)*, September 14-18, 2009, San Francisco, CA.
- Reviewer, Program Committee, *Generative and Developmental Systems Track (GDS 2009)*, at *Genetic and Evolutionary Computation Conference (GECCO 2009)*, July 8-12, 2009, Montréal, QC, Canada.
- Reviewer, Program Committee, *Spatial Computing Workshop (SCW 2008)*, at *2nd IEEE International Conference on Self-Adaptive and Self-Organizing Systems (SASO 2008)*, October 20-24, 2008, Venice, Italy.
- Session Chair, "Neural and Physiological Dynamics", *7th International Conference on Complex Systems (ICCS 2007)*, October 28-November 2, 2007, New England Complex Systems Institute (NECSI), Boston, MA.

Grant agencies

- Grant Reviewer, Agence Nationale de la Recherche (ANR), France, 2008
- Grant Reviewer, Natural Sciences and Engineering Research Council of Canada (NSERC), 2007

Advisory committees (recommendations on research & education)

- Expert Panel Member (of 8) for the FP7-ICT Support Action *ComplexEnergy: Complex Systems for an ICT-enabled Energy System*, identifying new research topics and assessing emerging global science & technology trends in ICT for future FET Proactive initiatives, 2010.
- Council Member (of 50) of the Complex Systems Society (CSS), 2009.

- Curriculum Committee Member (of 6) for the creation of the first *Erasmus Mundus* Master's and Doctoral Programs in Complex Systems (collaboration between Ecole Polytechnique, Paris; University of Warwick, UK; and Chalmers University of Technology, Sweden), 2009. See *Awarded Grants below*.
- Curriculum Committee Member (of 4) for the creation of the first French Master program in Complex Systems, based at the Ecole Polytechnique in Paris, 2008.
- Scientific Committee Member (of 40), Réseau National des Systèmes Complexes (RNSC), the French Complex Systems Network, writing recommendations about the main objectives of French research in complex systems, 2006, 2010.

Search committees & juries (selection of candidates)

- Search Committee Chair, Institut des Systèmes Complexes, Paris Ile-de-France (ISC-PIF), for 1 Software Engineer/Scientific Programmer position & 1 Webmaster/Communication position, 2009.
- Search Committee Member (2008) and Chair (2009, 2010), Institut des Systèmes Complexes, Paris Ile-de-France (ISC-PIF), for Postdoc Fellowships, 2008 (19 applicants, 9 interviewees, 4 ranked, 3 positions), 2009 (43 applicants, 8 interviewees, 5 ranked, 3 positions), 2010 (34 applicants, 9 interviewees, 6 ranked, 2 positions).
- Jury (of 5), French-Canadian Association for the Advancement of Science (ACFAS), *Marcel Vincent Award*, given yearly to an outstanding Canadian researcher in social sciences, 2006, 2007.

Memberships

- Member, Association for Computing Machinery (ACM)
- Member, Complex Systems Society (ECSS)
- Member, Institute of Electrical and Electronics Engineers (IEEE)
- Member, International Neural Network Society (INNS)
- Member, International Society of Artificial Life (ISAL)
- Member, New England Complex Systems Institute (NECSI)
- Member, Réseau National des Systèmes Complexes (RNSC)

GRANTS & SCHOLARSHIPS

Awarded project grants & personal scholarships

- *EMMC (Erasmus Mundus Masters Course), Masters in Complex Systems Science*, European Union Lifelong Learning Programme, 4 European partners (University of Warwick, Ecole Polytechnique Paris, Chalmers University of Technology, University of Gothenburg), 5-year funding for student scholarships and administrative costs, 2010-2015.
- *ASSYST (Action for the Science of complex SYstems and Socially Intelligent icT)*, European Coordination Action: FP7-ICT/FET-Proactive, 15 European partners, €900K (ISC-PIF: €175K), 36 months, 1/2009–12/2011.
- Goodman, P. H. (PI), Harris, F. C., Doursat, R., Nicolescu, M. N. & Markram, H. J. Continuation of *Large-Scale Biologically Realistic Models of Cortical & Subcortical Dynamics with Social Robotic Applications*, ONR Project Grant #N000149910880, \$801K (my share: \$66K), 7/2006–6/2009.
- Doursat, R. (PI) & Petitot, J. *Bridging the gap between visual perception and language: an exploration into the neural morphodynamics of cognitive schemas, categories and compositionality*, Personal Research Grant, Marie Curie International Reintegration Grant, European Union, €80K, 10/2004–9/2006.
- Doursat, R. (PI) & Petitot, J. *Dynamical connectionism and cognitive linguistics: Toward a new microstructure of semantics*, Personal Research Fellowship, Ecole Polytechnique, Paris, €12K, 10/1996–9/1997.
- Doursat, R. (PI) & Bienenstock, E. *A study of the possible neurobiological mechanisms underlying the compositionality of cognitive functions*, Personal Research Grant, Fyssen Foundation, Paris, €20K, 10/95–9/96.
- Doctoral scholarship, Ministry of Research and Technology, France, €33K, 10/1989–9/1991.
- Graduate stipend, Ecole Normale Supérieure (ENS), Paris (France's most selective school), €56K, 10/1985–9/89.

Employment from other project grants

- Peyriéras, N. (PI), Bourguine, P., Hirsinger, E., Mikula, K. & Sarti, A. *Embryomics: Reconstructing in space and time the cell lineage tree*, NEST Grant, European Union, €1.45M, 11/2005–10/2008.
- Goodman, P. H. (PI), Harris, F. C. & Markram, H. J. *Large-Scale, Synaptically Realistic Models of Cortical Microcircuit Dynamics*, ONR Grant #N000140010420, \$660K, 7/2003–6/2006.

Co-author of submitted project grant proposals

- *EMJD (Erasmus Mundus Joint Doctorate)*, Complex Systems Science, 4 EU partners, 5-year requested, 4/2010.
- *E2CP (social Web)*, Europe: FP7-ICT, 3 European partners, 17 individual supporters, €100K req, 12 mon, 3/2009
- *BIO-NEXT (cloud computing)*, Europe: COST-ICT, 20 individual participants, pre-proposal, 3/2009.
- *ComplexiT (immune system modeling)*, France: CNRS-PICS, 4 European partners, pre-proposal, 3/2009.
- *SynBioTIC (synthetic biology)*, France: ANR-DEFIS, 4 French partners, €900K requested, 36 months, 2/2009.

- *MEC@GEN* (biological development), France: ANR-SYSCOMM, 3 French partners, €500K req, 36 mon, 2/2009.
- *Non-Classical Computing* (bio-inspired engineering), US: NSF-PIRE, 17 individual sponsors, preproposal, 2/2009
- *EvoSpace* (spatial evolutionary dynamics), US: NSF-Ecology, 3 individual participants, 48 months, 1/2009.
- *AniMorph* (biological development), France: ANR-Open, 3 French partners, €800K req, 36 months, 11/2008.
- *EnergyWeb* (energy grid), Europe: FP7-COSI-ICT, 8 European partners, €4.13M requested, 36 months, 4/2008.

PUBLICATIONS (66)

In Preparation & Submitted (not included in total count)

4. Doursat, R., Sayama, H. & Michel, O., eds. (2010) *Morphogenetic Engineering: Toward Programmable Complex Systems*, in *NECSI "Studies on Complexity" Series*, Springer-Verlag. **In Preparation.**
3. Zou, Q., Doursat, R. & Goodman, P. H. (2010) The role of spatiotemporal correlations in the encoding and retrieval of synaptic patterns by STDP in recurrent spiking neural networks. **In Preparation.**
2. Doursat, R. & Ulieru, M. (2010) TBA. **In Preparation.**
1. Bourguine, P., Campana, M., Cunderlik, R., Drblikova, O., Faure, E., Lombardot, B., Luengo-Oroz, M.A., Melani, C., Remesikova, M., Rizzi, B., Savy, T., Zanella, C., Kollar, J., Colin, I., Desnoullez, S., Funabashi, M., Duloquin, L., Randoux, S., Courtade, E., Hirsinger, E., Santos, A., Beaurepaire, E., Herbomel, P., Suret, P., Lutfalla, G., Nicolas, J.-F., Doursat, R., Sarti, A., Mikula, K. & Peyriéras, N. (2010) Embryomics: Reconstructing the cell lineage tree as the core of the embryo. **In Preparation.**

Full Papers — Books, Journals, Conferences, Workshops, Reports (27)

Books & book chapters (4)

4. Petitot, J. & Doursat, R. (2010) *Cognitive Morphodynamics: Dynamical Morphological Models for Constituency in Perception and Syntax*, Peter Lang. **To appear.**
3. Ulieru, M., Palensky, P. & Doursat, R., eds. (2009) *IT Revolutions: 1st International ICST Conference, Venice, Italy, December 17-19, 2008, Revised Selected Papers*, LNICST 11, Springer-Verlag.
2. Doursat, R. (2008b) Organically grown architectures: Creating decentralized, autonomous systems by embryomorphic engineering. In *Organic Computing*, R. P. Würtz, ed., pp. 167-200, Springer-Verlag.
1. Bienenstock, E. & Doursat, R. (1991) Issues of representation in neural networks. In *Representations of Vision: Trends and Tacit Assumptions in Vision Research*, A. Gorea, ed., pp. 47-67, Cambridge University Press.

Peer-reviewed journals (8)

8. Ulieru, M. & Doursat, R. (2010) Emergent engineering: A radical paradigm shift. *ACM Transactions on Autonomous and Adaptive Systems (TAAS)*. **To appear.**
7. Hoelzer, G., Drewes, R., Meier, J. & Doursat, R. (2008) Isolation-by-distance and outbreeding depression are sufficient to drive parapatric speciation in the absence of environmental influences. *PLoS Computational Biology* **4(7)**: e1000126 [doi:10.1371/journal.pcbi.1000126].
6. Doursat, R. (2008a) The self-made puzzle: Integrating self-assembly and pattern formation under non-random genetic regulation. *InterJournal: Complex Systems* **2292**.
5. Doursat, R. (2006b) The growing canvas of biological development: Multiscale pattern generation on an expanding lattice of gene regulatory networks. *InterJournal: Complex Systems* **1809**.
4. Vert, G. & Doursat, R. (2006) An architectural approach utilizing fuzzy taxonomies and complex adaptive systems for identifying computer system attacks and developing responses. *WSEAS Trans. on Systems* **5(2)**: 409-414.
3. Doursat, R. & Petitot, J. (2005b) Dynamical systems and cognitive linguistics: Toward an active morphodynamical semantics. *Neural Networks* **18**: 628-638. **Selected for this special issue among less than 10% of the papers accepted at the IJCNN 2005 conference.**
2. Bienenstock, E. & Doursat, R. (1994) A shape-recognition model using dynamical links. *Network: Computation in Neural Systems* **5(2)**: 241-258.
1. Geman, S., Bienenstock, E. & Doursat, R. (1992) Neural networks and the bias/variance dilemma. *Neural Computation* **4**: 1-58. **Cited over 1500 times (Google Scholar).**

Peer-reviewed conference & workshop proceedings (12)

12. Doursat, R. (2009g) Facilitating evolutionary innovation by developmental modularity and variability. *Generative & Developmental Systems Workshop (GDS 2009)*, at *18th Genetic and Evolutionary Computation Conference (GECCO 2009)*, July 8-12, 2009, Montreal, Canada.

11. Doursat, R. (2008g) Spatial self-organization of heterogeneous, modular architectures. *Spatial Computing Workshop (SCW 2008)*, at *2nd IEEE International Conference on Self-Adaptive and Self-Organizing Systems (SASO 2008)*, October 20-24, 2008, Venice, Italy.
10. Doursat, R. & Ulieru, M. (2008b) Emergent engineering for the management of complex situations. *2nd International Conference on Autonomic Computing and Communication Systems (Autonomics 2008)*, September 23-25, 2008, Telecom Italia Labs, Turin, Italy.
9. Doursat, R. (2008f) The growing canvas of biological development: Multiscale pattern generation on an expanding lattice of gene regulatory networks. In *Unifying Themes in Complex Systems Vol VI*, A. A. Minai, D. Braha & Y. Bar-Yam, eds., Springer-Verlag. **This volume selected 77 papers from over 300 presented at the ICCS 2006 conference.**
8. Doursat, R. (2008d) Programmable architectures that are complex and self-organized: From morphogenesis to engineering. *11th International Conference on the Simulation and Synthesis of Living Systems (ALIFE XI)*, August 5-8, 2008, University of Southampton, Winchester, UK. In *Artificial Life XI*, S. Bullock, J. Noble, R. Watson & M. A. Bedau, eds., pp. 181-188, MIT Press.
7. Vert, G., Doursat, R. & Nasser, S. (2006) Towards utilizing fuzzy self-organizing taxonomies to identify attacks on computer systems and adaptively respond. *2006 IEEE World Congress on Computational Intelligence (WCCI/FUZZ-IEEE 2006)*, July 16-21, 2006, Vancouver, BC, Canada.
6. Doursat, R. & Bienenstock, E. (2006b) Neocortical self-structuration as a basis for learning. *5th International Conference on Development and Learning (ICDL 2006)*, May 31-June 3, 2006, Indiana University, Bloomington.
5. Vert, G. & Doursat, R. (2005) A fuzzy taxonomic approach for classifying and identifying system attacks and automating attack response. *4th WSEAS International Conference on Computational Intelligence, Man-Machine Systems and Cybernetics (CIMMACS 2005)*, November 17-19, 2005, Miami, FL.
4. Doursat, R. & Petitot, J. (2005a) Bridging the gap between vision and language: A morphodynamical model of spatial categories. *International Joint Conference on Neural Networks (IJCNN 2005)*, July 31-August 4, 2005, Montréal, QC, Canada.
3. Doursat, R. & Petitot, J. (1997) Modèles dynamiques et linguistique cognitive: vers une sémantique morphologique active. *6ème École d'été de l'Association pour la Recherche Cognitive (ARCo)*, July 5-13, 1997, Formation du CNRS, Bonas, France.
2. Bienenstock, E. & Doursat, R. (1990) Spatio-temporal coding and the compositionality of cognition. *Workshop on Temporal Correlations and Temporal Coding in the Brain*, April 25-27, 1990, Paris, France.
1. Bienenstock, E. & Doursat, R. (1989) Elastic matching and pattern recognition in neural networks. *nEuro'88 Conference*, June 6-9, 1988, Ecole Supérieure de Physique et Chimie Industrielles (ESPCI), Paris, France. In *Neural Networks: From Models to Applications*, L. Personnaz & G. Dreyfus, eds., pp. 472-482, IDSET, Paris.

Technical reports (3)

3. Petitot, J. & Doursat, R. (1998) Modèles dynamiques et linguistique cognitive: vers une sémantique morphologique active. Technical Report 9809, in *Rapports et documents du CREA*, Ecole Polytechnique, Paris.
2. Doursat, R., von der Malsburg, C. & Bienenstock, E. (1995) Coding metric with delayed temporal correlations: An oscillator model of graph-matching. Tech. Report, Inst. für Neuroinformatik, Ruhr-Universität Bochum, Germany.
1. Doursat, R., Konen, W., Lades, M., von der Malsburg, C., Vorbrüggen, J. C., Wiskott, L. & Würtz, R. P. (1993) Neural mechanisms of elastic pattern matching. Internal Report IRINI 93-01, Institut für Neuroinformatik, Ruhr-Universität Bochum, Germany.

Abstracts — Conferences, Workshops (17)

Peer-reviewed conference & workshop abstracts accepted as presentations (8)

8. Doursat, R. (2008e) A morphogenetic model of controlled self-organization. *5th European Conference on Complex Systems (ECCS 2008)*, September 14-19, 2008, Hebrew University, Jerusalem, Israel.
7. Doursat, R. (2008c) From morphogenesis to embryomorphic engineering. *"From Amorphous to Spatial Computing" Workshop*, July 7-8, 2008, Paris, France.
6. Hoelzer, G., Drewes, R. & Doursat, R. (2008) Speciation through spatial self-organization of the gene pool. *12th Evolutionary Biology Meeting (EBM 2008)*, September 24-26, 2008, Université de Provence, Marseille, France (presenter: G. Hoelzer).
5. Doursat, R. (2007e) The self-made puzzle: Integrating self-assembly and pattern formation under non-random genetic regulation. *7th International Conference on Complex Systems (ICCS 2007)*, October 28-November 2, 2007, New England Complex Systems Institute (NECSI), Boston, MA.

4. Doursat, R. (2006a) The growing canvas of biological development: Multiscale pattern generation on an expanding lattice of gene regulatory networks. *6th International Conference on Complex Systems (ICCS 2006)*, June 25-30, 2006, New England Complex Systems Institute (NECSI), Boston, MA.
3. Hoelzer, G., Drewes, R. & Doursat, R. (2006) Temporal waves of genetic diversity in a spatially explicit model of evolution: Heaving toward speciation. *6th International Conference on Complex Systems (ICCS 2006)*, June 25-30, 2006, New England Complex Systems Institute (NECSI), Boston, MA (presenter: G. Hoelzer).
2. Bienenstock, E. & Doursat, R. (1989) Of shapes, graphs and neural codes. *NATO Advanced Research Workshop on Neuro Computing: Algorithms, Architectures and Applications*, February 27-March 3, 1989, Les Arcs, France (presenter: E. Bienenstock).
1. Bienenstock, E. & Doursat, R. (1988) Graph-matching and shape recognition in neural networks. *1st Conference on Image Recognition and Neural Networks: From Signal Processing to Representation (NEURO-IMAGE 1988)*, October 6-7, 1988, Université de Bordeaux II, France.

Peer-reviewed conference & workshop abstracts accepted as posters (9)

9. Doursat, R. (2009c) Heterogeneous collective motion or moving pattern formation? The "self-made puzzle" of embryogenesis under the light of multi-agent modeling. *"Morphogenesis in Living Systems" Conference*, May 14-16, 2009, Université Paris Descartes, France.
8. Doursat, R. & Bienenstock, E. (2007) How activity regulates connectivity: A self-organizing complex neural network. *Ladislav Tauc Conference in Neurobiology 2007: Complexity in Neural Network Dynamics (Tauc 2007)*, December 13-14, 2007, Institut de Neurobiologie Alfred Fessard (INAF), CNRS, Gif-sur-Yvette, France.
7. Doursat, R., Goodman, P. H. & Zou, Q. (2007) Neocortical locks and keys: Coherence induction among complex, heterogeneous neuronal patterns. *Ladislav Tauc Conference in Neurobiology 2007: Complexity in Neural Network Dynamics (Tauc 2007)*, December 13-14, 2007, Institut de Neurobiologie Alfred Fessard (INAF), CNRS, Gif-sur-Yvette, France.
6. Faure, E., Lombardot, B., Luengo-Oroz, M., Campana M., Peyriéras, N., Doursat, R. & Bourguine, P. (2007) Active machine learning for embryogenesis. *4th European Conference on Complex Systems (ECCS 2007)*, October 1-5, 2007, Technische Universität Dresden, Germany.
5. Doursat, R. (2007a) Embryomorphic engineering: How to design hyper-distributed architectures capable of autonomous segmentation, rescaling and shaping. *Unconventional Computation Conference (UC 2007)*, March 21-23, 2007, Los Alamos National Laboratory (LANL) and Santa Fe Institute (SFI), Santa Fe, NM. OCP Science Best Poster Award in Unconventional Computing (2008) *International J. of Unconventional Computing* 4(2): i-ii.
4. Goodman, P. H., Doursat, R., Zou, Q., Zirpe, M. & Sessions, O. (2007) RAIN brains: Mammalian neocortex as a hybrid analog-digital computer. *Unconventional Computation Conference (UC 2007)*, March 21-23, 2007, Los Alamos National Laboratory (LANL) and Santa Fe Institute (SFI), Santa Fe, NM.
3. Doursat, R. & Bienenstock, E. (2006c) How activity regulates connectivity: A self-organizing complex neural network. *6th International Conference on Complex Systems (ICCS 2006)*, June 25-30, 2006, New England Complex Systems Institute (NECSI), Boston, MA.
2. Doursat, R. & Bienenstock, E. (2006a) The self-organized growth of synfire patterns. *10th International Conference on Cognitive and Neural Systems (ICCN 2006)*, May 17-20, 2006, Boston University, MA.
1. Doursat, R. & Goodman, P. H. (2006) Neocortical keys and locks: A neural model of associative learning by coherence induction between spike patterns and ongoing membrane potentials. *10th International Conference on Cognitive and Neural Systems (ICCN 2006)*, May 17-20, 2006, Boston University, MA.

Invited Talks (with Abstracts) — Conferences, Workshops (22)

Invited conference & workshop keynote presentations (3)

3. Doursat, R. (2010b) Architecture and self-organisation: Heading for the best of both worlds. *Gartner Enterprise Architecture Summit*, May 17-18, 2010, London, UK. **Keynote address.**
2. Doursat, R. (2010a) Embryomorphic engineering: From biological development to self-organized computational architectures. *4th EmergeNET Meeting: Engineering Emergence (EmergeNET4)*, April 19-20, 2010, St William's College, York, UK. **Keynote address.**
1. Doursat, R. (2007f) How to plan self-organization, control decentralization, and design evolution: Addressing the paradoxes of complex systems engineering with metaphors from biological development. *2nd International Conference on Bio-Inspired Models of Network, Information, and Computing Systems (BIONETICS 2007)*, December 10-13, 2007, Budapest, Hungary. **Keynote address.**

Invited conference & workshop talks (19)

19. Doursat, R. & Petitot, J. (2010b) [TBA]. *Symposium on Structured Flows on Manifolds: A General Dynamical Framework to Cognition*, at the "Cognition, Emotions and Society" Conference of the French Psychology Society (SFP), September 7-9, 2010, Université Charles-de-Gaulle Lille 3, France.
18. Doursat, R. (2010d) [TBA]. *2nd Summer Solstice International Conference on Discrete Models of Complex Systems (SOLSTICE 2010)*, June 16-18, 2010, LORIA, CNRS, Nancy, France.
17. Doursat, R. & Petitot, J. (2010a) [TBA]. *2nd Symposium on Language and Robots (LangRo 2010)*, June 2010 [TBA], Intelligent Systems and Robotics Institute (ISIR), Université Pierre et Marie Curie (Paris 6), France.
16. Doursat, R. (2010c) [TBA]. *2nd International Conference on Morphogenesis in Living Systems (MLS 2010)*, May 27-29, 2010, Université Paris Descartes, France.
15. Doursat, R. (2009i) Causing and influencing patterns by designing the agents: Complex systems made simpler. *4th Workshop on Causality in Complex Systems*, co-organized by DSTO, CSIRO (Australia), and ONR, AFRL (US), in association with the *Conference on Spatial Simulation for the Social Sciences (S4)*, November 25-27, 2009, Institut des Systèmes Complexes, Paris Ile-de-France.
14. Doursat, R. (2009h) Heterogeneous collective motion or moving pattern formation? The two sides of embryogenesis combined by multi-agent modeling into a "self-made puzzle". *Workshop on Quantitative Tissue Biology and Virtual Tissues (Biocomplexity X)*, October 28-November 1, 2009, The Biocomplexity Institute, Indiana University, Bloomington, IN.
13. Doursat, R. (2009f) Evolutionary developmental systems as "self-made puzzles" that can be programmed: Lessons from biological morphogenesis. Invited panelist (of 6), *Generative & Developmental Systems Workshop (GDS 2009)*, at *18th Genetic and Evolutionary Computation Conference (GECCO 2009)*, July 8-12, 2009, Montreal, Canada.
12. Doursat, R. (2009e) Heterogeneous collective motion or moving pattern formation? The self-made puzzle of embryogenesis under the light of multi-agent modeling. *2nd Paris Workshop on Multi-Agent Systems in Biology at Meso or Macroscopic scales (MASBio 2009)*, June 23, 2009, Université Pierre et Marie Curie, Paris, France.
11. Doursat, R. (2009d) Embryomorphic engineering: How elaborate, modular architectures can be self-organized, too. *1st International Morphogenetic Engineering Workshop (MEW 2009)*, June 19, 2009, Complex Systems Institute, Paris, France.
10. Doursat, R. (2009b) The self-made puzzle: Complex systems science as a design activity. *Workshop on "Aesthetic at the Heart of Science"*, in *The European Future and Emerging Technologies Conference (FET 2009): "Science Beyond Fiction"*, April 21-23, 2009, Prague, Czech Republic.
9. Doursat, R. (2009a) Mouvement collectif hétérogène ou formation de motifs en mouvement? Le puzzle auto-façonné de l'embryogenèse à la lumière des modèles multi-agents. *5ème École interdisciplinaire d'échanges et de formation en biologie (Berder 2009): "Spatialisation et localisation"*, March 29-April 4, 2009, Formation du CNRS, Berder (Brittany), France.
8. Doursat, R. (2008h) Paradox in approaching complexity: From natural to engineered complex systems. *IT Revolutions 2008*, December 17-19, 2008, Telecom Italia Future Centre, Venice, Italy.
7. Doursat, R. & Ulieru, M. (2008a) Guiding the emergence of structured network topologies: A programmed attachment approach. "Dynamics On and Of Complex Networks II" *Workshop (DOON II)*, at *5th European Conference on Complex Systems (ECCS 2008)*, September 14-19, 2008, Hebrew University, Jerusalem, Israel.
6. Doursat, R. (2007d) Of tapestries, ponds and RAIN: Toward fine-grain mesoscopic neurodynamics in excitable media. *International Workshop on Nonlinear Brain Dynamics for Computational Intelligence*, at *10th Joint Conference of Information Systems (JCIS 2007)*, July 20, 2007, Salt Lake City, UT.
5. Doursat, R. (2007c) Multiscale Embryomorphic Architectures. *Workshop on Scaling in Biological and Social Networks*, July 9-13, 2007, Santa Fe Institute (SFI), Santa Fe, NM.
4. Doursat, R. (2007b) Embryomorphic systems meta-design: Preparing for self-assembly, self-regulation and evolution. *7th Understanding Complex Systems Symposium (UCS 2007)*, May 14-17, 2007, Department of Physics, University of Illinois at Urbana-Champaign, IL.
3. Goodman, P. H. & Doursat, R. (2007) Large-scale biologically realistic models of cortical mesocircuit dynamics. *Computational Neuroscience, Sensory Augmentation, and Brain-Machine Interface*, April 25-26, 2007, Office of Naval Research (ONR), Arlington, VA.
2. Doursat, R. & Petitot, J. (2005c) Notes on the possibility of embodied computation based on the emergence of singularities in a large-scale complex dynamical system. *Workshop on Neurodynamics and Intentional Dynamic Systems*, at *International Joint Conference on Neural Networks (IJCNN 2005)*, August 5, 2005, Montréal, QC.

1. Doursat, R. (1995) The microdynamics of mental schemas. *Workshop on Morphodynamic Models for Language and Perception*, December 11-13, 1995, International Centre for Semiotic and Cognitive Studies (Umberto Eco & Patrizia Violi, dirs.), University of San Marino, Italy.

Individual invited seminars & talks (not included in total count)

Academic Institutions

36. **Université Libre de Bruxelles, Belgium** (hosts: **Marco Dorigo, Hugues Bersini**), Institute of Interdisciplinary Research & Development in Artificial Intelligence (IRIDIA), March 19, 2010 — Embryomorphic engineering: From biological development to artificial multi-agent organisms.
35. **Université de Nantes, France** (hosts: **Julien Cohen, Alexandre Dikovsky**), Laboratoire d'Informatique de Nantes Atlantique (LINA), February 11, 2010 — Ingénierie morphogénétique : du développement biologique aux systèmes auto-organisés programmables.
34. **Université Pierre et Marie Curie (Paris 6), France** (host: **Michel Gho**), Developmental Biology Laboratory, October 23, 2009 — Heterogeneous collective motion or moving pattern formation? The self-made puzzle of embryogenesis under the light of multi-agent modeling.
33. **University of West England, Bristol, UK** (host: **Alan F. T. Winfield**), Intelligent Autonomous Systems Laboratory, Bristol Robotics Laboratory, October 19, 2009 — Embryomorphic engineering: From biological development to artificial multi-agent organisms.
32. **London School of Economics, UK** (host: **Eve Mitleton-Kelly**), Complexity Research Program, June 26, 2009 — Complex systems as “self-made puzzles” that can be programmed: Lessons from biological morphogenesis.
31. **Genopole, Evry, France** (hosts: **Marie Beurton-Aimar, François Képès**), Epigenomics Program, June 25, 2009 — Complex systems and agent-based modeling in biology.
30. **The Open University, Milton Keynes, UK** (host: Jeff Johnson), Department of Design and Innovation, April 1, 2009 — The self-made puzzle: Complex systems and design.
29. **Université de Cergy-Pontoise, France** (host: **Laura Hernandez**), Laboratory for Theoretical Physics and Modelling, February 5, 2009 — A multi-agent computational model of biological morphogenesis based on non-random, programmable pattern formation and self-assembly.
28. **New England Complex Systems Institute (NECSI), Cambridge, MA** (host: **Yaneer Bar-Yam**), NECSI Winter School 2009, January 8, 2009 — Self-organization and variability of complex modular architectures as a prerequisite to evolutionary innovation.
27. **Université Pierre et Marie Curie (Paris 6), France** (host: **Michelle Thieullen**), Probabilities and Random Models Laboratory, December 12, 2008 — A multi-agent computational model of biological morphogenesis based on non-random, programmable pattern formation and self-assembly.
26. **Universitat Pompeu Fabra, Barcelona, Spain** (host: **Ricard Solé**), Complex Systems Lab, December 5, 2008 — Self-organization and variability of complex modular architectures as a prerequisite to evolutionary innovation.
25. **Université Paris-Sud 11 & INRIA, Orsay, France** (hosts: **Nicolas Bredeche, Marc Schoenauer**), Laboratoire de Recherche en Informatique, TAO Research Laboratory, November 10, 2008 — Spatial self-organization of heterogeneous, modular architectures.
24. **Ecole Polytechnique & CNRS, Paris, France** (host: **Paul Bourguin**), Centre de Recherche en Epistémologie Appliquée (CREA), March 25, 2008 — Architectures that are self-organized and complex: From morphogenesis to engineering.
23. **University of Otago, Dunedin, New Zealand** (host: **Martin Purvis**), Department of Information Science, February 12, 2008 — Architectures that are self-organized and complex: From morphogenesis to engineering.
22. **Victoria University of Wellington, New Zealand** (host: **Marcus Frean**), Artificial Intelligence Group, School of Mathematics, Statistics & Computer Science, February 5, 2008 — Architectures that are self-organized and complex: From morphogenesis to engineering.
21. **Institut des Systèmes Complexes, Paris Ile-de-France** (within the Morning Seminar Series), January 18, 2008 — The self-made puzzle: Integrating self-assembly and pattern formation under non-random genetic regulation.
20. **Ecole Polytechnique Fédérale de Lausanne (EPFL), Switzerland** (host: **Dario Floreano**), Laboratory of Intelligent Systems, Institut d'Ingénierie des Systèmes, January 16, 2008 — The self-made puzzle: Integrating self-assembly and pattern formation under non-random genetic regulation.
19. **Ecole Polytechnique Fédérale de Lausanne (EPFL), Switzerland** (hosts: **Felix Schürmann, Sean Hill, Henry Markram**), Blue Brain Project, Brain Mind Institute, January 16, 2008 — Toward a spiking mesoscopic neurodynamics.

18. **Utrecht University, The Netherlands** (host: **Paulien Hogeweg**), Theoretical Biology & Bioinformatics Group, Department of Biology, December 17, 2007 — The self-made puzzle: Integrating self-assembly and pattern formation under non-random genetic regulation.
17. **Indiana University, Bloomington, IN** (host: **James Glazier**), The Biocomplexity Institute, May 31, 2007 — Embryomorphic architectures.
16. **INRIA Futurs, Orsay, France** (host: **Hugues Berry**), ALCHEMY Research Lab, January 23, 2007 — Organically grown architectures: Embryogenesis and neurogenesis as new paradigms for decentralized systems design.
15. **Ecole Polytechnique & CNRS, Paris, France** (host: **Paul Bourguine**), Centre de Recherche en Epistémologie Appliquée (CREA), December 5, 2006 — Building the mesoscopic foundations of cognition: emergence and interaction of spatiotemporal patterns in complex dynamical neural systems.
14. **Johann Wolfgang Goethe-Universität Frankfurt am Main, Germany** (host: **Christoph von der Malsburg**), Frankfurt Institute for Advanced Studies (FIAS), November 3, 2006 — Genetics and epigenetics: Two models of self-organization in biological development.
13. **Ruhr-Universität Bochum, Germany** (host: **Rolf Würtz**), Institut für Neuroinformatik (INI), October 31, 2006 — Locks and keys in complex neural networks: The “mesocircuits” of cognition.
12. **Binghamton University SUNY, Binghamton, NY** (host: **Hiroki Sayama**), Department of Bioengineering, July 25, 2006 — Locks and keys in complex biosystems: From coherence induction to regulation.
11. **University of Massachusetts, Amherst, MA** (host: **Hava Siegelmann**), Biologically Inspired Neural & Dynamical Systems (BINDS) Laboratory, Department of Computer Science, July 24, 2006 — Locks and keys in complex biosystems: From coherence induction to regulation.
10. **Université de Sherbrooke, QC, Canada** (host: **Jean Rouat**), Department of Electrical & Computer Engineering, July 18, 2006 — Toward a rich neurodynamics at a mesoscopic level: Two models of resonance among networks of oscillatory and excitable units.
9. **McGill University, Montréal, QC, Canada** (host: **Andrew Hendry**), Evolution & Ecology Groups, Department of Biology, July 13, 2006 — Temporal waves of genetic diversity in a spatially explicit model of evolution: Heaving toward speciation.
8. **Université Laval, Québec, QC, Canada** (host: **Guy Mineau**), Department of Computer Science & Software Engineering, July 6, 2006 — Spatial language and linguistic space: Two models of conceptual categorization based on visual icons and semantic networks.
7. **Université de Montréal, QC, Canada** (host: **Lael Parrott**), Complex Systems Laboratory, Department of Geography, July 4, 2006 — From evo to devo: Two spatially extended models showing speciation and pattern formation.
6. **The MITRE Corporation, Washington, DC** (host: **Brandon S. Minnery**), Emerging Technology Office, May 2, 2006 — Neuromorphic mesocircuits: From neural computation to cognitive architectures via analog VLSI.
5. **University of Nevada, Reno, NV** (host: **George Bebis**), Computer Vision Laboratory, Department of Computer Science & Engineering, June 24, 2004 — Structural graph matching and morphological image transforms: Two paths toward the categorization of geometrical patterns.
4. **University of Nevada, Reno, NV** (host: **Philip H. Goodman**), Brain Computation Laboratory, Department of Computer Science & Engineering / School of Medicine, May 25, 2004 — An epigenetic development model of the nervous system.
3. **Max Planck Institute for Psycholinguistics, Nijmegen, The Netherlands** (host: **Willem Levelt**), Language Production Group, November 1992 — Compositionality in neural networks.
2. **Ruhr-Universität Bochum, Germany** (host: **Christoph von der Malsburg**), Institut für Neuroinformatik (INI), April 1991 — Representations in the nervous system and in artificial neural networks.
1. **Université de Montréal, QC, Canada** (host: **Jan Gecsei**), Département d'Informatique et de Recherche Opérationnelle, April 1988 — Graph matching and shape recognition.

General Public & Media Appearances

3. **French National Public Radio (France-Culture), Paris** (host: Xavier de la Porte), Show: "Place de la Toile" ("Web Square"), January 15, 2010 — What are complex systems? (30-mn interview).
2. **“La Cantine”, Paris, France** (host: **Christel Sorin**), Coworking Space for High-Tech Entrepreneurs, May 27, 2009 — The Web as a complex system: a self-organization that can be controlled?
1. **Conseil Régional d'Ile-de-France (Regional Government of the Paris Metropolitan Area)** (host: **Marc Lipinski**, Vice President for Research & Innovation), Public Forum on Research in Ile-de-France, March 3, 2009 — Best practices for the coordination of research (panel discussion).