INSTITUT NATIONAL DE RECHERCHE EN INFORMATIQUE ET EN AUTOMATIQUE

Project-Team CORTEX

Computational Neuroscience

Nancy - Grand Est

THEME BIO

Activity Report

2008

Table of contents

CORTEX is a project-team of the LORIA (UMR 7503) common to CNRS, INRIA, University Henri Poincaré Nancy 1 (UHP), University Nancy 2 and National Polytechnic Institute of Lorraine.

1. Team

Research Scientist
Frédéric Alexandre [Research Director (DR) INRIA, Team Leader, HdR]
Axel Hutt [CR]
Nicolas Rougier [CR]
Thierry Viéville [DR (half time in the project-team), HdR]
Thomas Voegtlin [CR]
Dominique Martinez [CR]

Faculty Member
Yann Boniface [Maître de conférences, U. Nancy 2]
Laurent Bougrain [Maître de conférences, UHP, on partial secondment at INRIA until september 2008]
Bernard Girau [Professeur des Universités, UHP, on partial secondment at INRIA until september 2008, HdR]

External Collaborator
Hervé Frezza-Buet [Enseignant-Chercheur à Supélec Campus de Metz]

Technical Staff
Edouardo Martin-Moraud [Junior technical staff (until october 2008)]

PhD Student
Lucian Aleçu [Supelec]
Maxime Ambard [NoE Gospel]
Hana Belmabrouk [ANR Pherosys]
Mauricio Cerda [Cordi]
Jérémy Fix [BDI-CNRS/Région (until december 2008)]
Thomas Girod [MESR]
Elham Ghassemi [Cordi/Région (from october 2008)]
Randa Kassab [Syria]
Nizar Kerkeni [Tunisia (half-time with Tunisia)]
Mathieu Lefort [MESR]
Maxime Rio [Cordi (from october 2008)]

Post-Doctoral Fellow
Samuel Mac Kennoch [(until october 2008)]
Noelia Montejo-Cervera [(until december 2008)]
Liang Nanying

Administrative Assistant
Martine Kuhlmann [part time in the project-team]

2. Overall Objectives

2.1. Overall Objectives

The goal of our research is to study the properties and computational capacities of distributed, numerical and adaptative networks, as observed in neuronal systems. In this context, we aim to understand how complex high level properties may emerge from such complex systems including their dynamical aspects. In close reference to our domain of inspiration, Neuroscience, this study is carried out at three scales, namely neurons, population, cerebral region.

1. **Neurons:** At the microscopic level, our approach relies on precise and realistic models of neurons and of the related dynamics, analyzing the neural code in small networks of spiking neurons (*cf.* § 3.2).
2. **Population of neurons:** At the mesoscopic level, the characteristics of a local circuit are integrated in a high level unit of computation, i.e. a dynamic neural field (*cf.* § 3.3). This level of description allows us to study larger neuronal systems, such as cerebral maps, as observed in sensori-motor loops.
3. **Higher level functions:** At the macroscopic level, the analysis of physiological signals and psychometric data is to be related to more behavioral hints. This is for instance the case with electroencephalographic (EEG) recordings, allowing to measure brain activity, including in brain computer interface paradigms (*cf.* § 3.4).

Very importantly, these levels are not studied independently and we target progresses at the interface between levels. The microscopic/mesoscopic interface is the place to consider both the analog and asynchronous/event-based mechanisms and derive computational principles coherent across scales. The mesoscopic/macroscopic interface is the place to understand the emergence of functions from local computations, by means of information flow analysis and study of interactions.

Learning is a central issue at each level. At the microscopic level, the pre/post synaptic interactions are studied in the framework of Spike Time Dependent Plasticity (STDP). At the mesoscopic level, spatial and temporal patterns of activity in neural population are the cues to be memorized (e.g. via the BCM rule). At the macroscopic level, behavioral skills are acquired along time, through incremental strategies, e.g. using conditioning, unsupervised or reinforcement learning.

Our research is linked to several scientific domains (*cf.* § 3.1). In the domain of computer science, we generate novel paradigms of distributed spatial computation and we aim at explaining their properties, intrinsic (e.g. robustness) as well as functional (e.g. self-organization). In the domain of cognitive science, our models are used to emulate various functions (e.g. attention, memory, sensori-motor coordination) which are consequently fully explained by purely distributed asynchronous computations. In the domain of neuroscience, we share with biologists, not only data analysis, but also frameworks for the validation of biological and computational assumptions in order to validate or falsify existing models. This is the best way to increase knowledge and improve methods in both fields.

In order to really explore these kinds of bio-inspired computations, the key point is to remain consistent with biological and ecological constraints. Among computational constraints, computations have to be really distributed, without central clock or common memory. The emerging cognition has to be situated (*cf.* § 3.6), i.e. resulting from a real interaction in the long term with the environment. As a consequence, our models are particularly well validated with parallel architectures of computations (e.g. FPGA, clusters, *cf.* § 3.5) and embodied in systems (robots) that interact with their environment (*cf.* § 3.6).

Accordingly, four topics of research have been carried out this year.

- Microscopic level (*cf.* § 6.1): neural code; time coding and synchronization; simulation; application to olfaction.
- Mesoscopic level (*cf.* § 6.2): motion perception; visual attention; motor anticipation; neural field implementation.
- Macroscopic level (*cf.* § 6.3): neural information processing; brain computer interface.

with a transversal topic related to:

- Embodied and embedded systems (*cf.* § 6.4): dedicated architectures.

3. Scientific Foundations

3.1. Computational neuroscience

Keywords: *computational models*, *neuroscience*, *population of neurons*, *spiking neurons*.

With regards to the progress that has been made in anatomy, neurobiology, physiology, imaging, and behavioral studies, computational neuroscience offers a unique interdisciplinary cooperation between experimental and clinical neuroscientists, physicists, mathematicians and computer scientists. It combines experiments with data analysis and functional models with computer simulation on the basis of strong theoretical concepts and aims at understanding mechanisms that underlie neural processes such as perception, action, learning, memory or cognition.

Today, computational models are able to offer new approaches of the complex relations between the structural and the functional level of the brain thanks to models built at several levels of description. In very precise models, a neuron can be divided in several compartments and its dynamics can be described by a system of differential equations. The spiking neuron approach (*cf.* § 3.2) proposes to define simpler models concentrated on the prediction of the most important events for neurons, the emission of spikes. This allows to compute networks of neurons and to study the neural code with event-driven computations.

Larger neuronal systems can be considered when the unit of computation is defined at the level of the population of neurons and when rate coding is supposed to bring enough information. Studying Dynamic Neural Fields (*cf.* § 3.3) consequently lays emphasis on information flows between populations of neurons (feed-forward, feed-back, lateral connectivity) and is well adapted to defining high-level behavioral capabilities related for example to visuomotor coordination.

Furthermore, these computational models and methods have strong implications for other sciences (e.g. computer science, cognitive science, neuroscience) and applications (e.g. robots, cognitive prosthesis) as well (*cf.* § 4.1). In computer science, they promote original modes of distributed computation (*cf.* § 3.5); in cognitive science, they have to be related to current theories of cognition (*cf.* § 3.6); in neuroscience, their predictions have to be related to observed behaviors and measured brain signals (*cf.* § 3.4).

3.2. Computational neuroscience at the microscopic level: spiking neurons and networks

Keywords: *computational neuroscience*, *neural code*, *olfaction*, *spiking neurons*, *synchronization of activity*.

Computational neuroscience is also interested in having more precise and realistic models of the neuron and especially of its dynamics. We consider that the latter aspect can not be treated at the single unit level only; it is also necessary to consider interactions between neurons at the microscopic scale.

On one hand, compartmental models describe the neuron at the inner scale, through various compartments (axon, synapse, cellular body) and coupled differential equations, allowing to numerically predict the neural activity at a high degree of accuracy. This, however, is intractable if analytic properties are to be derived, or if neural assemblies are considered. We thus focus on phenomenological punctual models of spiking neurons, in order to capture the dynamic behavior of the neuron isolated or inside a network. Generalized conductance based leaky integrated and fire neurons (emitting action potential, i.e. spike, from input integration) or simplified instantiations are considered in our group.

On the other hand, one central issue is to better understand the precise nature of the neural code. From rate coding (the classical assumption that information is mainly conveyed by the firing frequency of neurons) to less explored assumptions such as high-order statistics, time coding (the idea that information is encoded in the firing time of neurons) or synchronization aspects. At the biological level, a fundamental example is the synchronization of neural activities, which seems to play a role in olfactory perception: it has been observed that abolishing synchronization suppresses the odor discrimination capability. At the computational level, recent theoretical results show that the neural code is embedded in periodic firing patterns, while, more generally, we focus on tractable mathematical analysis methods coming from the theory of nonlinear dynamical systems.

For both biological simulations and computer science emerging paradigms, the rigorous simulation of large neural assemblies is a central issue. Our group is at the origin, up to our best knowledge, of the most efficient even-based neural network simulator, based on well-founded discrete event dynamic systems theory, and now extended to other simulation paradigms, thus offering the capability to push the state of the art on this topic.

3.3. Computational neuroscience at the mesoscopic level: dynamic neural field

Keywords: *behavioral model*, *computational neuroscience*, *cortical column*, *cortical model*, *population of neurons*.

Our research activities in the domain of computational neurosciences are also interested in the understanding of higher brain functions using both computational models and robotics. These models are grounded on a computational paradigm that is directly inspired by several brain studies converging on a distributed, asynchronous, numerical and adaptive processing of information and the continuum neural field theory (CNFT) provides the theoretical framework to design models of population of neurons.

This mesoscopic approach underlines that the number of neurons is very high, even in a small part of tissue, and proposes to study neuronal models in a continuum limit where space is continuous and main variables correspond to synaptic activity or firing rates in population of neurons. This formalism is particularly interesting because the dynamic behavior of a large piece of neuronal tissue can be studied with differential equations that can integrate spatial (lateral connectivity) and temporal (speed of propagation) characteristics and display such interesting behavior as pattern formation, travelling waves, bumps, etc.

The main cognitive tasks we are currently interested in are related to the autonomous navigation of a robot in an unknown environment (perception, sensorimotor coordination, planning). The corresponding neuronal structures we are modeling are part of the cortex (perceptive, associative, frontal maps) and the limbic system (hippocampus, amygdala, basal ganglia). Corresponding models of these neuronal structures are defined at the level of the population of neurons and functioning and learning rules are built from neuroscience data to emulate the corresponding information processing (filtering in perceptive maps, multimodal association in associative maps, temporal organization of behavior in frontal maps, episodic memory in hippocampus, emotional conditioning in amygdala, selection of action in basal ganglia). Our goal is to iteratively refine these models, implement them on autonomous robots and make them cooperate and exchange information, toward a completely adaptive, integrated and autonomous behavior.

3.4. Brain Signal Processing

Keywords: *brain-machine interfaces*, *machine learning techniques*, *spatio-temporal models*, *synchronization*.

The observation of brain activity and its analysis with appropriate data analysis techniques allow to extract properties of underlying neural activity and to better understand high level functions. This study needs to investigate and integrate, (i) in a single trial, information (ii) spread in several cortical areas and (iii) available at different scales (MUA, LFP, ECoG, EEG).

One major problem is how to be able to deal with the variability between trials. Thus, it is necessary to develop robust techniques based on stable features. Specific modeling techniques should be able to extract features investigating the time domain and the frequency domain. In the time domain, template-based unsupervised models allows to extract graphic-elements. Both the average technique to obtain the templates and the distance used to match the signal with the templates are important, even when the signal has a strong distorted shape. The study of spike synchrony is also an important challenge. In the frequency domain, features such as phases, frequency bands and amplitudes contain different pieces of information that should be properly identified using variable selection techniques. In both cases, compression techniques such as PCA can reduce the fluctuations of the cortical signal. Then, the developed models have to be able to track the drift of these features over the time.

Another problem is how to integrate information spreads in different areas and relate this information in a proper time window of synchronization to behavior. For example, feedbacks are very important to better understand a closed-loop control of hand grasp. But between the preparatory signal, the execution of the movement and the visual and somatosensory feedbacks a delay exists. Here, it is also necessary to use stable features to build a mapping between areas using supervised models taking into account a time window shift.

Several recoding techniques exist providing different kinds of information. Some of them provide very local information such as multiunit activities (MUA) and local field potential (LFP) in one or several well-chosen cortical areas. Other ones provide global information about close regions such electrocorticography (ECoG) or the whole sclap such as electroencephalography (EEG). If surface electrodes allow to easily obtain brain imaging, it is more and more necessary to better investigate the neural code.

3.5. Connectionist parallelism

Keywords: *FPGAs*, *brain-inspired hardware*, *connectionism*, *parallelism*.

Connectionist models, such as neural networks, are the first models of parallel computing. Artificial neural networks now stand as a possible alternative with respect to the standard computing model of current computers. The computing power of these connectionist models is based on their distributed properties: a very fine-grain massive parallelism with densely interconnected computation units.

The connectionist paradigm is the foundation of the robust, adaptive, embeddable and autonomous processings that we develop in our team. Therefore their specific massive parallelism has to be fully exploited. Furthermore, we use this intrinsic parallelism as a guideline to develop new models and algorithms for which parallel implementations are naturally made easier.

Our approach claims that the parallelism of connectionist models makes them able to deal with strong implementation and application constraints. This claim is based on both theoretical and practical properties of neural networks. It is related to a very fine parallelism grain that fits parallel hardware devices, as well as to the emergence of very large reconfigurable systems that become able to handle both adaptability and massive parallelism of neural networks. More particularly, digital reconfigurable circuits (e.g. FPGA, Field Programmable Gate Arrays) stand as the most suitable and flexible device for fully parallel implementations of neural models, according to numerous recent studies in the connectionist community. We carry out various arithmetical and topological studies that are required by the implementation of several neural models onto FPGAs, as well as the definition of hardware-targetted neural models of parallel computation.

This research field has evolved within our team by merging with our activities in behavioral computational neuroscience. Taking advantage of the ability of the neural paradigm to cope with strong constraints, as well as taking advantage of the highly complex cognitive tasks that our behavioral models may perform, a new research line has emerged that aims at defining a specific kind of brain-inspired hardware based on modular and extensive resources that are capable of self-organization and self-recruitment through learning when they are assembled within a perception-action loop.

3.6. The embodiment of cognition

Keywords: *behavior*, *cognitive science*, *embodiment*.

Recent theories from cognitive science stress that human cognition emerges from the interactions of the body with the world. Through motor actions, the body can orient toward objects to better perceive and analyze them. The analysis is performed on the basis of physical measurements and more or less elaborated emotional reactions of the body, generated by the stimuli. This will elicit other orientation activities of the body (approach and grasping or avoidance). This elementary behavior is made possible by the capacity, at the cerebral level, to coordinate the perceptive representation of the outer world (including the perception of the body itself) with the behavioral repertoire that it generates either on the physical body (external actions) or on a more internal aspect (emotions, motivations, decisions). In both cases, this capacity of coordination is acquired from experience and interaction with the world.

The theory of the situatedness of cognition proposes to minimize representational contents (opposite to complex and hierarchical representations) and privileges simple strategies, more directly coupling perception and action and more efficient to react quickly in the changing environment.

A key aspect of this theory of intelligence is the Gibsonian notion of affordance: perception is not a passive process and, depending on the current task, objects are discriminated as possible “tools” that could be used to act in the environment. Whereas a scene full of details can be memorized in very different and costly ways, a task-dependent description is a very economical way that implies minimal storage requirements. Hence, remembering becomes a constructive process.

For example with such a strategy, the organism can keep track of relevant visual targets in the environment by only storing the movement of the eye necessary to foveate them. We do not memorize details of the objects but we know which eye movement to perform to get them: The world itself is considered as an external memory.

Our agreement to this theory has several implications for our methodology of work. In this view, learning emerges from sensorimotor loops and a real body interacting with a real environment are important characteristics for a learning protocol. Also, in this view, the quality of memory (a flexible representation) is preferred to the quantity of memory.

4. Application Domains

4.1. Overview

Our application domain is twofold:

On one hand, neuro-scientists are end-users of our research. Data analysis is one issue, but the main outcomes concern the validation of biological assumptions either at a theoretical level or via numerical experiments and simulation of bio-processes. This includes algorithmic expertises and dedicated softwares.

On the other hand, science and technology of information processing is impacted. This concerns embedded systems such as in-silico implementations of bio-inspired processes, focusing on spatial and distributed computing. This also concerns embodied systems such as robotic implementation of sensori-motor loops, the bio-inspiration yielding such interesting properties as adaptivity and robustness.

5. Software

5.1. Spiking neural networks simulation

Keywords: *clock-based*, *event-driven*, *mvaspike*, *sirene*, *spiking neurons simulation*.

Participants: Dominique Martinez, Thierry Viéville.

A spiking neuron is usually modeled as a differential equation describing the evolution over time of its membrane potential. Each time the voltage reaches a given threshold, a spike is sent to other neurons depending on the connectivity. A spiking neural network is then described as a system of coupled differential equations. For the simulation of such a network we have written two simulation engines : (i) mvaspike based on an event-driven approach and (ii) sirene based on a time-driven approach.

- Mvaspike : The event-driven simulation engine was developed in C++ by O. Rochel during his PhD thesis and is available on http://gforge.inria.fr/projects/mvaspike. Mvaspike is a general event-driven purpose tool aimed at modeling and simulating large, complex networks of biological neural networks. It allows to achieve good performance in the simulation phase while maintaining a high level of flexibility and programmability in the modeling phase. A large class of spiking neurons can be used ranging from standard leaky integrate-and-fire neurons to more abstract neurons, e.g. defined as complex finite state machines.
- Sirene : The time-driven simulator engine was written in C and developed for the simulation of biologically detailed models of neurons —such as conductance-based neurons— and synapses. Its high flexibility allows the user to implement easily any type of neuronal or synaptic model and use the appropriate numerical integration routine (e.g. Runge-Kutta at given order).

5.2. DANA: Implementation of computational neuroscience mechanisms

Keywords: *computational neuroscience*, *neural fields*.

Participants: Nicolas Rougier, Thomas Girod, Jérémy Fix.

DANA (that stands for "Distributed Asynchronous Numerical Adaptive) is a multi-platform C++/Python framework that supports distributed, asynchronous, numerical and adaptive computation which is closely related to both the notion of artificial neural networks and cellular automaton. From a conceptual point of view, the computational paradigm supporting the library is grounded on the notion of a unit that is essentially a potential that can vary along time under the influence of other units and learning. Those units are organized into groups that form a network: a network is made of one to several groups and a group is made of a set of several units. Each unit can be linked to any other unit (including itself) using a weighted link. DANA library offers a set of core classes needed to design and run such networks. However, what is actually computed by a unit or what is learned is far beyond the scope of the library and have to be specified by the user.

5.3. ENAS: Event Neural Assembly Simulation

Keywords: *computational neuroscience*.

Participants: Frédéric Alexandre, Jérémy Fix, Axel Hutt, Nicolas Rougier, Thierry Viéville.

ENAS (that stands for "Event Neural Assembly Simulation") is neither a new "simulator", nor a new "platform", but a set of new routines available for such existing tools. This set of routines is organized into classes that allow to simulate and analyze so called "event neural assemblies". ENAS has been designed to become a plug-in of the DANA and MVASpike softwares as well 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. Decision-making platform

Keywords: *decision-making*.

Participants: Laurent Bougrain, Nizar Kerkeni.

GINNet (Graphical Interface for Neural Networks) is a decision-aid platform written in Java, intended to make neural network teaching, use and evaluation easier, by offering various parametrizations and several data pre-treatments. GINNet is based upon a local library for dynamic neural network developments called DynNet. DynNet (Dynamic Networks) is an object-oriented library, written in Java and containing base elements to build neural networks with dynamic architecture such as Optimal Cell Damage and Growing Neural Gas. Classical models are also already available (multi-layer Perceptron, Kohonen self-organizing maps, ...). Variable selection methods and aggregation methods (bagging, boosting, arcing) are implemented too.

The characteristics of GINNet are the following: Portable (100% Java), accessible (model creation in few clicks), complete platform (data importation and pre-treatments, parametrization of every models, result and performance visualization). The characteristics of DynNet are the following: Portable (100% Java), extensible (generic), independent from GINNet, persistent (results are saved in HML), rich (several models are already implemented), documented.

This platform is composed of several parts:

1. Data manipulation: Selection (variables, patterns), descriptive analysis (stat., PCA..), detection of missing, redundant data.
2. Corpus manipulation: Variable recoding, permutation, splitting (learning, validation, test sets).
3. Supervised networks: Simple and multi-layer perceptron.
4. Competitive networks: Kohonen maps, Neural Gas, Growing Neural Gas.
5. Metalearning: Arcing, bagging, boosting.
6. Results: Error curves, confusion matrix, confidence interval.

DynNet and GINNet are free softwares, registrated to the APP and distributed under CeCILL license, Java 1.4 compatible (http://ginnet.gforge.inria.fr). GINNet is available as an applet. For further information, see http://gforge.inria.fr/projects/ginnet (news, documentations, forums, bug tracking, feature requests, new releases...)

5.5. Neural network synthesis on FPGA

Keywords: *FPGA*, *digital circuits*, *parallelism*.

Participant: Bernard Girau.

To date the majority of neural network implementations have been in software. Despite their generally recognised performances, the high cost of developing ASICs (Application Specific Integrated Circuits) has meant that only a small number of hardware neural-computing devices has gone beyond the research-prototype stage in the past. With the appearance of large, dense, highly parallel FPGA circuits, it has now become possible to realize large-scale neural networks in hardware, with the flexibility and low cost of software implementations.

Though easier than ASIC development, implementations on FPGAs still require a significant amount of work, especially for connectionists who are not very familiar with such tools as the VHDL language, synthesis tools, etc. Therefore, we are designing a software project that automatically specifies, parametrizes and implements neural networks according to various application and technological constraints (e.g. area of targeted FPGAs, required precision, etc). With respect to previous years, less efforts have been put this year onto this software. They have focused on arithmetic precision handling, by allowing multiprecision implementations as well as by defining heuristics to optimize the various handled precisions.

5.6. EEG acquisition module for OpenViBE

Keywords: *Brain-Computer Interface*, *EEG*, *OpenVibe*.

Participant: Laurent Bougrain.

In the domain of Brain-Computer Interface (BCI), we developed an acquisition module to interface the OpenViBE plateform (http://www.irisa.fr/bunraku/OpenViBE) to an EEG (electroencephalographic) amplifier by TMSi. This module allows to send data collected from our experiments to this well-known platform. We aim to compare our algorithms with the ones developed by the other community members.

6. New Results

6.1. Spiking neurons

Participants: Maxime Ambard, Hana Belmabrouk, Yann Boniface, Dominique Martinez, Noelia Montejo-Cervera, Thierry Vieville, Thomas Voegtlin.

How do neurons encode information? This question is central in the field of neuroscience. Information can be conveyed locally in the brain by chemical mechanisms or direct electrical couplings. Over long distances, information is encoded in the spatiotemporal pattern of action potentials generated by a population of neurons. The exact features of these spike trains that carry information between neurons is largely unknown. The most commonly used hypothesis is based on the mean firing rate of individual cells, but this is by no means the only one. In recent years, a strong debate has opposed partisans of codes involving mean firing rates against researchers in favor of temporal codes in which the precise temporal structure of the spike train is taken into account.

Here, we investigate how information is encoded in the precise timing of individual spikes, rather than in the mean firing rate (*cf.* § 3.2): (i) We exploit the dynamic response properties of individual neurons to perform computations and propose STDP rules to force neurons to spike at desired times. (ii) We show that synchronized neural assemblies may arise as a consequence of inhibitory coupling. This finding is supported by computional modeling and data analysis of experimental recordings in the olfactory system. (iii) We adress the problem of numerical simulation and propose efficient event-driven strategies for spiking neural networks. (iv) Finally, on-going work aiming at applying spiking neural networks to artificial vision and olfaction is presented.

6.1.1. Time Coding using Neuronal Response Properties

The temporal coding hypothesis states that neuronal information is encoded in the precise timing of action potentials sent by neurons. In realistic neuron models, the timing of an output spike depends on the timing of input synaptic currents, in a way that is classically described by the Phase Response Curve.

We have developed a new theory of time coding, that exploits dynamic response properties in order to perform computations. This theory takes advantage of the fact that the effect of synaptic currents depends on the internal state of the post-synaptic neuron. This has implications for temporal coding: an action potential that arrives on a synapse has an implicit meaning, that depends on the position of the postsynaptic neuron on the firing cycle.

We have shown that it is possible to train artificial neural networks using this principle. For that, we have developed biologically plausible learning rules, that are based on Spike Timing Dependent Plasticity (STDP). More precisely, we investigated how STDP can be used to achieve minimization of an error criterion, using two possible mechanisms :

- Supervised spike prediction : Neurons learn to spike at desired times. This work has been pursued in collaboration with Samuel McKennoch (postdoc in the cortex group in 2008) and Linda Bushnell, from the Department of Electrical Engineering of the Washington University at Seattle. Results were accepted for publication in a journal article (in 2009) and another article is currently in preparation.
- Adaptive synchronization: This mechanism is unsupervised, and it refers to the framework of unsupervised generative models. Neurons receive an external input (excitation) and a prediction of the input (inhibition), derived from an internal representation. Synaptic efficacies are optimized so that the neurons of a population learn to spike synchronously, even though their external input taken alone would have the effect of desynchronizing them. Resynchronization is performed through inhibition; in this sense, the inhibitory cells learn to cancel the phase of excitatory cells. This work suggests a functional role for neural synchrony and oscillations in biological systems [14].

6.1.2. Neural synchronization and network oscillation

A fundamental question in computational neuroscience is to understand how interactions between neurons underlie sensory coding and information storage. In the first relay of the insect olfactory system, odorant stimuli trigger synchronized activities in neuron populations. Synchronized assemblies may arise as a consequence of inhibitory coupling, because they are disrupted when inhibition is pharmacologically blocked. Using computational modelling, we studied the role of inhibitory, noisy interactions in producing stimulus-specific synchrony. So far, experimental data and modelling studies indicate that fast inhibition induces neural synchrony, but it remains unclear how desynchronization occurs. From theoretical analysis and computer simulations, we found that slow inhibition plays a key role in desynchronizing neurons. Depending on the balance between fast and slow inhibitory inputs, particular neurons may either synchronize or desynchronize. The complementary roles of the two synaptic time scales in the formation of neural assemblies suggest a wiring scheme that produces stimulus-specific inhibitory interactions and endows inhibitory sub-circuits with properties of binary memories. The relative number between fast GABA-A and slow GABA-B inputs regulates synchrony and determines whether particular projection neurons engage in the neural assembly [12].

6.1.3. Numerical simulation of spiking neurons

We have developed two simulators for the numerical simulation of spiking neural network models (*cf.* § 5.1). In sirene, a time-stepping method approximates the membrane voltage of neurons on a discretized time whereas, in mvaspike, an event-driven engine computes the timings of spikes exactly.

In pure event-driven strategies, the spike timings are analytically given and are calculated with an arbitrary precision (up to the machine precision). This scheme allows an exact simulation where no spike is missed. However only a limited class of simplified neuron models of integrate-and-fire type is amenable to exact simulations. Time-stepping strategies are generic since they can be applied to any model. Classical integration schemes of Runge-Kutta type have to be modified to properly handle the discontinuities of integrate-and-fire neuron dynamics generated by the resettings and the synaptic events. However when the membrane potential crosses threshold twice during one time step (the first crossing is from below and the second is in the downward direction), the spike event may be missed. Due to the discontinuous nature of integrate-and-fire network, a failure to detect a spike may cause dramatic changes on the behavior of the system and artificial dynamical states may be created if the time step is badly chosen. Moreover a fundamental limitation on the accuracy of time-stepping methods is imposed by the smoothness of the postsynaptic potentials.

During the past year, we defined a new simulation scheme that combines the advantages of the two approaches and consists of a discretization of the voltage state-space. Our scheme, that we call voltage-stepping, retains the advantages of the accuracy and the activity-dependent computational cost of event driven strategies while allowing a generic simulation of any neural model. The numerical simulation is reduced to a local event-driven method that induces an implicit activity-dependent time discretization. A neuron that evolves slowly allows long time steps and has a low computational cost whereas small time steps are required for fast varying neurons. We show analytically that such a scheme leads to a high-order algorithm so that it accurately approximates the neuronal dynamics. Therefore, our voltage-stepping method outperforms time-stepping schemes of Runge-Kutta type in terms of simulation time and accuracy. Voltage stepping is currently being implemented in mvaspike. For more information, see (Zheng, Tonnelier and Martinez "Voltage-stepping schemes for the simulation of spiking neural networks", J. Comput. Neurosci., in press).

6.1.4. Application of spiking neurons to artificial olfaction

One of our objectives is to extract computational principles from our current understanding of the biological system and use them in artificial sensory devices.

In the context of fast processing, biological neurons can perform with only one spike per neuron, using relative latencies or time-to-first-spikes after stimulus onset as an information carrier. Evidence for latency coding has been found in the visual and tactile systems. Latency coding makes sense only if one considers the first spike with respect to a reference signal: the first spike after stimulus onset, or after a particular event in the stimulus dynamics. In the visual system, sudden movements of the eyes called saccades, sample the visual input into discrete snapshots. After each saccade, a new image is encoded into neural activities to be further processed by the brain. Similarly to the saccades in vision, sniffing might provide an external reference in olfaction. Olfactory receptors are sensitive to the air flow and mitral cells in the rat olfactory bulb exhibit a slow subthreshold oscillation in the theta band that is phase-locked to the respiratory cycle.

We therefore suggest that breathing acts as a *clock* or a temporal frame of reference and that the olfactory system makes use of the time-to-first spike paradigm for fast odour recognition. To investigate this hypothesis we first analyzed experimental data recorded in the olfactory bulb from rats (cf. Neuroinformatique project in 7.2). Preliminary results indicate that first spike latency provides a reliable and rapid means of representing input strength and that the relationship is well described by a logarithmic function. In the framework of the associated team BioSens (cf. Biosens project in 7.4), we then constructed a micro-electronic nose model using a semiconductor gas sensor array which incorporates spiking neurons encoding sensory information as suggested by our experimental findings. We found that the generated latency code reproducibly discriminates between odours. The properties of this device (compactness, low power consumption) make it suitable for embedded gas sensor applications. This study pioneers the translation of neurophysiological findings into hardware for the processing of electronic noses

6.2. Dynamic Neural Fields

Participants: Frédéric Alexandre, Yann Boniface, Laurent Bougrain, Mauricio Cerda, Jérémy Fix, Hervé Frezza-Buet, Bernard Girau, Thomas Girod, Axel Hutt, Mathieu Lefort, Nicolas Rougier, Thomas Voegtlin, Thierry Viéville.

The work reported this year represents both extensions of previous works and new results linked to the notion of neural population, considered at (i) a formal level (theorical studies of neural fields), (ii) a numerical level (interface with the spike level) and (iii) a more embodied one (implementations).

6.2.1. Formal Level

6.2.1.1. Algorithmic adjustment of neural field parameters

Revisiting in the discrete case maps proposed by the CNFT (Continuous Neural Field Theory), we propose algorithmic mechanisms allowing to choose a right set of parameters in order to both (i) guarantee the stability of the calculation and (ii) tune the shape of the output map [31]. We obtain an easy to implement procedure that guarantees the convergence of the map onto a fixed point, even with large sampling steps. Furthermore, we report why rectification is the minimal required non-linearity to obtain usual neural-field behaviors. We also propose a way to control and tune these behaviors (filtering, selection, tracking, remanence). Beyond these algorithmic results, the idea of studying neural computations as discrete dynamical systems and not only the discretization of a continuous system is emphasized here. The outcome is shared as an open-source plug-in module, called `EnaS` (*cf.* § 5.3 and see http://enas.gforge.inria.fr), to be used in existing simulation software.

6.2.1.2. Synchronous and Asynchronous Computations

We have studied dynamic neural fields in the framework of visual attention that explains attention as being an emergent property of such dynamic neural fields. The fundamental property of the model is its facility to select a single stimulus out of several perfectly identical input stimuli by applying asynchronous computation. In the absence of external noise and with a zero initial state, the theoretical mathematical solution of the field equation predicts the final equilibrium state to equally represent all of the input stimuli. This finding is valid for synchronous numerical computation of the system dynamics where elements of the spatial field are computed all together at each time point. However, asynchronous computation, where elements of the spatial field are iterated in time one after the other yields different results leading the field to move towards a single stable input pattern. This behavior is in fact quite similar to the effect of noise on dynamic fields. We have studied this phenomenon in some details and characterized the relation between noise, synchronous evaluation (the "regular" mathematical integration) and asynchronous evaluation in the case of a simple dual particle system. More generally, we aim at explaining the behavior of a general differential equation system when it is considered as a set of particles that may or may not be iterated by synchronous computations.

6.2.1.3. The power spectrum of neural population activity subjected to external inputs

The brain represents a network of small neural networks, whose inter-network connections exhibit temporal time delays and the sub-networks are spatially extended populations of neurons involving axonal conduction delays [6]. To better understand the information processing in such a network subjected to external inputs [7], the study examined a network of two neural populations linked to each other by excitatory and inhibitory feedback connections. This topology resembles the primary sensory system in electric fish, namely the feedback system of the electrosensory lateral line lobe and the nucleus praeeminentialis. The two neural populations assumed population firing rates involving no intra-network connections but inter-network connections only. This assumption reflects the experimental findings. Since it is well-known that electric fish receives spatially-correlated noisy input, the external stimuli have been chosen to be spatially correlated Gaussian noise uncorrelated in time. In addition the feedback between the networks is topographic, i.e. space-dependent. We find [9] that the power spectrum of the network activity exhibits a single strong peak at gamma-frequencies if the spatial correlation range of the external input is much larger than the spatial range of the networks feedback system. This finding shows good accordance to the experimental findings in electric fish.

6.2.2. Numerical level

6.2.2.1. Reconciling clock and event based simulation method of neural networks

Although the spike-trains in neural networks are mainly constrained by the neural dynamic itself, global temporal constraints (refractoriness, time precision, propagation delays, ..) are also to be taken into account. These constraints have been revisited and their consequences developed at the modelization and simulation level. Regarding the former point, their obvious consequences in terms of the amount of information in a spike train have been discussed, including the review of the impact at the level of the network dynamics, thanks to recent theoretical results. To which extend the "neural code" contained in spike trains is related to a metric appears to be a key point, a generalization of the Victor-Purpura metric family being proposed for temporal constrained causal spike trains. Regarding the former point, the consequences of these time constraints at the simulation level have been developed, showing event-based simulation of time-constrained networks can be impacted and somehow improved in this context: the underlying data-structures are strongly simplified, while event-based and clock-based mechanisms can be easily mixed. These ideas are applied this year to punctual conductance based generalized integrate and fire neural network simulation, while spike-response model simulation is also revisited within this framework. It is a perspective of this work to further consider their application to neural fields.

6.2.2.2. From spikes to frequency

Dynamic Neural Fields as they have been introduced in previous sections are mainly concerned with the functional modeling of a population of neurons where a single neuron activity is represented by a continuous bounded scalar value (e.g. firing rate or membrane potential). The implementation for such fields require *de facto* the discretization of the equation at both the spatial and temporal levels. However, if we now consider using spiking neurons with precise spike timing, we can bypass the temporal discretization and free ourselves from the numerical scheme we may use to integrate the equation. The question is thus to know whether the dynamic neural field theory can resist such dramatic transformation of the equation. We have investigated this question and designed several elementary models based on the dynamic of spiking neurons. We've found experimentally those models to be qualitatively equivalent to their mean-frequency counterpart without being able yet to mathematically prove the convergence. This lead us to consider the hardware implementation of such networks since we now have strong asynchrony in the formal model and the implementation should be straightforward.

6.2.3. Embodied level

6.2.3.1. Motion detection

We develop bio-inspired neural architectures to detect, extract and segment the direction and speed components of the optical flow within sequences of images. The structure of these models derives from the course of the optical flow in the human brain. It begins in the retina and receives various treatments at every stages of its magnocellular pathway through the thalamus and the cortex. Our models mostly handle the properties of three cortical areas called V1 (primary visual area), MT (middle temporal), and MST (middle superior temporal): the MT area detects patterns of movement, while spatio-temporal integration is made at the local level by V1 and at the global level by both MT and MST.

This work faces many concrete difficulties, such as specular effects, shadowing, texturing, occlusion and aperture problems. Moreover, the complexity of this task must be dealt with within the implementation constraint of real-time processing.

Recent works have focused on two improvements of our initial models.

- Introduction of feedback excitatory interactions within the neural layer that extracts the optical flow. Combined with the excitatory and inhibitory interactions that diffuse coherent motion information within the receptive fields that cover an object, these new feedback interactions solve the aperture problem for simple objects [17].
- We have generalized previous works related to orientation selectivity and optical flow extraction [16]. This work is related to our hardware implementation activities, since it has led to a flexible implementation of various types of orientation filters based on similar hardware components.

6.2.3.2. Numerical and Distributed Mechanisms of Motor Anticipation

The PhD thesis of J. Fix [1] (supervised by F. Alexandre and N. Rougier) aimed at understanding complex cognitive functions using computer simulations built on the current knowledge of the brain. The proposed models and simulations are built on the paradigm of dynamic neural fields, that are used in order to study in which way complex cognitive capabilities can be the emergent result of the interaction of elementary units. In this thesis, we are interested in the modeling of visual attention, with and without eye movements. To guide the development of these models, we propose in the first part a review of the current psychological and physiological data on visual attention, before proposing a computational model of visual attention without saccadic eye movement. Then, we study in the second part the way we can integrate saccadic eye movements in our models based on the current anatomical and physiological data on the oculomotor control in the primate. The performances of the different proposed mechanisms are evaluated by simulating visual search tasks with saccadic eye movements [36]. This work also makes us able to study a computational paradigm that relies on distributed, asynchronous, numerical and adaptive computation which permits to consider further developments of the proposed mechanisms on parallel architectures.

6.2.3.3. Modeling the electroencephalographic power spectrum during general anaesthesia

Anaesthesia plays an important role in medical surgery though its neural mechanism is still poorly understood. Besides several different molecular and behavioral phenomena, the administration of anaesthetic agents affects the power spectrum of electroencephalographic activity (EEG) in a characteristic way. The study aims to describe the power spectrum changes in EEG subject to the concentration of the specific anaesthetic agent propofol. The work [8] developed a neural model involving two neuron types and synapse types while taking into account the synaptic effect of propofol. The mathematical derivation of the power spectrum allows for the investigation of suitable physiological parameters which reproduce the experimental effect of propofol. Several mathematical conditions on physiological parameters have been derived and the EEG-power spectrum during the administration of different concentration levels of propofol has been modeled successfully.

6.2.3.4. Emotional learning

In order to obtain really autonomous systems, goals must be automatically extracted from the environment and create a motivation to act. In that aim, through a simple bio-inspired model, we have proposed [20] to endow a robot with pain and pleasure perception, have examined how emotions can arise and be the basis for respondant and operant conditioning. A preliminary architecture has been tested on a wheeled robot and will be developed further.

6.3. Higher level functions

Participants: Frédéric Alexandre, Laurent Bougrain, Axel Hutt, Nanying Liang, Randa Kassab, Nizar Kerkeni.

This year, our activities concerned information analysis and interpretation and the design of numerical distributed and adaptive algorithms in interaction with biology and medical science. To better understand cortical signals we choose a top-down approach for which data analysis techniques extract properties of underlying neural activity. To this end several unsupervised methods and supervised methods are investigated and integrated to extract features in measured brain signals.

6.3.1. Template-based neural networks for pattern recognition of graphic elements

We developed a new template-based machine learning technique for pattern recognition of graphic elements (templates) such as event-related potential, auditory evoked potential, k-complex or sleep spindle, which are embedded in electroencephalographic (EEG) signals. The reliable estimation of such templates is difficult in a single trial due to the low signal-to-noise ratio (SNR) of EEG signals. We first explicitly have estimated the template using the averaging techniques point-to-point averaging, cross-correlation alignment and dynamic time warping [24]. Then, we have combined two complementary algorithms to robustly detect evoked potentials in noisy EEG signals for brain-computer interfaces (BCIs). In addition, we have modified the learning vector quantization (LVQ) algorithm with a non-identity assignment using the minimum-norm least-square algorithm, in the same scheme used by extreme learning machine (ELM). The proposed LVQ has been evaluated using the Wadsworth P300 speller dataset from BCI competition III. The experimental results show that the proposed algorithm improves the accuracy with less computational units compared to original LVQ and ELM algorithms [39].

6.3.2. Local Field Potential analysis during movement preparation

In collaboration with the Mediterranean Institute for Cognitive Neuroscience (INCM), we are interested to achieve the essential scientific knowledge to develop a brain-machine interface (BMI) for the use of cortical activity for controlling a commercially available biologically inspired robotic hand, such as the Shadow Dexterous Hand. Local Field Potentials are measured in primary motor cortex (M1) and investigated to extract features such as the amplitude of frequencies in the beta band. This analysis aims to predict the direction of the movement during the preparation phase. The multilayer perceptron as well as bayes classifiers are used to estimate the posterior probability of each direction.

6.3.3. Brain-computer interfaces for patients

In collaboration with Supelec Campus de Metz, and the Center for motor reeducation (Flavigny, France) we study how to exceed the current obstacles of brain-computer interfaces developing algorithms to allow their use in a context of home care. Indeed, the association of the specific techniques that we develop, our experiment and the immersive rooms included in our laboratory owes us to allow to improve the use of this new means of communication. More precisely, we are about to develop a whole data processing sequence able to allow a person evolving/moving in residence to interact with various elements such as its daily newspaper. Such an interaction is based solely on electro-encephalographic recordings allowing to detect a mental task specifically dependent on a particular order or a reaction to one visual or auditive stimulus also specific to one order. Two conditions of use will be more particularly studied: displacement and the distance.

6.3.4. Detection of synchronization in Local Field Potentials

The brain represents a network of brain areas whose interaction is still poorly understood. It is supposed that the interaction mechanism between these areas is based on the synchronization of the dendritic activities in the areas. Since Local Field Potentials (LFPs) reflect this activity, we focus on the study of LFPs obtained experimentally to better understand the inter-area information exchange. In collaboration with the Max Planck Institute for Brain Research in Frankfurt (until April 2008) and the Max Planck Institute for Biological Cybernetics (from May 2008), we investigate the synchronization of LFPs obtained intracranially from various monkey brain areas. The corresponding experiment combines visual attention and motor action and thus allows for the study of the visio-motor feedback loop. The data analysis aims to detect time windows of increased phase synchronization between brain areas and relates these time windows to the monkey behavior. Since the experimental trials vary in duration, multi-trial methods are not optimal. Consequently, we have developed and applied a single-trial method based on a clustering algorithm.

6.3.5. Decoding Finger Flexion from ECoG

EEG-BCIs have been well studied in the past decades and implemented into several famous applications, such as P300 speller and wheelchair controller. However, these interfaces are indirect due to low spatial resolution of EEG. Recently, direct ECoG-BCIs attracted intensive attention because ECoG provides a higher spatial resolution and signal quality. This makes possible the localization of the source of neural signals with respect to certain brain functions. We built a mapping for finger control using ECoG provided by BCI competition IV. The method for finger flexion prediction includes feature extraction and selection. Results show that the predicted finger movement is highly correlated with the true movement when we use band-specific amplitude modulation. Our mapping won this competition.

6.3.6. Information analysis and interpretation

Before 2008, the Cortex team was in the INRIA "Cognitive systems" program. We proposed to exclusively orient our activities in Computational Neuroscience and to belong to the INRIA "Biological systems" program. This was done for all the permanent staff. One PhD student (Randa Kassab) is finishing her PhD (defense at the begining of 2009) on the previous non biologically inspired domain of activity of the Cortex team related to machine learning [10], [21], [22]. This activity will not be described here.

6.4. Embodied and embedded systems

Participants: Yann Boniface, Hervé Frezza-Buet, Bernard Girau, Mathieu Lefort, Nicolas Rougier.

6.4.1. InterCell

Our research in the field of dedicated architectures and connectionist parallelism mostly focuses on embedded systems (*cf.* §3.5). Nevertheless we are also involved in a new project that considers coarse-grain parallel machines as implementation devices. The core idea of this InterCell project (part of the MIS axis of the CPER (*cf.* §7.1); *cf.* also intercell.metz.supelec.fr) is to map fine grain computation (cells) to the actual structure of PC clusters. The latter rather fit coarse grain processing, using relatively few packed communication, which a priori contradicts neural computing. Another fundamental feature of the InterCell project is to promote interaction between the parallel process and the external world. Both features, cellular computing and interaction, allow to consider the use of neural architectures on the cluster on-line, for the control of situated systems, as robots.

This year, the setting up of the cluster itself (installation, cooling devices, network) has been achieved, as well as the testing of the parxxl middleware (http://gforge.inria.fr/projects/parxxl/) performances. Hervé Frezza-Buet has started the design and the development of the middleware layer responsible for the interactivity feature of InterCell. He has designed a specific reference mechanism that allows to name millions of cells without storing millions of references during computation.

6.4.2. Neural synthesis

Three main axes appear in our study of connectionist parallelism in conjunction with reconfigurable digital hardware : automatic neural synthesis on FPGAs, dedicated embeddable implementations, and new hardware-adapted frameworks of neural computation.

Our activities in the first axis reduce this year to the software improvements depicted in § 5.5.

6.4.3. Specific implementations

In the field of dedicated embeddable neural implementations, we use our expertise in both neural networks and FPGAs so as to propose efficient implementations of applied neural networks on FPGAs.

Recent works in this axis have mainly focused on implementations of neural models to extract the optical flow from image sequences (this is related to our research on motion perception, cf § 6.2). We have designed a flexible implementation of various types of orientation filters based on similar hardware components, thanks to a generalized approach of previous works related to orientation selectivity [16]. We also have improved previous implementation methods to handle the high number of local interconnections in neural models for optical flow extraction [26].

Moreover, our previous works on implementations of spiking neural networks have exhibited the principle of interlaced pipelined local loops. We have used a similar principle in a collaboration with the MAIA team about the FPGA implementation of distributed harmonic control for dynamic trajectory planning. The originality of this work is that the convergence properties of our implementation and its optimality is theoretically and experimentally justified [40].

6.4.4. Brain-inspired hardware

Our activities on dedicated architectures have strongly evolved in the last years, as described in [2]. We now focus on the definition of brain-inspired hardware-adapted frameworks of neural computation. The long-term goal is to define and implement modular and extensive resources that are capable of self-organization and self-recruitment through learning when they are assembled within a perception-action loop. This goal gathers our expertise in neural hardware implementations and behavioral models for sensori-motor tasks.

Our works are based here on dynamic neural fields. In order to cope with hardware connectivity requirements, we have defined a model of dynamic spiking neural fields (in the context of visual attention) that only handles local lateral connections within bio-inspired maps of spiking neurons. We have also addressed the problem of the costful local storage of lateral kernels by defining hardware-friendly lateral kernels based on non-euclidean norms.

As we have done for the early stages of visual perception, we now study the hardware implementation of neural primitives for sensori-motor control. Central pattern generators are neural models based on coupled excitatory and inhibitory neurons that may be assembled to generate rhythmic patterns to control periodic activities required by motor tasks in robots. We have started implementation works for these models [28], and we are currently working on the embedded adaptation of the parameters that tune the rhythmic patterns.

7. Other Grants and Activities

7.1. Regional initiatives

7.1.1. Action Modeling, Simulation and Interaction of the CPER

Participants: Frédéric Alexandre, Hervé Frezza-Buet, Nicolas Rougier.

In the framework of the Contrat de Projet État Région, we are contributing to the axis MIS (Modeling, Interaction and Simulation) through the project InterCell whose goal is to study massive cellular computations in an interactive framework (*cf.* § 6.4).

7.2. National initiatives

7.2.1. DGE Ministry grant COMAC "Optimized multitechnique control of aeronautic composite structures"

Participant: Laurent Bougrain.

The goal of this three-years project is to develop a powerful system of control on site, in production and in exploitation, of aeronautical pieces made of composite. It takes up the challenge of the precise, fast and local inspection on composite pieces of aeronautical structures new or in service by using techniques of non-destructive control more effective and faster to increase the lifespans of the structures of planes. This project requires a decision-making system including fast methods of diagnostic based on several optical technics as non-destructive control.

7.2.2. Bio-inspired spatial computing: ARC Amybia

Participant: Bernard Girau.

Our regular collaborations with researchers from the Maia team has shown that we share common computation paradigms based on massively distributed and local models that are inspired by biological systems. This has led us to join our efforts in an original collaboration within the Amybia project led by Nazim Fatès (ARC INRIA), together with Hugues Berry who works on similar models by exploring a bio-inspired approach to propose challenging paradigms for spatial computing within the Alchemy team. This collaboration is also linked with our hardware implementation activities, since it has resulted in an embedded implementation of a biological inspired model for the decentralized gathering of computing agents [19].

7.2.3. ARC MACCAC

Participants: Frédéric Alexandre, Thierry Viéville.

Since neuronal information processing is related to the brain bio-electrical activity, measured by current neuro imaging techniques at different time and space scales, from neurons to the brain as a whole (e.g. LFP, ECoG, EEG, MEG), the analysis of such complex data coming from these measurements requires the parallel development of suitable models. Namely, these models have to be, on the one hand, close enough to phenomenology, taking into account the various type of bio-electrical activity and their scales relations, in order to propose a coherent representation of information processing in the brain (from neurons to neuronal populations, cortical columns, brain area, etc). On the other hand, these models must be well posed and analytically tractable. This requires a constant interaction between neurobiology, modeling and mathematics. In this spirit, this project, directed by Bruno Cessac (ODYSSEE), aims to tackle the following questions: (i) Mesoscopic modeling of cortical columns, bifurcations, and imaging. (ii) Statistical analysis of spike trains.

The CORTEX team brings its computer science expertise, mainly regarding the question (ii) [34], [33], [5] and the OI modality regarding the question (i) [35], [18] during this 1st year, while collaboration with other teams (ALCHEMY (INRIA); CORTEX (INRIA); INCM (CNRS); LJAD (U NiceCNRS); ODYSSEE (INRIA)) is targeted for the 2nd year [31].

7.2.4. ANR project PHEROSYS

Participants: Dominique Martinez, Hana Belmabrouk.

This collaborative project in systems Biology (ANR-BBSRC SysBio) with INRA (Paris, FR) and the University of Sussex (UK) explores olfactory coding in the insect pheromone pathway through models and experiments. More information available at http://www.informatics.sussex.ac.uk/research/projects/PheroSys/index.php/.

7.2.5. ANR project MAPS

Participants: Frédéric Alexandre, Yann Boniface, Elham Ghassemi, Nicolas Rougier, Thierry Viéville.

This collaborative project with INCM (Marseille), UMR Perception and Movement (Marseille) and LIRIS (Lyon) aims at re-examining the relationship between structure and function in the brain, taking into account the topological (spatial aspects) and hodological (connectivity) constraints of the neuronal substrate. We think that those constraints are fundamental for the understanding of integrative processes, from the perception level to the motor level and the initiation of coordinated actions [31], [34].

7.2.6. Project of the CNRS NeuroInformatics program on olfaction

Participants: Dominique Martinez, Noelia Montejo-Cervera.

The project "Olfactory coding" (2008-2009) from the CNRS program "Neuroinformatics" with the CNRS UMR5020 (Lyon) explores the role of spike timing in olfactory coding.

7.2.7. Project of the CNRS NeuroInformatics program on reinforcement learning

Participants: Frédéric Alexandre, Hervé Frezza-Buet, Nicolas Rougier.

In this collaboration with the MAIA team, Supelec Campus de Metz and the Interative and Cognitive Neuroscience Centre in Bordeaux, we are developing bio-inspired reinforcement learning procedures, on the basis of experimental data from behavioral recordings in rats.

7.3. European initiatives

7.3.1. NoE GOSPEL

Participants: Maxime Ambard, Dominique Martinez.

GOSPEL (General Olfaction and Sensing Projects on a European Level, 2004-2008) was a Network of Excellence (NoE) under funding of the European Commission in the 6th framework programme. The aim of GOSPEL was to structure the European research in the field of Artificial Olfaction with the declared goal of establishing Europe as a world leader in this field. More information is available at http://www.gospel-network.org.

7.3.2. FP7-ICT project NEUROCHEM

Participants: Dominique Martinez, Noelia Montejo-Cervera.

The european project NEUROCHEM explores biologically inspired computation for chemical sensing, in collaboration with the University of Barcelona, the royal institute of technology (Sweden), INRA (Paris), the university of Manchester, the university Pompeu Fabra (Spain), CNR-IMM (Italy) and the university of Leicester. More information is available at http://www.neurochem-project.org/

7.4. International cooperation

7.4.1. INRIA Associate Team BIOSENS

Participant: Dominique Martinez.

BIOSENS (2006-2008) was a collaboration between the Cortex team at INRIA and the Smart Sensory Integrated Systems lab from the Hong Kong University of Science and Technology. The objective of BIOSENS was to develop biologically inspired sensory processing for artificial vision and olfaction.

7.4.2. INRIA associate team CorTexMex

Participants: Bernard Girau, Yann Boniface, Nicolas Rougier, Mauricio Cerda.

We are working with the Computer science department of the INAOEP (national institute of astrophysics, optics and electronics of Puebla) and the Polytechnic University of Victoria (both in Mexico) on massively distributed connectionist models for embedded perception, within the INRIA associate team CorTexMex led by Bernard Girau.

Some perceptive tasks cannot be performed satisfactorily by standard algorithms due to the over simplified nature of classical models compared to the intrinsic complexity of the environment. To alleviate this problem, the research line of our team is directed to using brain-inspired models of perception. But the high computational cost of these models usually exceeds the time-multiplexed bounded computational resources of conventional systems. A solution lies in alternative hardware/software based processing architectures, supporting biological realism and providing the large scale computational resources to satisfy application constraints. The CorTexMex associate team focuses on the analysis, methods and techniques for the embedded implementation of bio-inspired connectionist processing for perception tasks on reconfigurable devices under a hardware/software approach. The main goal is to provide methods able to handle the massive distribution and the connection complexity of these models, as well as their specific recurrent differential computations. Another goal is to provide bio-inspired connectionist processing models to be embedded and directly integrated in perception-action loops.

Our works have been mostly oriented towards the study of the properties of massively distributed elementary computations in bio-inspired models for vision in order to provide efficient implementation into reconfigurable logic devices [26], [16]. Other activities have extended our works to sensori-motor systems, for which we develop and implement connectionist and massively distributed models, such as CPG models (central pattern generators) [28].

7.4.3. Common project with Tunisia

Participants: Laurent Bougrain, Bernard Girau, Nizar Kerkeni.

We are working with the faculty of medicine in Monastir on physiological signal interpretation (EEG, EMG, EOG). Following our works about the discrimination of vigilance states and of the different stages of sleep, we now focus on embedded connectionist processings of physiological signals, through INRIA STIC-Tunisia project num. 07/01 [4]. This project has recently evolved towards the study of embedded neural network models in the specific field of computer-brain interfaces, in relation with the works depicted in § 6.3.

7.4.4. Common project with United Kingdom

Participant: Axel Hutt.

The project partner is the Herriot-Watts University of Edinburgh and the project aims to study stochastic effects in neural networks. To this end the Royal Society of Scotland supported the initial visit in Edinburgh to discuss first mathematical details and software implementations besides a schedule for future common activities.

8. Dissemination

8.1. Leadership within the scientific community

8.1.1. Responsabilities

- Responsible for the axis MIS "Modeling, Interaction Simulation", of the CPER with the Lorraine Region (F. Alexandre).
- Head of the Network Grand-Est for Cognitive Science (F. Alexandre)
- Member of the steering committee of the ARP PIRSTEC (Prospective on cognitive science and technology for the ANR) (F. Alexandre)
- Member of the scientific committe of the Neuroinformatic CNRS program (F. Alexandre)

8.1.2. Review activities

- Reviewing for journals: Pattern Recognition Letters, International Journal of Computer Mathematics, Annals of Mathematics and Artificial Intelligence (F. Alexandre); NCA (Neural Computing and Applications) (L. Bougrain); Physical Review E, Physical Review Letters, Journal of Biological Physics, J. Physics A, SIAM J. Applied Mathematics, Phyisca D, PLoS Computational Biology, Europhysics Letters, Nonlinearity (A. Hutt);
- Reviewing for conferences: AMINA'08 conference (Applications Médicales de l'Informatique: Nouvelles Applications), November 2008 (L. Bougrain and F. Alexandre)
- Member of program committees: CAP'08, NeuroComp08, MCSEAI'08, ARCo'08, BioMed'08 (F. Alexandre); Reconfig'08 (B. Girau); Amina'08 (L. Bougrain);
- Expertise for the European Commission (FP7; ICT) (F. Alexandre), for grants submitted to Dutch National Science Foundation (A. Hutt)
- Expertise for several programs of the ANR and member of the evaluation committee of the program "Domaines Emergents" (F. Alexandre)

8.1.3. Workshops, conferences and seminars

- Organization of conferences: special session about "Brain-Machine interfaces" at the AMINA'08 conference (Applications Médicales de l'Informatique: Nouvelles Applications) in November 2008 (L. Bougrain)

- Invited talks: "brain-computer interfaces" at the biomedical department of the Valparaiso university (Chile) on in April 2008 (L. Bougrain); Laboratory Neurobiology of Adaptive Processes, University Pierre et Marie Curie (F. Alexandre); Coordinacion de Ciencias Computacionales, Instituto Nacional de Astrofisica, Optica y Electronica, Puebla (Mexique), 18/04/2007 (N. Rougier); Department of Physics, University of Bielefeld, April 2008 (A. Hutt); Workshop “Stochastic Waves and Coherent Structures” at SIAM Conference "Nonlinear waves", Rome, July 2008 (A. Hutt); Workshop “Dynamic field theory and applications” at Dynamics and Applications, Porto, September 2008 (N. Rougier); Workshop “Computational Vision”, Marseilles, October 2008 (N. Rougier); Max Planck Institute for Biological Cybernetics Tuebingen, December 2008 (A. Hutt); INSERM U825 Cerebral Imaging and Neurologic Handicaps (F. Alexandre).

8.1.4. International cooperations

- International cooperation: A. Hutt has started a common project with the Herriot-Watts University of Edinburgh which aims at studying stochastic effects in neural networks. To this end the Royal Society of Scotland supported the initial visit in Edinburgh to discuss first mathematical details and software implementations besides a schedule for future common activities;
- F. Alexandre and T. Viéville have been invited by Dr. Rodrigo Salas, from Universidad de Valparaiso / Facultad de Ciencias / Departamento de Ingenieria Biomedical for a two weeks prospective joined work on “Flexible architectures of Artificial Neural Networks models that learn under changing environments”, as part of a CONICYT international exchange project; F. Alexandre, T. Viéville and B. Cessac (ODYSSEE) have started a collaboration with Pr. A. Palacios from CNV, Univ of Valparaiso, about parametric estimation of spike train statistics in order to evaluate to which extends are correlations an important in the retina, which is still an open question;
- F. Alexandre and N. Rougier together with L. Boves, E. Den Os and T. Fitch submitted a proposal for an ESF Research Networking Programme about Language models of Evolution, Acquisition and Processing.

8.2. Teaching

- Courses given at different levels (LMD) by most team members, in computer science and in cognitive science;
- Member of PhD and HDR defense committees (F. Alexandre, B. Girau, D. Martinez, N. Rougier);
- Co-supervision of PhD in Tunisia (F. Alexandre).
- Co-organization of the summer school STIC’2008, 14-20 July 2008, Sousse, Tunisia (http://www.ltim.org/ecolestic2008/) and teaching for the course on “machine learning for numerical data” (F. Alexandre, L. Bougrain)
- Frédéric Alexandre and Thierry Viéville have been invited as teachers at the *VI Escuela de Verano en Sistemas Complejos*, 7 to the 11 of January of the 2008 Summer School of Complex System (http://www.iscv.cl) co-organized by Pr. Adrian Palacios.
- Frédéric Alexandre and Thierry Viéville, with Bruno Cessac (ODYSSEE) have been invited as speaker at the *Séminaire Algorithmique et Programmation des Professeurs de Mathématiques en Classes Préparatoires* for a presentation about *Neurosciences Computationelles: le cerveau est il un bon modèle de réseaux de neurones ?* [29].

8.3. Miscellaneous

- “Le cerveau dans tout ses états”, Fête de la Science, Saint-Dizier, 2008 (N. Rougier)

9. Bibliography

Year Publications

Doctoral Dissertations and Habilitation Theses

[1] J. FIX. *Mécanismes numériques et distribués de l'anticipation motrice*, Ph. D. Thesis, Université Henri Poincaré - Nancy I, 10 2008, http://tel.archives-ouvertes.fr/tel-00336194/en/.

[2] B. GIRAU. *Du parallélisme connexionniste à une pratique de calcul distribué numérique bio-inspiré*, Ph. D. Thesis, Université Nancy II, 12 2007, http://tel.archives-ouvertes.fr/tel-00337399/en/.

Articles in International Peer-Reviewed Journal

[3] F. ALEXANDRE. *Cortical basis of communication: local computation, coordination, attention*, in "Neural Networks", 2008, http://hal.inria.fr/inria-00335971/en/.

[4] M. BOUBAKER, K. BEN KHALIFA, B. GIRAU, M. DOGUI, M. H. BEDOUI. *On-Line Arithmetic Based Reprogrammable Hardware Implementation of LVQ Neural Network for Alertness Classification*, in "IJCSNS International Journal of Computer Science and Network Security", vol. 8, 2008, p. 260-266, http://hal.inria.fr/inria-00338767/en/.

[5] B. CESSAC, T. VIÉVILLE. *On Dynamics of Integrate-and-Fire Neural Networks with Adaptive Conductances*, in "Frontiers in neuroscience", vol. 2, 2008, http://hal.inria.fr/inria-00338369/en/.

[6] A. HUTT. *Local excitation-lateral inhibition interaction yields oscillatory instabilities in nonlocally interacting systems involving finite propagation delay*, in "Physics Letters A", vol. 372, 2008, p. 541-546, http://hal.inria.fr/inria-00332987/en/.

[7] A. HUTT, A. LONGTIN, L. SCHIMANSKY-GEIER. *Additive noise-induced Turing transitions in spatial systems with application to neural fields and the Swift-Hohenberg equation*, in "Physica D: Nonlinear Phenomena", vol. 237, 2008, p. 755-773, http://hal.inria.fr/inria-00332982/en/.

[8] A. HUTT, L. SCHIMANSKY-GEIER. *Anesthetic-induced transitions by propofol modeled by nonlocal neural populations involving two neuron types*, in "Journal of Biological Physics", 2008, http://hal.inria.fr/inria-00332998/en/.

[9] A. HUTT, C. SUTHERLAND, A. LONGTIN. *Driving neural oscillations with correlated spatial input and topographic feedback*, in "Physical Review E", vol. 78, 2008, p. 021911-1–021911-7, http://hal.inria.fr/inria-00332994/en/.

[10] R. KASSAB, F. ALEXANDRE. *Incremental Data-driven Learning of a Novelty Detection Model for One-Class Classification with Application to High-Dimensional Noisy Data*, in "Machine Learning", 2008, http://hal.inria.fr/inria-00337973/en/.

[11] R. MARTIN, C. HOUSSEMAND, C. SCHILTZ, Y. BURNOD, F. ALEXANDRE. *Is there a continuity between categorical and coordinate spatial relations coding? Evidence from a grid/no-grid working memory paradigm*, in "Neuropsychologia / Neuropsychologica", vol. 46, 2008, p. 576-594, http://hal.inria.fr/inria-00175249/en/.

[12] D. MARTINEZ, N. MONTEJO. *A Model of Stimulus-Specific Neural Assemblies in the Insect Antennal Lobe*, in "PLoS Computational Biology", vol. 4, 2008, http://hal.inria.fr/inria-00336099/en/.

[13] N. P. ROUGIER. *Implicit and Explicit Representations*, in "Neural Networks", vol. To appear, 2008, http://hal.inria.fr/inria-00336167/en/.

[14] T. VOEGTLIN. *Adaptive Synchronization of Activities in a Recurrent Network*, in "Neural Computation", 2008, http://hal.inria.fr/inria-00338250/en/.

International Peer-Reviewed Conference/Proceedings

[15] L. ALECU, H. FREZZA-BUET. *Are Neural Fields Suitable for Vector Quantization?*, in "ICMLA'08, États-Unis d'Amérique San Diego", 2008-12, p. 239-244, http://hal-supelec.archives-ouvertes.fr/hal-00351275/en/.

[16] H. BARRON-ZAMBRANO, C. TORRES-HUITZIL, M. CERDA. *Flexible Architecture for Three Classes of Optical Flow Extraction Algorithms*, in "International Conference on ReConFigurable Computing and FPGAs, Mexique Cancun", 2008, http://hal.inria.fr/inria-00331663/en/.

[17] M. CERDA, B. GIRAU. *A neural model with feedback for robust disambiguation of motion*, in "European Symposium on Artificial Neural Networks - ESANN'2008, Belgique Bruges", 2008, http://hal.inria.fr/inria-00331645/en/.

[18] S. CHEMLA, T. VIÉVILLE, F. CHAVANE. *Biophysical cortical column model for optical signal analysis*, in "AREADNE Research in Encoding and Decoding of Neural Ensembles, Grèce Santorini", 2008, http://hal.inria.fr/inria-00338370/en/.

[19] B. GIRAU, C. TORRES-HUITZIL. *Fast Implementation of a bio-inspired model for decentralized gathering*, in "International Conference on ReConFigurable Computing and FPGAs - ReConFig'08, Mexique Cancun", 2008, http://hal.inria.fr/inria-00337397/en/.

[20] G. GRENET, F. ALEXANDRE. *Behavior learning using emotional conditioning*, in "IROS Workshop "From motor to interaction learning in robots", France Nice", Olivier Sigaud and Jan Peters and Sethu Vijayakumar, 2008, http://hal.inria.fr/inria-00335922/en/.

[21] R. KASSAB, J.-C. LAMIREL. *A Multi-level Abstraction Model for Competitive Learning Neural Networks*, in "Artificial Intelligence and Applications - AIA 2008, Autriche Innsbruck, Austria", 2008, http://hal.inria.fr/inria-00332320/en/.

[22] R. KASSAB, J.-C. LAMIREL. *Feature-Based Cluster Validation for High-Dimensional Data*, in "Artificial Intelligence and Applications - AIA 2008, Autriche Innsbruck, Austria", 2008, http://hal.inria.fr/inria-00332310/en/.

[23] J.-C. LAMIREL, A. PHUONG TA, M. ATTIK. *Novel Labeling Strategies for Hierarchical Representation of Multidimensional Data Analysis Results*, in "AIA - IASTED, Autriche Innbruck", 2008, http://hal.inria.fr/inria-00337304/en/.

[24] N. LIANG, L. BOUGRAIN. *Averaging techniques for single-trial analysis of oddball event-related potentials*, in "4th International Brain-Computer Interface workshop, Autriche Graz", 2008, http://hal.inria.fr/inria-00337070/en/.

[25] E. MARTIN MORAUD, J. G. HALE, G. CHENG. *Constraint-based Ground contact handling in Humanoid Robotics Simulation*, in "2008 IEEE/RAS International Conference on Robotics and Automation - ICRA 2008 Workshop on Contact Models for Manipulation and Locomotion, États-Unis d'Amérique Pasadena, CA", 2008, http://hal.inria.fr/inria-00350114/en/.

[26] C. TORRES-HUITZIL, B. GIRAU, M. ARIAS-ESTRADA. *Biologically-inspired Digital Architecture for a Cortical Model of Orientation Selectivity*, in "18th International Conference on Artificial Neural Networks - ICANN 2008 Biologically-Inspired Digital Architecture for a Cortical Model of Orientation Selectivity Lecture Notes in Computer Science, Tchèque, République Prague", V. KURKOVA, R. NERUDA, J. KOUTNÍK (editors), Lecture Notes in Computer Science, vol. 5164, Springer, 2008, p. 188-197, http://hal.inria.fr/inria-00337391/en/.

[27] C. TORRES-HUITZIL, B. GIRAU, A. BOUMAZA, B. SCHERRER. *Embedded harmonic control for trajectory planning in large environments*, in "International Conference on ReConFigurable Computing and FPGAs - ReConFig 08, Mexique Cancun", 2008, http://hal.inria.fr/inria-00337628/en/.

[28] C. TORRES-HUITZIL, B. GIRAU. *Implementation of Central Pattern Generator in an FPGA-based Embedded System*, in "18th International Conference on Artificial Neural Networks - ICANN 2008 Artificial Neural Networks - ICANN 2008 Lecture Notes in Computer Science, Tchèque, République Prague", V. KURKOVA, R. NERUDA, J. KOUTNÍK (editors), Lecture Notes in Computer Science, vol. 5164, Springer, 2008, p. 179-187, http://hal.inria.fr/inria-00337390/en/.

National Peer-Reviewed Conference/Proceedings

[29] F. ALEXANDRE, B. CESSAC, T. VIÉVILLE. *Neurosciences Computationelles: le cerveau est il un bon modèle de réseaux de neurones ?*, in "Séminaire Algorithmique et Programmation des Professeurs de Mathématiques en Classes Préparatoires, France Marseille", 2008, http://hal.inria.fr/inria-00338371/en/.

Workshops without Proceedings

[30] L. ALECU, H. FREZZA-BUET. *An Empirical Evaluation Framework for Qualifying Dynamic Neural Fields*, in "Deuxième conférence française de Neurosciences Computationnelles, "Neurocomp08", France Marseille", 2008, http://hal.archives-ouvertes.fr/hal-00331551/en/.

[31] F. ALEXANDRE, J. FIX, A. HUTT, N. P. ROUGIER, T. VIÉVILLE. *On practical neural field parameters adjustment*, in "Deuxième conférence française de Neurosciences Computationnelles, "Neurocomp08", France Marseille", 2008, http://hal.archives-ouvertes.fr/hal-00331571/en/.

[32] H. BELMABROUK, J.-P. ROSPARS, J. EZZINE, D. MARTINEZ. *Rôle de l'inhibition intra- et interglomérulaire dans la synchronisation neuronale et le codage phéromonal chez manduca sexta*, in "Deuxième conférence française de Neurosciences Computationnelles, "Neurocomp08", France Marseille", 2008, http://hal.archives-ouvertes.fr/hal-00331601/en/.

[33] B. CESSAC, H. ROSTRO, J.-C. VASQUEZ, T. VIÉVILLE. *Statistics of spikes trains, synaptic plasticity and Gibbs distributions.*, in "Deuxième conférence française de Neurosciences Computationnelles, "Neurocomp08", France Marseille", 2008, http://hal.archives-ouvertes.fr/hal-00331541/en/.

[34] B. CESSAC, H. ROSTRO, J.-C. VASQUEZ, T. VIÉVILLE. *To which extend is the "neural code" a metric ?*, in "Deuxième conférence française de Neurosciences Computationnelles, "Neurocomp08", France Marseille", 2008, http://hal.archives-ouvertes.fr/hal-00331567/en/.

[35] S. CHEMLA, T. VIÉVILLE, F. CHAVANE. *Biophysical cortical column model for optical signal analysis*, in "Deuxième conférence française de Neurosciences Computationnelles, "Neurocomp08", France Marseille", 2008, http://hal.archives-ouvertes.fr/hal-00331587/en/.

[36] J. FIX, N. P. ROUGIER, F. ALEXANDRE. *A computational approach to the covert and overt deployment of spatial attention*, in "Deuxième conférence française de Neurosciences Computationnelles, "Neurocomp08", France Marseille", 2008, http://hal.archives-ouvertes.fr/hal-00331580/en/.

[37] T. GIROD, F. ALEXANDRE. *Mécanisme d'auto-organisation corticale : un modèle basé sur la règle de plasticité synaptique BCM*, in "Deuxième conférence française de Neurosciences Computationnelles, "Neurocomp08", France Marseille", 2008, http://hal.archives-ouvertes.fr/hal-00331561/en/.

[38] M. G. KAABI, G. ZHENG, A. TONNELIER, D. MARTINEZ. *Simulation de réseaux de neurones intègre-et-tire non linéaires par discrétisation du potentiel*, in "Deuxième conférence française de Neurosciences Computationnelles, "Neurocomp08", France Marseille", 2008, http://hal.archives-ouvertes.fr/hal-00331595/en/.

[39] N. LIANG, L. BOUGRAIN. *Non-identity Learning Vector Quantization applied to evoked potential detection*, in "Deuxième conférence française de Neurosciences Computationnelles, "Neurocomp08", France Marseille", 2008, http://hal.archives-ouvertes.fr/hal-00331590/en/.

Scientific Books (or Scientific Book chapters)

[40] B. GIRAU, A. BOUMAZA, B. SCHERRER, C. TORRES-HUITZIL. *Block-synchronous harmonic control for scalable trajectory planning*, in "Robotics, Automation and Control", A. LAZINICA (editor), I-Tech Publications, 2008, p. 85-110, http://hal.inria.fr/inria-00337634/en/.

Research Reports

[41] J. SOYEZ. *Bibliométrie : Apports et limites dans la compréhension de l'environnement scientifique et technologique, l'exemple des neurosciences computationnelles*, RT-0356, Rapport Technique, 2008, http://hal.inria.fr/inria-00327742/en/.

Other Publications

[42] A. HUTT, M. MUNK. *Detection of phase synchronization in multivariate single brain signals by a clustering approach*, 2008, http://hal.inria.fr/inria-00333013/en/.