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Dynamical systems for dealing with classification tasks in industrial environments

Manuel G. Bedia[1] and Juan M. Corchado[2]

[1]Dpto. de Informática, Universidad Carlos III, Av. de la Universidad, s/n
28911 -Madrid, Spain.
[2]Dpto. Informática y Automática, Universidad de Salamanca. Pl. de la Merced, s/n,
37008 - Salamanca, Spain

Abstract. Intelligent techniques that emulate characteristics of biological systems offer opportunities for industrial applications with new and interesting capabilities. In the competitive economic environment these control techniques can provide products with high competitive values. The technique shown in this paper, based in bio-inspired neural networks, is used to illustrate these principles.

1 Introduction

In this paper we deal with computation over dynamical systems modeled by recurrent neural networks in order to propose a new approach for classification problems. We want to explore what type of applications can be obtained if we consider computation processes by dynamical models. The ability to process sequential information has long been seen as one of the most important functions of living and artificial intelligent systems. In spite of the history of studies of sequential learning and memory, little is known about dynamical principles of storing and remembering of multiple events and their temporal order by neural networks. We are interested in a principle called *winnerless competition* that can be a very useful mechanism to model sequential and scheduled processes.

2 Overview of relevant previous models

Information about the environment is generally encoded by biological systems into neural sequences in animal sensory nervous systems. There is a growing body of evidence [8], [3] that, in some systems, the representation of information comes through both identity and temporal encoding. To build a reasonable dynamical theory of such an encoding in order to reproduce it in an artificial way, we must understand the principles on which the dynamics of these sensory networks is based. First we will show the features of previos biological processing models as a guide to our analysis using dynamical systems.

Neural Dynamical Networks: The most common nonlinear dynamical models for classification problems (representation and recognition) are the Hopfield net [1]. In these models, each stimulus is represented by a set of connections among the network's elements. The behavior expressed depends on the number of different attractors and determines the number of different stimuli that the system can represent or recognize. The main idea behind a Hopfield network is that, during a learning stage, a long-acting stimulus is used to modify specific sets of connections until a steady-state behavior specific for that stimulus is obtained:

- Although a Neural dynamical network is a dynamical system, it is static (or stationary) after convergence.
- Time does not play an intrinsic role in the encoding or decoding of the input.
- The number m of stimuli allowed in a system of N neurons is relatively limited: $m < 0.14N$. Such systems therefore have hard capacity limits.

Mesoscopic models: Walter Freeman and collaborators [4], [5], [6] have developed dynamical models that simulate the global behavior of neuron population. These models of population dynamics (called "mesoscopic" models because of their intermediate scale) reproduce several and important propierties for classification. For example, Freeman's models generate transient and reproducible waveforms that uniquely depend on the stimulus; they can thus be used for recognition. However,

- These models do not explicitly model individual neurons, groups of synchronized neurons, or network topology
- It is proposed to explain macroscopic signals and difficult to assess without explicit description of their underlying causes.

Learning Classification model: These type of models [8]have been presented some years ago and try to address quantitatively the levels of neural activity, convergent and divergent connectivities, and the function of classification. Their results clearly show that the classification task can be implemented by such network structure, with non-specific or random connections, simple Hebbian learning, and mutual inhibition. It is proposed a model that is able to implement discrimination between classes and grouping of similar inputs into the same class. Nevertheles,

- Similar to the Hopfield networks, the system is static (or stationary) after training and learning.
- The role of time is left out for further investigation.
- They restrict the analysis to the spatial aspects of the representation of inputs but not mixtures (with common features).

2.1 Schema of a new framework

The key problem is to obtain a model for classification with the features shown above (adaptability, flexibility, robustness, etc.) simultaneously. In order to find a system that illustrate the coexistence of these, we propose a schema of a system with two essential properties:

- Recognition: The recognition task is the ability of the system to distinguish one input from the rest, assuming uncorrelated input patterns.
- Classification: The classification problem is defined as the capability of a the system to identify which is the index of a pattern in the memory-storage.

We need two models in order to combine both discriminating (Recognition stage) and generalizing abilities (Classification stage). Two different system composed of coupled dynamical chains of non-linear oscillators is studied when the unit at each site is an active oscillator. We show that, with a particular set of coupling coefficients, the system may exhibit a wide variety of stable patterns.

3 Winnerless competition networks

We are interested in how the information is processed by computation with chaos (steady states, limit cycles and strange attractors) because chaos gives us the possibility of manage sequential processes. We are going to discuss a new direction in information dynamics namely the *Winnerless Competition (WLC) behavior* [10]. 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 ($N \geq 3$ always)

$$\begin{cases} \dot{x}_1 = x_1(1 - x_1 - \alpha_1 x_2 - \beta_1 x_3) \\ \dot{x}_2 = x_2(1 - \beta_2 x_1 - x_2 - \alpha_2 x_3) \\ \dot{x}_3 = x_3(1 - \alpha_3 x_1 - \beta_3 x_2 - x_3) \end{cases}$$

where $\alpha_i,\ \beta_i > 0 \quad i = 1, 2, 3$.
We are interested in the behavior of the solutions for the system in different cases. To do it, we calculate the fixed points:

$$\{a = (a_1, a_2, a_3)/\ \dot{x}(a) = 0\}$$

The posible equilibrium solutions may be expressed as points in the $3D$-space: the origin, three single-component solutions of the form $(a_i \neq 0, a_j = 0, a_k = 0)$, three two-component solutions of the form $\{a_i = 0, a_j \neq 0, a_k \neq 0\}\ i, j, k = 1, 2, 3$ and a three-component equilibrium solution $p = (p_1, p_2, p_3)$. As a result of the assumption $x > 0$, neither $(0, 0, 0)$ nor the two-component equilibrium point are stable, so we focus attention to the following points:

$$e_1 = (1, 0, 0),\ e_2 = (0, 1, 0),\ e_3 = (0, 0, 1) \text{ and } p = (p_1, p_2, p_3)$$

Let us take the following condition on the coefficients $\alpha_i < 1$, $\beta_i > 1$ and $(1-\alpha) < (\beta - 1)$. Hence its stability is determined by the eigenvalues of the matrix

$$S = -\begin{pmatrix} 1 & \alpha & \beta \\ \beta & 1 & \alpha \\ \alpha & \beta & 1 \end{pmatrix}$$

It is not difficult to prove that if we study the eigenvalues of the points e_i over the axes we obtain three saddle points. Then, we perform the stability analysis of the only interior equilibrium point $p = (p_1, p_2, p_3)$ to know the global behavior of the system. The eigenvalues of S on p can be written as

$$\lambda_1 = -(1 + \alpha + \beta) < 0$$
$$\lambda_2 = (\tfrac{\alpha+\beta}{2} - 1) + i(\tfrac{\sqrt{3}}{2}(\alpha - \beta)) \equiv a + ib \text{ with } a > 0$$
$$\lambda_3 = (\tfrac{\alpha+\beta}{2} - 1) - i(\tfrac{\sqrt{3}}{2}(\alpha - \beta)) \equiv a - ib \text{ with } a > 0$$

To know the global behavior of the system we focus at p that is, in the first direction, a saddle point and in the other directions it shows unstable orbits. The global behavior is a non-periodic albeit almost cyclic phenomena. A heteroclinic contour *works* as a global attractor with p as a saddle point. The key problem in the realization of the WLC principle is the robustness against noise and, simultaneously, the sensitivity of the switching to the incoming input. Consequently, each orbit can be associated with a stimulus and thus "encode" it.

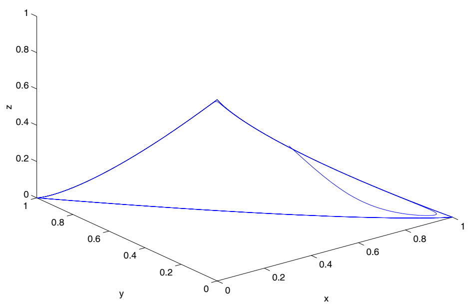

Fig. 1. Topology of the behavior in the phase space of WLC neurons net in a $3D$. The axes represent the addresses of the oscillatory connections between the processing units.

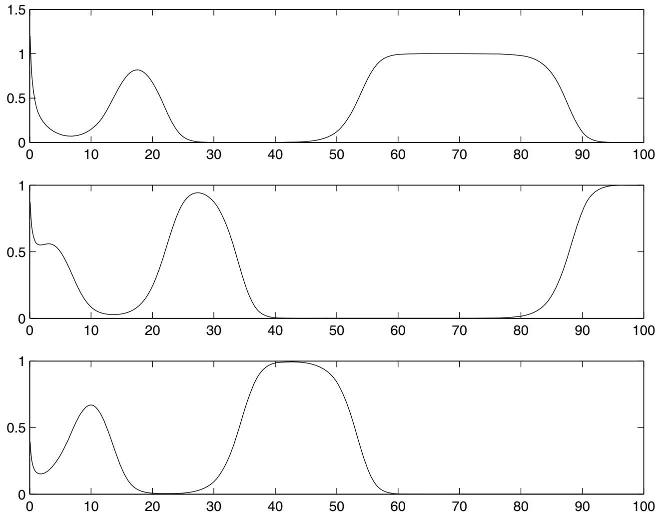

Fig. 2. Dynamics of the three units of the network. It is shown the sequence of the three oscillators delayed between them.

3.1 Characteristics

- Large Capacity: It can be shown that the system has a large number of attractors. Thus, there exist at least 2^N different distributions of the amplitudes of oscillations along the chain, and each one can "code" an arbitrary sequence of two symbols (at rest and oscillating) [2].
- Replication of a stimulus pattern: The mutual synchonization of oscillations may lead to the replication by a disordered chain of a given stimulus carried buy the other patterned chain. If the first chain has got oscillators in-phase motions (stimulus), the amplitude distribution of in-phase motions in the second chain is the given pattern: after a transient process, the synchronization of oscillations occurs, with some oscillators close to the state of rest and other oscillators excited. The system disordered replicates the shape of the stimulus contained in the first one in a rather faithful way.
- Splitting mixed inputs: What does it happen if the system shapes an stimulus when de chain is not disordered? Where the interactions occurs in the presence of a pattern in the second system (which, has been earlier replicated on it) it is found that the final patterns in this case have significant traces of both stimulus (the last and the new one). Thus, it is a possibility thinking about replications of patterns that includes mixed stimulus, because the system is sensitive to the properties of initial distributions.

3.2 Advantages of dealing with Lotka-Volterra systems

Why do we study such a Lotka-Volterra models? We have shown above mathematical calculations that allow the representation of Winnerless competition processes emerging in a generalized Lotka-Volterra systems. Also, it is easy to show how this type of process is generalizable to any dynamical system, and how any dynamical system can be represented by using recurrent neural networks. From this point of view, the consecuences 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 conclusion, we assume the Lotka-Volterra systems approximate arbitrarily closely the dynamics of any finite-dimensional dynamical system for any finite time and we will concentrate in showing them as typical representations in neural nets.

4 Developing industrial applications emulating biological systems

There are many opportunities to apply intelligent control techniques to create products with a competitive advantage. However, in order to detect these opportunities, we need to have a broad perspective of what constitutes, in our case, a classification problem. Using intelligent techniques to complement, rather than replace, conventional techniques will facilitate the acceptance in the industrial community [11]. Tools such as neural and bio-inspired algorithms open new possibilities and allow engineers to extend the functionality of a systems beyond its traditional boundaries and be more creative in the ways that they need to use intelligent techniques to solve problems. While numerous applications of intelligent algorithmics have been described in literature, few companies have used those tools to include in new products. The needs for systems that deal classification tasks vary widely among the different market segments but a researcher should recognize the particular capability provided by a new intelligent technique and target the application at a specific market segment where there is a critical need for that capability. This paper has shown a proposal of bio-inspired neural networks in order to use it for applications in process industries when could be necessary systems with features as adaptability, flexibility and robustness simultaneously.

One of the most important area in engineering applications is without any doubt the planning and scheduling activities, where is shown an increasing interest about classification of measurements [12]. The applications of the proposal tools can be divided roughly in two groups:

– Methods for indexing and giving basic information for production planning or to plan the suitable storage levels that utilises usually a data intensive approach. The data available is in many cases incomplete and uncertain. Bio-inspired neural network algorithms can be used here, where the applicability of traditional methods is limited because of before mentioned reasons.

– Production planning and scheduling is an area, which very often is characterised by a high degree of uncertainty, which makes it obvious to investigate the possibilities for development of planning and scheduling systems using uncertainty techniques. These methods have the potential to contribute much more to the solutions of traditional industrial problems.

In addition to classical methods, bio-inspired neural networks and dynamical approaches can be extensively used in processes of bioengineering fields. The tools used in these systems fall mainly into two categories: classification methods and modelling that also partly overlap with each other. In practical modelling applications, it is neccesary systems that show appropriate management tools for linked variables, such as the cell concentration, substrate concentration and secondary metabolite concentrations, making a serious problem in controlling bio-processes. The proposal of this paper tries to propose an approach and new tools to face these types of problems.

5 Summary and Conclusions

The model discussed here is a particular example (using control and synchronization of spatio-temporal patterns) to transfer and process information between different neural assemblies for classification problems in, eventualliy, any 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 classification 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). In dissipative systems, the initial phase volume 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).

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.

How can both conditions coexist? This is only possible if a system is active [3]. An active system uses external sources of energy to increase a small distance between initial states caused by similar stimuli, independent of the initial state of the network. Because the system is active, small initial differences between representations can grow rapidly over time. Time thus plays a critical role in separating representations. The framework that we are looking for should therefore behave as active (and sensitive), nonlinear, dissipative systems.

In control applications, measurement problems and methods for classification of measurements seem to be of primary importance. Also inspection methods based on intelligent methods are getting more and more importance. There is a growing number of industrial applications of intelligent methods varying from expert systems to fuzzy logic, neural networks and genetic algorithms. Based on the experiences from biological studies and dynamical mathematical methods seem to have benefits in several areas and uses. Development seems to go to the direction of paying more attention in all application fields and hybrid methods combining the advantages of different algorithms.

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