ubicua, natural y sencilla para los usuarios, acercándose cada vez más a la visión de la Inteligencia Ambiental [4].

Es necesario que las nuevas tecnologías se adapten a las necesidades de los usuarios, tanto para mejorar la calidad de trabajo como para lograr desarrollos tecnológicos y de gestión que supongan ventajas competitivas diferenciales. El sistema presentado posee la ventaja de ser fácilmente adaptable a otros posibles campos o líneas de aplicación futuras de características similares.

Agradecimientos. Este trabajo se ha llevado a cabo gracias a los proyectos MCYT TIC2003-07369-C02-02 y JCYL-2002-05 proyecto SA104A05. Especial agradecimiento a Telefónica Móviles y a Sokymat por el apoyo prestado, así como por la tecnología proporcionada.

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Applications of bio-inspired dynamical tools in manufacturing and engineering environments

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Abstract. This paper raises the question of whether some notions resident in Complex Systems and, in particular, in a type of processes that emerge in *Lotka-Volterra systems* [1, 21] can contribute to design and improve intelligent artifacts for dealing with problems in Systems Engineering related on the stability-plasticity dilemma. The ***Stability-Plasticity dilemma*** [11] speaks us about the difficulty to build tools that remain adaptive (plastic) in response to significant inputs, but remain stable in response to irrelevant input. In this paper it is proposed a model that, from a non-linear dynamical approach and based on recent results of olfactory systems, shows a way to implement mechanisms that satisfy both of these conditions.

Keywords: Complex nonlinear dynamic system, "Stability-Plasticity" dilemma, Spatio-temporal neural coding, design for emergence.

1 Introduction

In the real world, computing devices should be able to respond intelligently to gaps in their knowledge and to situations that have not been specified in their design. In the future, and at the present, it starts to be necessary artefacts able to exhibit robust and versatile behaviour in open-ended environments and give sensible responses in unforeseen situations. To achieve these goals, it is necessary rethinking how systems should be designed and what are the models and notions to include intelligence in systems that understand their environments and their users while operating autonomously or in cooperation with people in complex, dynamic spatial environments. This paper raises the question of whether some notions resident in

Complex Systems and, in particular, in a type de processes that emerge in Lotka-Volterra systems [1, 21] can contribute to design and improve intelligent artifacts for dealing with problems in Systems Engineering related on the stability-plasticity dilemma. The Stability-Plasticity dilemma [11] speaks us about the difficulty to build tools that remain adaptive (plastic) in response to significant inputs, but remain stable in response to irrelevant input. In this paper it is proposed a model that, from a non-linear dynamical approach and based on models of olfactory systems, shows a way to implement mechanisms that satisfy both of these conditions.

2 Engineering Complex Systems

By complex systems, we mean systems whose perceived complicated behaviors can be attributed of the following characteristic: nonlinear and discontinuous relationships among elements. Complex Systems engineering is not another discipline like industrial, electrical, mechanical, and chemical engineering. It is an integrative discipline that crosses the boundaries of these disciplines and, of course, others.

Thus, systems engineering deals with "everything," in the sense of the exploration, understanding, and design of how everything fits together. From this perspective, systems engineers see systems from a structural and functional perspective [22].

Engineering Complex Systems finds how the structure of a system influences in the dynamics of its adaptive behavior and its underlying mechanisms. Understanding the interactions among environmental complexity and structural complexity is the central problem in the study of adaptive behavior of artefacts [23]. In Figure 1, it is shown a squema of the development process to field a production system. Some authors find in a continuous and iterative redesigning the central role in processes of industrial Design [23].

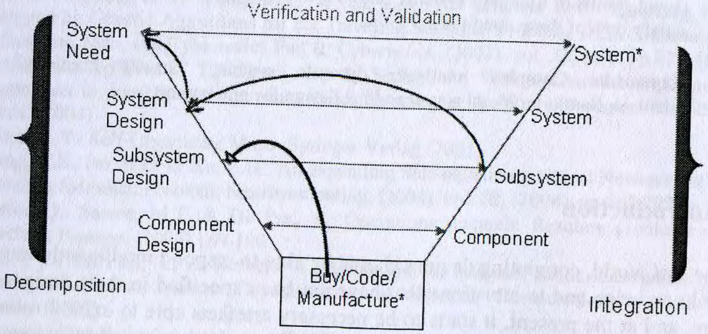

Fig. 1. Development process to field a production system [23]

We propose face up to theses design processes by an analytic approach -- dynamical analysis-- to demonstrate how fundamental limitations of engineering for the development of highly complex systems can be solved. It is underlined that the

construction of complex systems should be based in strategies modelled by biological evolution, where nature has solved problems that we still are facing up to in everyday situations.

3 The role of computation in simple brains

The knowledge about higher brain centres in insects and how they affect the insect's behaviour has increased significantly in recent years by experimental investigations. A large body of evidence suggests that higher brain centres of insects are important for learning, short-term and long-term memory and play an important role for context generalisation [4]. One of the most interesting goals to achieve is to understand the relationship between sequential memory encoding processes and the higher brain centres in insects in order to develop a general "insect-brain" control architecture to be implemented on simple robots.

Some biological systems, like several insects, have brains that show a type of computation that may be described functionally by non-linear dynamics [20]. In previous papers [2, 6], it has been focused on how a Lotka-Volterra system [1, 21] can be the support to model any non-linear system and what are the typical processes that emerge in Lotka-Volterra systems. After that, it was also shown how Continuous Recurrent Neural Networks (CRNNs) [12] can be used to model non-linear systems, in particular, Lotka-Volterra systems [7, 8]. This approach finds out a way to model cognitive systems from a practical viewpoint [5].

Obtaining real data about higher brain centres (and how do they affect an insect's behaviour) it is now possible to stop the functioning of particular neurons under investigation during phases of experiments and gradually reestablish the functioning of the neural circuit [10]. At the present, we know that higher brain centres in insects are related on autonomous navigation, multi-modal sensory integration, and to an insect's behavioral complexity generally; evidence also suggests an important role for context generalization, short-term and long-term memory [18]. For a long time, insects have inspired robotic research in a qualitative way but insect nervous systems have been under-exploited as a source for potential robot control architectures. In particular it often seems to be assumed that insects only perform 'reactive' behavior, and more complex control will need to be modeled on 'higher' animals.

Although various attempts at modeling the complex dynamics in insect brains have been made [17, 21], we feel it is easier the proposal of using a simple CRNN (Continuous and recurrent neural network) as the framework to implement competing processes between neurons that generate spatio-temporal patterns to codify memory in a similar way simplest living systems do. After that, the particular aim is to explore a way to build sequential memory generated by recurrent neural networks of competing neuron inspired in how higher brain centres in insects work and how this might suggest control architectures of insect-inspired robotic systems.

3.1 Spatio-temporal neural coding and Winnerless competition systems

It would be very interesting to understand how the information is processed by computation from a dynamical viewpoint (in terms of steady states, limit cycles and strange attractors) because it gives us the possibility of manage sequential processes [9, 16]. In this section it is discussed a new direction in information dynamics namely the Winnerless Competition (WLC) behavior. The main point of this principle is the transformation of the incoming spatial inputs into identity-temporal output based on the intrinsic switching dynamics of a dynamical system. In the presence of stimuli the sequence of the switching, whose geometrical image in the phase space is a heteroclinic contour, uniquely depends on the incoming information. Consider the Lotka-Volterra system (N=3):

$$\dot{a}_1 = a_1[1-(a_1+\rho_{12}a_2+\rho_{13}a_3)]$$
$$\dot{a}_2 = a_2[1-(a_2+\rho_{21}a_1+\rho_{23}a_3)]$$
$$\dot{a}_3 = a_3[1-(a_3+\rho_{31}a_2+\rho_{32}a_2)]$$

If the following matrix and parameter conditions are satisfied,

$$(\rho_{ij}) = \begin{pmatrix} 1 & \alpha_1 & \beta_1 \\ \beta_2 & 1 & \alpha_2 \\ \alpha_3 & \beta_3 & 1 \end{pmatrix}$$

$$0 < \alpha_i < 1 < \beta_i$$

When the coefficients fulfill that $\alpha_1 = \alpha_2 = \alpha_3 < 1$ and $\beta_1 = \beta_2 = \beta_3 > 1$, we have three cases:

1. Stable equilibrium with all three components simultaneously present/working.
2. Three equilibria (1,0,0), (0,1,0) and (0,0,1) all stable, each one attainable depending on initial conditions.
3. Neither equilibrium points nor periodic solutions are asymptotically stable and we have wandering trajectories defining Winnerless Competition (WLC) behavior

Which are the advantages of dealing with Lotka-Volterra systems? It has been shown above how a Winnerless competition process can emerge in a generalized Lotka-Volterra systems. It is known the proof about how this type of process is generalizable to any dynamical system and how any dynamical system can be represented by using recurrent neural networks [14].

From this point of view, the consequences obtained in our approach can be extended for all cases. We have only a boundary condition: the Lotka-Volterra system must be of any dimension N greater than three to find Winnerless competition

behavior. In the following, we assume the Lotka-Volterra systems approximate arbitrarily closely the dynamics of any finite-dimensional dynamical system for any finite time and we will assume and concentrate in showing them as a type of neural nets with great interest for applications [13].

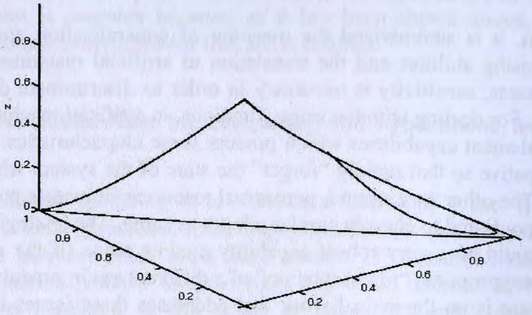

Fig. 2. Topology of the behavior in the phase space of WLC neurons net in a 3D. The axes represent the addresses of the oscillatory connections between the processing units (α = 0.5, β = 1.8, x(0) = 1.01, y(0) = 1.01, z(0) = 0.01).

4 The "Stability-Plasticity" dilemma

The problem, we are interested about, is how to design intelligent systems showing simultaneously the following features: adaptability (or flexibility) and robustness. The coexistence of these characteristics implies systems able to distinguish (i.e., recognize) one input from the others (assuming uncorrelated input patterns) but showing capabilities to identify which is the index of a pattern in the memory-storage (classification) [11].

In this paper, it is shown that it is not necessary to use two models in order to combine both discriminating (recognition stage) and generalizing abilities (classification stage). Only one complex system composed of coupled non-linear elements is enough if the strength of the coupling coefficients is suitable for such situation. These ideas are inspired in several works interested in how the olfactory system of insects works [17] and in their odor representation skills: odor patterns are reproducible and, on the other hand, systems are sensitive to small variations in the inputs, so that fine discriminations between similar but not identical stimuli are possible.

In the language of non-linear dynamics, this is possible only if the system is strongly dissipative, in other words, if it is able to forget its initial state that is rapidly compressed and all trajectories converge to attractors (fixed points, closed trajectories or limit cycles, strange attractors, or other specific trajectories such as homoclinic/heteroclinic trajectories).

With these notions in mind, in next sections it is proposed a model able to solve the fundamental contradiction between sensitivity and robustness to the noise.

4.1 Generalization vs. sensivity

In this section, it is summarized the meaning of generalization and robustness in insects' processing abilities and the translation to artificial machines. In perceptual systems of insects, sensitivity is necessary in order to discriminate distinct but very closed odours. For dealing with the same situations, in artificial machines, it would be necessary implement capabilities which possess these characteristics: they should be strongly dissipative so that rapidly "forget" the state of the system when the stimulus is turned off. The other way around, perceptual resources in insects present the ability to recognize inputs and to classify similar odours as same. The analogue characteristic in machines could be a very robust capability against noise (if the noise drives the system to an inappropriate "representation" of a different environmental stimulus).

To date, there is no theoretical work that addresses these issues in a satisfactory way. The problem is complex because, as it has been shown above, the systems should have, simultaneously, features that are in conflict.

4.2 Winnerless competition systems helps to deal with the Stability-Plasticity dilemma

Some features of the winnerless competition systems seem to be very promising to use these systems to model the activity and the design of intelligent artefacts. We will focus on some of the results of the theoretical studies on systems of n elements coordinated with excitement/inhibition relations [15]. These systems show:

- Large Capacity: A heteroclinic (spatiotemporal) representation provides greatly increased capacity to the system. Because sequences of activity are combinatorial across elements and time, overlap between representations can be reduced, and the distance in phase space between orbits can be increased.
- Sensitivity (to similar stimulus) and, simultaneously, capacity for categorization: This is because the heteroclinic linking of a specific set of saddle points is always unique. Two like stimuli, activating greatly overlapping subsets of a network, may thus become easily separated because small initial differences will become amplified in time.
- Robustness: in the following sense, the attractor of a perturbed system remains in a small neighborhood of the "unperturbed" attractor (robustness as topological similarity of the perturbed pattern).

It has been shown that from the dynamic of the system, some properties emerge. As example, in [19], is described a simple chaotic system of coupled oscillators that shows a complex and fruitful adaptive behaviour: the interaction among the activity of elements in the model and external inputs give rise to an emergence of searching rules from basic properties of nonlinear systems (rules which have not been pre-programmed explicitly) and with obvious adaptive value. More in detail: the adaptive

rules are autonomous (the system selects an appropriate rule with no instructions from outside), and they are the result of interaction between intrinsic dynamics of the system and dynamics of the environment. These rules emerge, in a spontaneous way, because of the non-linearity in the simple system.

To date, there is no theoretical work that addresses these issues in a satisfactory way. The problem is complex because, as it has been shown above, the systems should have, simultaneously, features that are in conflict.

4.3 Winnerless competition for computing and applications for predictive modeling

The task of predictive modeling is to forecast a course of events from a set of observations. In essence, predictive modeling synthesizes the nonlinear mapping from the inputs to the outputs. There are a huge number of industrial fields (diagnosis, control and estimation) related on prediction and some interests in the industrial world. Predictive modeling is the focus of many industrial and commercial applications [24]: It can be used for diagnosis in which a set of fault hypotheses is identified and the system solves a classification problem, it can also be used for control in which the system has to output control actions that will impact the future state of the system, etc. The proposed model using heteroclinic trajectories for computing purposes shows advantages for these industrial interests. It is known [7] that computing with heteroclinic orbits adds to the classical computing the feature of high sensitivity to initial conditions increasing. If we consider artefacts with computation processes ordered by winnerless competition behaviour, the artefact would have great ability to process, manage and store sequential information. Other interesting field of application is Neural cryptography, that is dedicated to analyzing the application of stochastic algorithms, especially neural network algorithms, for use in encryption and cryptanalysis. The ability of WLC to explore the solution space could also be used in the field of Cryptanalysis to generate new kind of attacks on existing algorithms based on the idea that any function could be reproduced by a neural network, so it will be possible to find the exact solution, at least theoretically, breaking the algorithm. Still there are no practical applications due to the recently of the development of the field, but it could be used specially over applications where the keys could be continually generated and the system could be in a continuous evolving mode. The ability to process sequential information has long been seen as one of the most important functions of "intelligent" systems [15]. As it will be shown afterwards, winnerless competition principle appears as a major type of mechanism of sequential memory processing. The underlying concept is that sequential memory can be encoded in a (multidimensional) dynamical system by means of heteroclinic trajectories connecting several saddle points. Each of the saddle points is assumed to be remembered for further action [1].

5 Concluding remarks

This paper proposes a system architecture for coding and to build a memory inspired in the brain of insects (a class of models whose stimulus-dependent dynamics reproduces spatio-temporal features observed in higher brain centres of insects [17]. Beyond the biological observations which suggested these investigations, recurrent neural networks where WLC can emerge provide an attractive model for computation because of their large capacity as well as their robustness to noise contamination. The model discussed here shows an interesting tool (using control and synchronization of spatio-temporal patterns) to transfer and process information between different neural assemblies for classification problems in, eventually, several industrial environments. The proposed model is able to solve the fundamental contradiction between sensitivity and generalizing of the recognition, multistability and robustness to the noise in real processes. In the income inputs classification is useful to get models that could be reproducible. In the language of non-linearity, this is possible only if the system is strongly dissipative (in otherwords, if it can rapidly forget its initial state). On the other hand, a useful classificator system should be sensitive to small variations in the inputs, so that fine discriminations between similar but not identical stimuli are possible. Winnerless competition principle shows both features.

This paper has described a methodology that realize a kind of design for emergence, i.e., design techniques for purposive agents where behaviour is not strictly programmed but robustly emerges from the interaction of the various components (each with local intelligence). Future projects related on the development of smart components and techniques for the design of ambitious classes of scalable robotic systems, incorporating emergence and adaptation mechanisms, provides new perspectives to traditional computing.

To finish, why is interesting building such a kind of bio-inspired systems based in Winnerless competition processes? Because of its features. If evolution has chosen the nonlinear dynamical phenomena as the basis of the adaptive behaviour patterns of the living organisms and these systems show, in one hand, the coexistence of sensitivity (ability to distinguish distinct, albeit similar, inputs) and robustness (ability to classify similar signals receptions as the same one), then if we are able to reproduce the same characteristics in artificial intelligent architectures, will make it easier to go beyond the actual limitations into the intelligent systems applied to the real problems.

Acknowledgments. This work has been supported in part by the EU 6th Framework programme (Spark project, reference: IST-2003-2-004690).

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Supervised and Distributed Model-Based Diagnosis

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Abstract. This work presents a proposal to diagnose distributed subsystems that form a global system using model-based diagnosis. The diagnosis is supervised and distributed since the system is formed by several nodes located separately, but there is a centered system that manages some information about the system. The distributed subsystems have two different type of information, private and public data. It means, that the whole information about the system is not known. The central coordination system has to diagnose the system based only on public information. In order to obtain the fault diagnosis, a distributed algorithm has been defined to detect the components that fail in a distributed system. Also some definitions about model-based diagnosis have been redefined to be adapted to distributed fault diagnosis.
Keywords: Model-based Diagnosis, Supervised Distributed Systems, Central Coordination Agent.

1 Introduction

Nowadays the hardware and software systems are generally composed of a large number of distributed nodes that interact with the physical world via a set of sensors, actuators or users. Examples of such systems are ad-hoc wireless networks, modular robots, automobiles, Web Services and intranets.

Fault diagnosis permits to determine why a system correctly designed does not work as it is expected. The diagnosis aim is to detect and to identify the reason of the unexpected behavior, or in other words, to identify the parts which fail in a system. Our proposal is based on DX community approaches [1], [2]. These works were proposed to find out the discrepancies between the observed and correct behavior of the system.

The traditional diagnostic tools can be considered as a single diagnostic agent with a model of the whole system to be diagnosed, but in some systems, however, such a single agent approach is not desirable. Moreover the integration of knowledge into one model of the system is infeasible if the system is too large, dynamic or distributed over different local entities. In some systems, the knowledge integration can proceed from different local diagnostic processes situated in different nodes (it is called spatially distributed) or precedent of different fields of expertise (it is called semantically distributed [3]).

In previous works, the fault diagnosis for systems are classified as follows: