Activity Report 2012

Team MNEMOSYNE

Mnemonic Synergy

RESEARCH CENTER
Bordeaux - Sud-Ouest

THEME
Computational Medicine and Neuro-sciences

Table of contents

Team MNEMOSYNE

Keywords: Computational Neuroscience, Machine Learning, Autonomous Robotics, Decision Making, Memory, Adaptive Systems

Team hosted by Institut des Maladies Neurodégénératives, IMN, UMR 5293, Bordeaux NeuroCampus

Creation of the Team: February 01, 2012 .

1. Members

Research Scientists

Frédéric Alexandre [Team Leader, DR, HdR]
Nicolas Rougier [CR, HdR]
Thierry Viéville [DR (half time in the project-team), HdR]

Faculty Member

André Garenne [Associate Professor, Université Bordeaux Segalen]

Administrative Assistant

Anne-Laure Gautier [part time in the project-team]

2. Overall Objectives

2.1. Summary

At the frontier between integrative and computational neuroscience, we propose to model the brain as a system of active memories in synergy and in interaction with the internal and external world and to simulate it *as a whole and in situation*.

In integrative and cognitive neuroscience (*cf.* § 3.1), on the basis of current knowledge and experimental data, we develop models of the main cerebral structures, taking a specific care of the kind of mnemonic function they implement and on their interface with other cerebral and external structures. Then, in a systemic approach, we build the main behavioral loops involving cerebral structures connecting a wide spectrum of actions to various kinds of sensations. We observe at the behavioral level the properties emerging from the interaction between these loops.

We claim that this approach is particularly fruitful for investigating cerebral structures like the basal ganglia and the prefrontal cortex, difficult to comprehend today because of the rich and multimodal information flows they integrate. We expect to cope with the high complexity of such systems, inspired by behavioral and developmental sciences, explaining how behavioral loops gradually incorporate in the system various kinds of information and associated mnesic representations. As a consequence, the underlying cognitive architecture, emerging from the interplay between these sensations-actions loops, results from a *mnemonic synergy*.

In computational neuroscience (*cf.* § 3.2), we concentrate on the efficiency of local mechanisms and on the effectiveness of the distributed computations at the level of the system. We also take care of the analysis of their dynamic properties, at different time scales. These fundamental properties are of high importance to allow the deployment of very large systems and their simulation in a framework of high performance computing (*cf.* § 5.1). Running simulations at a large scale is particularly interesting to evaluate over a long period a consistent and relatively complete network of cerebral structures in realistic interaction with the external and internal world. We face this problem in the domain of autonomous robotics (*cf.* § 3.4) and ensure a real autonomy by the design of an artificial physiology and convenient learning protocoles.

We are convinced that this original approach also permits to revisit and enrich algorithms and methodologies in machine learning (*cf.* § 3.3) and in autonomous robotics (*cf.* § 3.4), in addition to elaborate hypotheses to be tested in neuroscience and medicine, while offering to these latter domains a new ground of experimentation similar to their daily experimental studies.

2.2. Highlights of the Year

As a good illustration of our thematic shift from models of visuomotor functions to applications to neurodegenerative diseases, this recent publication in PNAS [1] proposes that the Degus, a rodent from Chile used for the design of models of the retina, is also an animal model for the Alzheimer disease.

3. Scientific Foundations

3.1. Integrative and Cognitive Neuroscience

The human brain is often considered as the most complex system dedicated to information processing. This multi-scale complexity, described from the metabolic to the network level, is particularly studied in integrative neuroscience, the goal of which is to explain how cognitive functions (ranging from sensorimotor coordination to executive functions) emerge from (are the result of the interaction of) distributed and adaptive computations of processing units, displayed along neural structures and information flows. Indeed, beyond the astounding complexity reported in physiological studies, integrative neuroscience aims at extracting, in simplifying models, regularities in space and functional mechanisms in time. From a spatial point of view, most neuronal structures (and particularly some of primary importance like the cortex, cerebellum, striatum, hippocampus) can be described through a regular organization of information flows and homogenous learning rules, whatever the nature of the processed information. From a temporal point of view, the arrangement in space of neuronal structures within the cerebral architecture also obeys a functional logic, the sketch of which is captured in models describing the main information flows in the brain, the corresponding loops built in interaction with the external and internal (bodily and hormonal) world and the developmental steps leading to the acquisition of elementary sensorimotor skills up to the most complex executive functions.

Three important characteristics are worth mentioning concerning these loops. Firstly, each of them sets a closed relation between the central nervous system and the rest of the world. This includes the external world (possibly including other intelligent agents), but also the internal world, with hormonal, physiological and bodily dimensions. Secondly, each of these loops can be described as a loop relating sensations to actions, in the wide sense of these terms: effectively, action can refer to acting in the real world, but also to modifying physiological parameters or controling neuronal activation. These loops have different constants of time, from immediate reflexes and sensorimotor adjustments to long term selection of motivation for action, the latter depending on hormonal and social parameters. Thirdly, each of the loops performs a learning reinforced by a primary (physiologically significant) or pseudo reward (sub-goal to be learned). As an illustration, we can mention respondent conditioning detecting stimuli anticipatory of primary rewards, episodic learning detecting multimodal events, and also more local phenomena like self-organization of topological structures. The gradual establishment of these loops and their mutual interactions give an interpretation of the resulting cognitive architecture as a synergetic system of memories.

In summary, integrative neuroscience builds, on an overwhelming quantity of data, a simplifying and interpretative grid suggesting homogenous local computations and a structured and logical plan for the development of cognitive functions. They arise from interactions and information exchange between neuronal structures and the external and internal world and also within the network of structures.

This domain is today very active and stimulating because it proposes, of course at the price of simplifications, global views of cerebral functioning and more local hypotheses on the role of subsets of neuronal structures in cognition. In the global approaches, the integration of data from experimental psychology and clinical studies leads to an overview of the brain as a set of interacting memories, each devoted to a specific kind of information processing [31]. It results also in longstanding and very ambitious studies for the design of cognitive architectures aiming at embracing the whole cognition. With the notable exception of works initiated by [27], most of these frameworks (e.g. Soar, ACT-R), though sometimes justified on biological grounds, do not go up to a *connectionist* neuronal implementation. Furthermore, because of the complexity of the resulting frameworks, they are restricted to simple symbolic interfaces with the internal and external world and to (relatively) small-sized internal structures. Our main research objective is undoubtly to build such a general purpose cognitive architecture (to model the brain *as a whole* in a systemic way), using a connectionist implementation and able to cope with a realistic environment.

3.2. Computational Neuroscience

From a general point of view, computational neuroscience can be defined as the development of methods from computer science and applied mathematics, to explore more technically and theoretically the relations between structures and functions in the brain [33], [21]. During the recent years this domain has gained an increasing interest in neuroscience and has become an essential tool for scientific developments in most fields in neuroscience, from the molecule to the system. In this view, all the objectives of our team can be described as possible progresses in computational neuroscience. Accordingly, it can be underlined that the systemic view that we promote can offer original contributions in the sense that, whereas most classical models in computational neuroscience focus on the better understanding of the structure/function relationship for specific structures, we aim at exploring synergies between structures. Consequently, we target interfaces and interplay between heterogenous modes of computing, which is rarely addressed in classical computational neuroscience.

We also insist on another aspect of computational neuroscience which is, in our opinion, at the core of the involvement of computer scientists and mathematicians in the domain and on which we think we could particularly contribute. Indeed, we think that our primary abilities in numerical sciences imply that our developments are characterized above all by the effectiveness of the corresponding computations: We provide biologically inspired architectures with effective computational properties, such as robustness to noise, self-organization, on-line learning. We more generally underline the requirement that our models must also mimick biology through its most general law of homeostasis and self-adaptability in an unknown and changing environment. This means that we propose to numerically experiment such models and thus provide effective methods to falsify them.

Here, computational neuroscience means mimicking original computations made by the neuronal substratum and mastering their corresponding properties: computations are distributed and adaptive; they are performed without an homonculus or any central clock. Numerical schemes developped for distributed dynamical systems and algorithms elaborated for distributed computations are of central interest here [18], [26] and were the basis for several contributions in our group [32], [29], [34]. Ensuring such a rigor in the computations associated to our systemic and large scale approach is of central importance.

Equally important is the choice for the formalism of computation, extensively discussed in the connectionist domain. Spiking neurons are today widely recognized of central interest to study synchronization mechanisms and neuronal coupling at the microscopic level [19]; the associated formalism [24] can be possibly considered for local studies or for relating our results with this important domain in connectionism. Nevertheless, we remain mainly at the mesoscopic level of modeling, the level of the neuronal population, and consequently interested in the formalism developped for dynamic neural fields [16], that demonstrated a richness of behavior [20] adapted to the kind of phenomena we wish to manipulate at this level of description. Our group has a long experience in the study and adaptation of the properties of neural fields [29], [30] and their use for observing the emergence of typical cortical properties [23]. In the envisioned development of more complex architectures and interplay between structures, the exploration of mathematical properties such as stability and boundedness and the observation of emerging phenomena is one important objective. This objective is also associated with that of capitalizing our experience and promoting good practices in our software production (*cf.* § 5.1). In summary, we think that this systemic approach also brings to computational neuroscience new case studies where heterogenous and adaptive models with various time scales and parameters have to be considered jointly to obtain a mastered substratum of computation. This is particularly critical for large scale deployments, as we will discuss in § 5.1).

3.3. Machine Learning

The adaptive properties of the nervous system are certainly among its most fascinating characteristics, with a high impact on our cognitive functions. Accordingly, machine learning is a domain [25] that aims at giving such characteristics to artificial systems, using a mathematical framework (probabilities, statistics, data analysis, etc.). Some of its most famous algorithms are directly inspired for neuroscience, at different levels. Connectionist learning algorithms implement, in various neuronal architectures, weight update rules, generally derived from the hebbian rule, performing non supervised (e.g. Kohonen self-organizing maps), supervised (e.g. layered perceptrons) or associative (e.g. Hopfield recurrent network) learning. Other algorithms, not necessarily connectionist, perform other kinds of learning, like reinforcement learning. Machine learning is a very mature domain today and all these algorithms have been extensively studied, at the theoretical and practical levels, with much success. They have also been related to many functions (in the living and artificial domains) like discrimination, categorisation, sensorimotor coordination, planning, etc. and several neuronal structures have been proposed as the substratum for these kinds of learning [22], [15]. Nevertheless, we believe that, as for previous models, machine learning algorithms remain isolated tools, whereas our systemic approach can bring original views on these problems.

At the cognitive level, most of the problems we face do not rely on only one kind of learning and require skills that have been learned previously. That is the reason why cognitive architectures are often referred to as systems of memory, communicating and sharing information for problem solving. Instead of the classical view in machine learning of a flat architecture, a more complex network of modules must be considered here, as it is the case in the domain of deep learning. In addition, our systemic approach brings the question of incrementally building such a system, with a clear inspiration from developmental sciences. In this perspective, modules can generate internal signals corresponding to internal goals, predictions, error signals, able to supervise the learning of other modules (possibly endowed with a different learning rule), supposed to become autonomous after an instructing period. A typical example is that of episodic learning (in the hippocampus), storing declarative memory about a collection of past episods and supervising the training of a procedural memory in the cortex.

At the behavioral level, as mentionned above, our systemic approach underlines the fundamental links between the adaptive system and the internal and external world. The internal world includes proprioception and interoception, giving information about the body and its needs for integrity and other fundamental programs. The external world includes physical laws that have to be learned and possibly intelligent agents for more complex interactions. Both also involve sensors and actuators that are the interfaces with these worlds and close the loops. Within this rich picture, machine learning generally selects one situation that defines useful sensors and actuators and a corpus with properly segmented data and time, and builds a specific architecture and its corresponding criteria to be satisfied. In our approach however, the first question to be raised is to discover what is the goal, where attention must be focused on and which previous skills must be exploited, with the help of a dynamic architecture and possibly other partners. In this domain, the behavioral and the developmental sciences, observing how and along which stages an agent learns, are of great help to bring some structure to this high dimensional problem.

At the implementation level, this analysis opens many fundamental challenges, hardly considered in machine learning : stability must be preserved despite on-line continuous learning; criteria to be satisfied often refer to behavioral and global measurements but they must be translated to control the local circuit level; in an incremental or developmental approach, how will the development of new functions preserve the integrity and stability of others? In addition, this continous re-arrangement is supposed to involve several kinds of learning, at different time scales (from msec to years in humans) and to interfer with other phenomena like variability and meta-plasticity.

In summary, our main objective in machine learning is to propose on-line learning systems, where several modes of learning have to collaborate and where the protocoles of training are realistic. We promote here a *really autonomous* learning, where the agent must select by itself internal resources (and build them if not available) to evolve at the best in an unknown world, without the help of any *deus-ex-machina* to define parameters, build corpus and define training sessions, as it is generally the case in machine learning. To that end, autonomous robotics (*cf.* § 3.4) is a perfect testbed.

3.4. Autonomous Robotics

Autonomous robots are not only convenient platforms to implement our algorithms; the choice of such platforms is also motivated by theories in cognitive science and neuroscience indicating that cognition emerges from interactions of the body in direct loops with the world and develops interesting specificities accordingly. For example, internal representations can be minimized (opposite to building complex and hierarchical representations) and compensated by more simple strategies [17], more directly coupling perception and action and more efficient to react quickly in the changing environment (for example, instead of memorizing details of an object, just memorizing the eye movement to foveate it: the world itself is considered as an external memory). In this view for the *embodiment of cognition*, learning is intrinsically linked to sensorimotor loops and to a real body interacting with a real environment.

A real autonomy can be obtained only if the robot is able to define its goal by itself, without the specification of any high level and abstract cost function or rewarding state. To ensure such a capability, we propose to endow the robot with an artificial physiology, corresponding to perceive some kind of pain and pleasure. It may consequently discriminate internal and external goals (or situations to be avoided). This will mimick circuits related to fundamental needs (e.g. hunger and thirst) and to the preservation of bodily integrity. An important objective is to show that more abstract planning capabilities can arise from these basic goals.

A real autonomy with an on-line continuous learning as described in § 3.3 will be made possible by the elaboration of protocols of learning, as it is the case, in animal conditioning, for experimental studies where performance on a task can be obtained only after a shaping in increasingly complex tasks. Similarly, developmental sciences can teach us about the ordered elaboration of skills and their association in more complex schemes. An important challenge here is to translate these hints at the level of the cerebral architecture.

As a whole, autonomous robotics permits to assess the consistency of our models in realistic condition of use and offers to our colleagues in behavioral sciences an object of study and comparison, regarding behavioral dynamics emerging from interactions with the environment, also observable at the neuronal level.

In summary, our main contribution in autonomous robotics is to make autonomy possible, by various means corresponding to endow robots with an artificial physiology, to give instructions in a natural and incremental way and to prioritize the synergy between reactive and robust schemes over complex planning structures.

4. Application Domains

4.1. Overview

One of the most original specificity of our team is that it is part of a laboratory in Neuroscience (with a large spectrum of activity from the molecule to the behavior), focused on neurodegenerative diseases and consequently working in tight collaboration with the medical domain. As a consequence, neuroscientists and the medical world are considered as the primary end-users of our researches. Beyond data and signal analysis where our expertise in machine learning may be possibly useful, our interactions are mainly centered on the exploitation of our models. They will be classically regarded as a way to validate biological assumptions and to generate new hypotheses to be investigated in the living. Our macroscopic models and their implementation in autonomous robots will allow an analysis at the behavioral level and will propose a systemic framework, the interpretation of which will meet aetiological analysis in the medical domain and interpretation of intelligent behavior in cognitive neuroscience.

The study of neurodegenerative diseases is targeted because they match the phenomena we model. Particularly, the Parkinson disease results from the death of dopaminergic cells in the basal ganglia, one of the main systems that we are modeling. The Alzheimer disease also results from the loss of neurons, in several cortical and subcortical regions. The variety of these regions, together with large mnesic and cognitive deficits, require a systemic view of the cerebral architecture and associated functions, very consistent with our approach.

Of course, numerical sciences are also impacted by our researches, at several levels. At a global level, we will propose new control architectures aimed at providing a higher degree of autonomy to robots, as well as machine learning algorithms working in more realistic environment. More specifically, our focus on some cognitive functions in closed loop with a real environment will address currently open problems. This is obviously the case for planning and decision making; this is particularly the case for the domain of affective computing, since motivational characteristics arising from the design of an artificial physiology allow to consider not only cold rational cognition but also hot emotional cognition. The association of both kinds of cognition is undoublty an innovative way to create more realistic intelligent systems but also to elaborate more natural interfaces between these systems and human users.

At last, we think that our activities in well-founded distributed computations and high performance computing are not just intended to help us design large scale systems. We also think that we are working here at the core of informatics and, accordingly, that we could transfer some fundamental results in this domain.

5. Software

5.1. Positioning

Our previous works in the domain of well-defined distributed asynchronous adaptive computations [32], [29], [34] have already made us define a library (DANA [3]), closely related to both the notion of artificial neural networks and cellular automata. From a conceptual point of view, the computational paradigm supporting the library is grounded on the notion of a unit that is essentially a (vector of) potential that can vary along time under the influence of other units and learning. Those units can organized into layers, maps and network.

More generally, we gather in the middleware EnaS (that stands for *Event Neural Assembly Simulation*; cf. http://gforge.inria.fr/projects/enas) our numerical and theoretical developments, allowing to simulate and analyze so called "event neural assemblies". Enas has been designed as a plug-in for our simulators (e.g. DANA or MVASpike) as other existing simulators (via the NeuralEnsemble meta-simulation platform) and additional modules for computations with neural unit assembly on standard platforms (e.g. Python or the Scilab platform).

We will also have to interact with the High Performance Computing (HPC) community, since having large scale simulations at that mesoscopic level is an important challenge in our systemic view of computational neuroscience. Our approach implies to emulate the dynamics of thousands, or even millions, of integrated computational units, each of them playing the role of a whole elementary neural circuit (e.g. the microcolumn for the cortex). Mesoscopic models are considered in such an integrative approach, in order to exhibit global dynamical effect that would be hardly reachable by compartment models involving membrane equations or even spiking neuron networks.

The vast majority of high performance computing softwares for computational neuroscience addresses sub-neural or neural models [19], but coarser grained population models are also demanding for large scale simulations, with fully distributed computations, without global memory or time reference, as it is specified in (*cf.* § 3.2).

5.2. Dana

Participant: Nicolas Rougier.

DANA [28] is a python framework (http://dana.loria.fr) whose computational paradigm is grounded on the notion of a unit that is essentially a set of time dependent values varying under the influence of other units via adaptive weighted connections. The evolution of a unit's value are defined by a set of differential equations expressed in standard mathematical notation which greatly ease their definition. The units are organized into groups that form a model. Each unit can be connected to any other unit (including itself) using a weighted connection. The DANA framework offers a set of core objects needed to design and run such models. The modeler only has to define the equations of a unit as well as the equations governing the training of the connections. The simulation is completely transparent to the modeler and is handled by DANA. This allows DANA to be used for a wide range of numerical and distributed models as long as they fit the proposed framework (e.g. cellular automata, reaction-diffusion system, decentralized neural networks, recurrent neural networks, kernel-based image processing, etc.).

5.3. ENAS: Event Neural Assembly Simulation

Participants: Frédéric Alexandre, Nicolas Rougier, Thierry Viéville.

EnaS (that stands for “Event Neural Assembly Simulation”) is a middleware implementing our last numerical and theoretical developments, allowing to simulate and analyze so called "event neural assemblies". The recent achievements include (in collaboration with the Neuromathcomp EPI): spike trains statistical analysis via Gibbs distributions, spiking network programing for exact event's sequence restitution, discrete neural field parameters algorithmic adjustments and time-constrained event-based network simulation reconciling clock and event based simulation methods. It has been designed as plug-in for our simulators (e.g. DANA or Mvaspike) as other existing simulators (via the NeuralEnsemble meta-simulation platform) and additional modules for computations with neural unit assembly on standard platforms (e.g. Python or the Scilab platform).

5.4. Virtual Enaction

Participants: Frédéric Alexandre, André Garenne, Nicolas Rougier, Thierry Viéville.

The computational models studied in this project have applications that extend far beyond what is possible to experiment yet in human or non-human primate subjects. Real robotics experimentations are also impaired by rather heavy technological constraints; for instance, it is not easy to dismantle a given embedded system in the course of emerging ideas. The only versatile environment in which such complex behaviors can be studied both globally and at the level of details of the available modeling is a virtual environment, as in video games, Such a system can be implemented as «brainy-bot» (a programmed player based on our knowledge of the brain architecture) which goal is to survive in a complete manipulable environment.

In order to attain this rather ambitious objective we are going to both (i) deploy an existing open-source video game middleware in order to be able to shape the survival situation to be studied and (ii) revisit the existing models in order to be able to integrate them as an effective brainy-bot. It will consist of a platform associated to a scenario that would be the closest possible to a survival situation (foraging, predator-prey relationship, partner approach to reproduction) and in which it would be easy to integrate an artificial agent with sensory inputs (visual, touch and smell), emotional and somatosensory cues (hunger, thirst, fear, ..) and motor outputs (movement, gesture, ..) connected to a "brain" whose architecture will correspond to the major anatomical regions involved in the issues of learning and action selection (cortex areas detailed here, basal ganglia, hippocampus, and areas dedicated to sensorimotor processes). The internal game clock will be slowed down enough to be able to run non trivial brainy-bot implementations.

6. New Results

6.1. Introduction

2012 is the year of birth of the Mnemosyne team; it is also a year of transition, since most of its members were previously in the Cortex project-team in Nancy. Accordingly, this year was partly devoted to ongoing projects in the Cortex team and to the initiation of the first activities in Mnemosyne. Apart from the results listed below, corresponding to the extension of current projects from the Cortex team to our new topics, we have also begun to study models of episodic and semantic memory at the interface between the hippocampus and the cortex and interaction between models of the basal ganglia and the prefrontal cortex.

6.2. Systemic view of visuomotor transformations

Visuomotricity was an important topic in our activities in the Cortex team. We are pursuing these activities in ongoing projects (particularly the ANR Keops project, cf. § 7.1), and extend them according to a systemic view, integrating new information flows from the external world and from other neuronal structures:

- We consider the role of non-standard cells in the retina [11], reported as responsible for fast event-detection in the visual flow.
- We have initiated a modeling study of the retina-thalamus-cortex information flow and particularly of its non-specific pathway [9] that can account for attentional mechanisms.

7. Partnerships and Cooperations

7.1. National Initiatives

7.1.1. ANR

7.1.1.1. ANR project KEOPS

Participants: Frédéric Alexandre, Thierry Viéville.

We are implicated in this «ANR Internal White Project» involving NEUROMATHCOMP and CORTEX Inria EPI in France with the U. of Valparaiso, U. Tecnica Frederico Santa-Maria, and U. Chile. The project addresses the integration of non-standard behaviors from retinal neural sensors, dynamically rich, sparse and robust observed in natural conditions, into neural coding models and their translation into real, highly non-linear, bio-engineering artificial solutions. An interdisciplinary platform for translation from neuroscience into bioengineering will seek convergence from experimental and analytical models, with a fine articulation between biologically inspired computation and nervous systems neural signal processing (coding / decoding) [9], [10].

7.2. International Initiatives

7.2.1. Inria Associate Teams

7.2.1.1. Cortina, associate team with Chile

Participants: Frédéric Alexandre, Thierry Viéville.

The goal of this associate team initiated within the Cortex team is to combine our complementary expertise, from experimental biology and mathematical models (U de Valparaiso and U Federico Santa-Maria) to computational neuroscience (CORTEX/MNEMOSYNE and NEUROMATHCOMP), in order to develop common tools for the analysis and formalization of neural coding and related sensory-motor loops. Recording and modeling spike trains from the retina neural network, an accessible part of the brain, is a difficult task that our partnership can address, what constitute an excellent and unique opportunity to work together sharing our experience and to focus in developing computational tools for methodological innovations.

8. Dissemination

8.1. Scientific Animation

8.1.1. Responsabilities

- F. Alexandre and T. Viéville are members (and moderators) of the scientific committee of NeuroComp, the initiative to gather the french community in Computational Neuroscience (annual conference and web site: http://www.neurocomp.fr/).

8.1.2. Review activities

- Reviewing for journals: Applied Intelligence, Cognitive Computation, J. Physiol. (F. Alexandre)
- Member of program committees of conferences: AMINA, CAP, CWPR, JCIB, SAB, TAIMA (F. Alexandre)
- Reviewing for the Fonds Recherche Quebec, the CNRS, the ANR and several french regional and territorial agencies (F. Alexandre)

8.1.3. Workshops, conferences and seminars

Organization of conferences and workshops:

- Robots & Corps, Conférence ARCO / IPAC, 18/10/2012 (N. Rougier)
- EuroScipy 2012, Brussels, Belgium (N. Rougier)
- Organization of the The NeuroComp/KEOpS'12 workshop, Beyond the retina: from computational models to outcomes in bioengineering. Focus on architecture and dynamics sustaining information flows in the visuomotor system. Bordeaux, October the 10th and 11th (F. Alexandre and T. Viéville). http://www.neurocomp.fr/neurocomp-2012
- Invited Talks given to the IPAC Seminar (Nancy), to the Annual Forum in Cognitive Science at University of Nancy, to the Seminar Bordeaux Neuroscience, to the second French-Chinese workshop on Network Dynamics and Synaptic Plasticity in the Central Nervous System (F. Alexandre).

8.2. Teaching - Supervision - Juries

8.2.1. Teaching

Many courses are given in universities and schools of engineers at different levels (LMD) by most team members, in computer science, in applied mathematics, in neuroscience and in cognitive science.

F. Alexandre has given a lecture to the Master/Doctorate program in Neuroscience, University of Valparaiso.

N. Rougier has given this year a tutorial on scientific visualization at Euroscipy 2012, Brussels.

8.2.2. Juries

We also participate to many juries each year.

8.3. Popularization

We have a strong activity for popularization of science:

- The other half-time of Thierry Viéville's activity is dedicated to popularization of science (http://science-info-lycee.fr, http://www.inria.fr/mecsci, http://interstices.info) with about 10 conferences and 20 days of scientific animation [8], [7].
- "Les Robots, le futur... demain ?", Les cafés des sciences et techniques, Bibliothèque Intercommunale, Epinal, 22 novembre 2012 (N. Rougier)
- Meeting with the general public for the national scientific film festival, Nancy, 2012 (N. Rougier)
- Exchange with a scientific journalist (5 days in Nancy, 5 days in Paris), 2012 (N. Rougier)

9. Bibliography

Publications of the year

Articles in International Peer-Reviewed Journals

[1] A. O. ARDILES, C. C. TAPIA-ROJAS, M. MANDAL, F. ALEXANDRE, A. KIRKWOOD, N. C. INESTROSA, A. G. PALACIOS. *Postsynaptic dysfunction is associated with spatial and object recognition memory loss in a natural model of Alzheimer's disease.*, in "Proceedings of the National Academy of Sciences", August 2012, vol. 109, n° 34, p. 13835-40 [*DOI :* 10.1073/PNAS.1201209109], http://hal.inria.fr/hal-00746807.

[2] G. DETORAKIS, N. P. ROUGIER. *A Neural Field Model of the Somatosensory Cortex: Formation, Maintenance and Reorganization of Ordered Topographic Maps*, in "PLoS ONE", July 2012, vol. 7, n° 7, e40257, http://hal.inria.fr/hal-00716355.

[3] N. P. ROUGIER, J. FIX. *DANA: Distributed (asynchronous) Numerical and Adaptive modelling framework*, in "Network: Computation in Neural Systems", December 2012, vol. 23, n° 4, p. 237-253 [*DOI :* 10.3109/0954898X.2012.721573], http://hal.inria.fr/hal-00718780.

[4] W. TAOUALI, N. P. ROUGIER, F. ALEXANDRE. *Visual Target Selection Emerges from a Bio-inspired Network Topology*, in "Studies in Computational Intelligence", 2012, http://hal.inria.fr/inria-00636517.

Articles in Non Peer-Reviewed Journals

[5] T. VIÉVILLE. *La liberté numérique commence où l'ignorance informatique finit.*, in "Tangente Éducation", September 2012, n° 22, http://hal.inria.fr/hal-00763504.

International Conferences with Proceedings

[6] B. CESSAC, R. SALAS FUENTES, T. VIÉVILLE. *Using event-based metric for event-based neural network weight adjustment*, in "20th European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning", Bruges, Belgique, Louvain-La-Neuve : I6doc.com, April 2012, 18 pp, http://hal.inria.fr/hal-00755345.

National Conferences with Proceeding

[7] F. DUFOUR, M. HACHET, G. GIRAUDON, P. GUITTON, T. VIÉVILLE. *Comment utiliser le 3.0 pour que notre MINF soit ubiquitaire, participatif et attractif ?*, in "Vers un musée de l'informatique et de la société numérique en France.", Paris, France, I. ASTIC, P.-E. MOUNIER-KUHN, P. PARADINAS (editors), http://minf.cnam.fr, November 2012, http://hal.inria.fr/hal-00756476.

[8] P. GUITTON, V. POIREL, T. VIÉVILLE. *Médiation Scientifique en Sciences du Numérique : il faut piger pourquoi on clique !*, in "Journées Hubert Curien 2012 Rencontre internationale de la médiation scientifique", Nancy, France, B. SCHIELE (editor), http://www.jhc2012.eu, September 2012, http://hal.inria.fr/hal-00756485.

Conferences without Proceedings

[9] C. CARVAJAL, T. VIÉVILLE, F. ALEXANDRE. *Konio Pathway: An Instinctive Visual Mechanism for Survival and Decision Making?*, in "NeuroComp/KEOpS'12 workshop beyond the retina: from computational models

to outcomes in bioengineering. Focus on architecture and dynamics sustaining information flows in the visuomotor system.", Bordeaux, France, October 2012, http://hal.inria.fr/hal-00756471.

[10] H. NASSER, O. MARRE, S. KRARIA, T. VIÉVILLE, B. CESSAC. *Analyzing large-scale spike trains data with spatio-temporal constraints*, in "NeuroComp/KEOpS'12 workshop beyond the retina: from computational models to outcomes in bioengineering. Focus on architecture and dynamics sustaining information flows in the visuomotor system.", Bordeaux, France, October 2012, http://hal.inria.fr/hal-00756467.

[11] E. TEFTEF, T. VIÉVILLE. *Formalization of the input/output retinal transformation regarding non-standard ganglion cells behavior*, in "NeuroComp/KEOpS'12 workshop beyond the retina: from computational models to outcomes in bioengineering. Focus on architecture and dynamics sustaining information flows in the visuomotor system.", Bordeaux, France, October 2012, http://hal.inria.fr/hal-00756453.

Scientific Books (or Scientific Book chapters)

[12] F. ALEXANDRE. *Une approche systémique du réseau cérébral*, in "Les Réseaux", E. LETONTURIER (editor), Les essentiels d'Hermès, CNRS Editions, August 2012, p. 129-140, http://hal.inria.fr/hal-00746781.

[13] G. DOWEK, J.-P. ARCHAMBAULT, E. BACCELLI, C. CIMELLLI, A. COHEN, C. EISENBEIS, T. VIÉVILLE, B. WACK. *Informatique et Sciences du Numérique - Spécialité ISN en Terminale S*, Eyrolles, August 2012, 303, http://hal.inria.fr/hal-00765220.

Other Publications

[14] P.-B. JOLY, T. VIÉVILLE. *Planète Sciences et Planète Numérique : une belle passerelle de l'un à l'autre.*, December 2012, Publication dans le numéro spécial "50 ans de Planète Sciences" édité par http://www.planete-sciences.org, http://hal.inria.fr/hal-00765227.

References in notes

[15] F. ALEXANDRE. *Biological Inspiration for Multiple Memories Implementation and Cooperation*, in "In V. Kvasnicka P. Sincak, J. Vascak and R. Mesiar, editors, International Conference on Computational Intelligence", 2000.

[16] S. AMARI. *Dynamic of pattern formation in lateral-inhibition type neural fields*, in "Biological Cybernetics", 1977, vol. 27, p. 77–88.

[17] D. H. BALLARD, M. M. HAYHOE, P. K. POOK, R. P. N. RAO. *Deictic codes for the embodiment of cognition*, in "Behavioral and Brain Sciences", 1997, vol. 20, n^{o} 04, p. 723–742, http://dx.doi.org/10.1017/S0140525X97001611.

[18] D. BERTSEKAS, J. TSITSIKLIS. *Parallel and Distributed Computation: Numerical Methods*, Athena Scientific, 1997.

[19] R. BRETTE, M. RUDOLPH, T. CARNEVALE, M. HINES, D. BEEMAN, J. BOWER, M. DIESMANN, A. MORRISON, P. H. GOODMAN, F. C. JR. HARRIS, M. ZIRPE, T. NATSCHLÄGER, D. PECEVSKI, B. ERMENTROUT, M. DJURFELDT, A. LANSNER, O. ROCHEL, T. VIEVILLE, E. MULLER, A. DAVISON, S. E. BOUSTANI, A. DESTEXHE. *Simulation of networks of spiking neurons: a review of tools and strategies*, in "Journal of Computational Neuroscience", 2007, vol. 23, n^{o} 3, p. 349–398.

[20] S. COOMBES. *Waves, bumps and patterns in neural field theories*, in "Biol. Cybern.", 2005, vol. 93, p. 91-108.

[21] P. DAYAN, L. ABBOTT. *Theoretical Neuroscience : Computational and Mathematical Modeling of Neural Systems*, MIT Press, 2001.

[22] K. DOYA. *What are the computations of the cerebellum, the basal ganglia and the cerebral cortex?*, in "Neural Networks", 1999, vol. 12, p. 961–974.

[23] J. FIX, N. P. ROUGIER, F. ALEXANDRE. *A dynamic neural field approach to the covert and overt deployment of spatial attention*, in "Cognitive Computation", 2011, vol. 3, n° 1, p. 279-293 [*DOI :* 10.1007/s12559-010-9083-Y], http://hal.inria.fr/inria-00536374/en.

[24] W. GERSTNER, W. KISTLER. *Spiking Neuron Models: Single Neurons, Populations, Plasticity*, Cambridge University Press, Cambridge University Press, 2002.

[25] T. MITCHELL. *Machine Learning*, Mac Graw-Hill Press, 1997.

[26] D. MITRA. *Asynchronous relaxations for the numerical solution of differential equations by parallel processors*, in "SIAM J. Sci. Stat. Comput.", 1987, vol. 8, n° 1, p. 43–58 [*DOI :* 10.1137/0908012].

[27] R. O'REILLY, Y. MUNAKATA. *Computational Explorations in Cognitive Neuroscience: Understanding the Mind by Simulating the Brain*, MIT Press, Cambridge, MA, USA, 2000.

[28] N. P. ROUGIER, J. FIX. *DANA: Distributed (asynchronous) Numerical and Adaptive modelling framework*, in "Network: Computation in Neural Systems", December 2012, vol. 23, n° 4, p. 237-253 [*DOI :* 10.3109/0954898X.2012.721573], http://hal.inria.fr/hal-00718780.

[29] N. ROUGIER, A. HUTT. *Synchronous and Asynchronous Evaluation of Dynamic Neural Fields*, in "J. Diff. Eq. Appl.", 2009.

[30] N. ROUGIER. *Dynamic Neural Field with Local Inhibition*, in "Biological Cybernetics", 2006, vol. 94, n° 3, p. 169-179.

[31] L. SQUIRE. *Memory systems of the brain: a brief history and current perspective*, in "Neurobiol. Learn. Mem.", 2004, vol. 82, p. 171-177.

[32] W. TAOUALI, T. VIÉVILLE, N. ROUGIER, F. ALEXANDRE. *No clock to rule them all*, in "Journal of Physiology", 2011, vol. 105, n° 1-3, p. 83-90.

[33] T. TRAPPENBERG. *Fundamentals of Computational Neuroscience*, Oxford University Press, 2002.

[34] T. VIÉVILLE. *An unbiased implementation of regularization mechanisms*, in "Image and Vision Computing", 2005, vol. 23, n° 11, p. 981–998, http://authors.elsevier.com/sd/article/S0262885605000909.