Bio-inspired Memory Generation by Recurrent Neural Networks

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Abstract. 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. In this paper, we focus on artificial recurrent neural networks that model non-linear systems, in particular, Lotka-Volterra systems. After studying the typical behavior and processes that emerge in appropiate Lotka-Volterra systems, we analyze the relationship between sequential memory encoding processes and the higher brain centres in insects in order to propose a way to develop a general 'insect-brain' control architecture to be implemented on simple robots.

1 Introduction

What do we name "computation"? Let us say a system shows the capability to compute if it has memory (or some form of internal plasticity) and it is able to determine the appropiate decision (or behavior, or action), given a criteria and making calcultations and using what it senses from the outside world. Some biological systems, like several insects, have brains that show a type of computation that may be described functionally by non-linear dynamics [13]. In this paper, we focus on how we can build an artificial recurrent neural network that model non-linear systems (in particular, Lotka-Volterra systems [1]). After studying the typical behavior and processes that emerge in Lotka-Volterra systems [13], we will analyze the relationship between sequential memory encoding processes and the higher brain centres in insects. What is known 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 [3]. At the present, we know that higher brain centres in insetcs are related on autonomous navigation, multi-modal sensory integration, and to an insect's behavioural complexity generally; evidence also suggests an important role for context

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generalisation,short-term and long-term memory [11]. 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' behaviour, and more complex control will need to be modelled on 'higher' animals. Although various attempts at modelling the complex dynamics in insect brains have been made (e.g. [9], [14]), here it is proposed a simple CRNN (continuos and recurrent neural network) that could be the framework to implement competing processes between neurons that generates spatio-temporal patterns to codify memory in a similar way simplen living systems do. The particular aim of this paper is to provide a simple model 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.

2 Neural Network Computation from a Dynamical-System Viewpoint

Modern dynamical systems theory is concerned with the qualitative understanding of asymptotic behaviors of systems that evolve in time. With complex nonlinear systems, defined by coupled differential, difference or functional equations, it is often impossible to obtain closed-form (or asymptotically closed form) solutions. Even if such solutions are obtained, their functional forms are usually too complicated to give an understanding of the overall behavior of the system. In such situations qualitative analysis of the limit sets (fixed points, cycles or chaos) of the system can often offer better insights. Qualitative means that this type of analysis is not concerned with the quantitative changes but rather what the limiting behavior will be [8]. Here we are interested in analyzing the capacity of neural networks using heteroclinic trajectories for computing purposes [1].

2.1 Spatio-temporal Neural Coding and 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 [2]. We are going to discuss 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 ($N \geq 3$ 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

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

Which are the advantages of dealing with Lotka-Volterra systems?, Why do we study such a Lotka-Volterra models? We have shown above how a Winnerless competition proces 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 [7]. 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 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 [6].

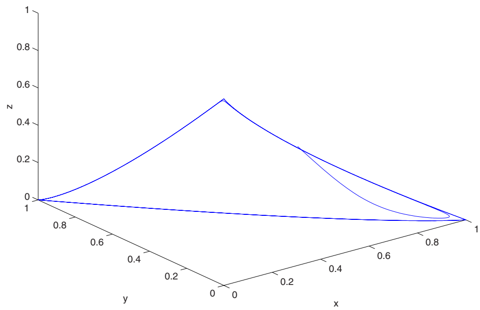

Fig. 1. Topology of the behavior in the phase space of WLC neurons net in a $3D$. The axes represent the addresses of the oscillatory connections between the processing units.

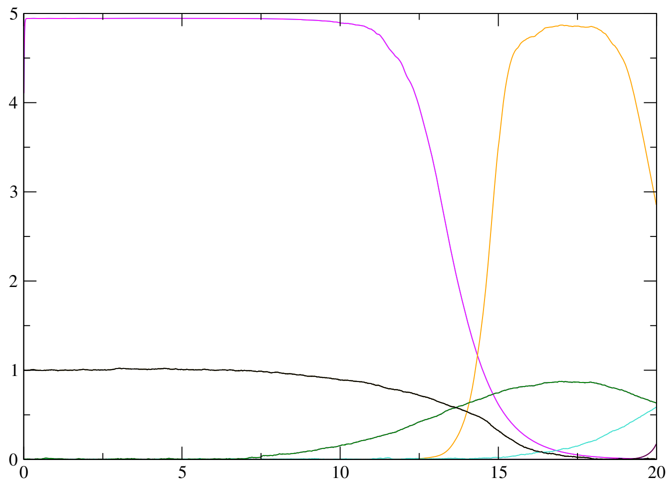

Fig. 2. Dynamics of some units of a WLC network. It is shown the sequence of the neurons oscillating and delayed between them.

3 Winnerless Competition Related to CRNNs: Model Description

We define a Recurrent Neural Network consisting in a set of N interconnected neurons which update their activation values asynchronously and independently of other neurons (all neurons are both input and output neurons). For a particular set of values of the connections, the network may have only a finite number of stable configurations where the network stores pattern (values of the connections and topology of the network are in direct correspondence to the stable configurations patterns). Given a RNN and an initial value x_0, the network evolves to an equilibrium state if f is suitably chosen. Every processing unit in such a network can be described by,

$$x_i(t+1) = f[x_i(t)],\ x(0) = x_0$$

The set of initial conditions in the neighborhood of x_0 which converge to the same equilibrium state is then identified with the state. If we choose the simplest case (f is linear and $y = f(x) = x$), the equilibrium condition will be after a relaxation process, $x_i(t+1) = x_i(t) = y_i,\ x(0) = x_0$. If we adopt a continuous-time framework, the network equations are:

$$\dot{x}_i = -x_i + \sum_{j=1}^{n} w_{ij} x_j$$

It is easy to proof it because if we use a finite difference schemes for discretization,

$$\frac{dx_i}{dt} \simeq \frac{\triangle x}{\triangle t} = \frac{(x(t+\triangle t) - x(t))}{\triangle t}$$

The first equation becomes $x_i(t+\triangle t) = (1-\triangle t)x_i(t) + \triangle t F(s_i)$, and taking $\triangle t$ as unity,

$$x_i(t+1) = F[s_i(t)]$$

So, the output of each neuron is

$$\dot{y}_i = \frac{dy_i}{dx_j}\frac{dx_j}{dt} = \lambda[-x_i + \sum_{j=1}^{n} w_{ij} x_j]$$

If we change the function f and select a non-linear expression (e.g. Sigmoidal function), $y = f(x) = \frac{1}{1+e^{-x}}$, and the network equations:

$$\dot{x}_i = -x_i + \sum_{j=1}^{n} w_{ij} x_j$$

And substituting the values that follow:

$$\frac{dy_i}{dx_j} = y_i(1-y_i)$$

and

$$y_i = \frac{1}{1+e^{-x_j}} \leftrightarrow x_j = -ln(\frac{1-y_i}{y_i})$$

$$\dot{y}_i = \frac{dy_i}{dx_j}\frac{dx_j}{dt} = y_i(1-y_i)[ln(\frac{1-y_i}{y_i}) + \sum_{j=1}^{n} w_{ij} y_j]$$

The 2nd factor in the first term $(1-y_i)$ is omitted without changing a qualitative feature of the dynamics. For simplicity, the term of the logarithm can be replaced by a positive constant (this replacement does not change the qualitative behaviour of the dynamics).

$$\dot{y}_i = y_i[\mu + \sum_{j=1}^{n} w_{ij} y_j]$$

that, as it can be seen, takes the form of a Lotka-Volterra system. Then it has been shown how we can build easily a Lotka-Volterra system through a RNN just using a sigmoidal function in every neuron. By adjusting the parameters w_{ij} and μ to the WLC conditions, we can guarantee a way to implement sequential memory in order to apply in control architectures of robots. We want to focus, with particular attention, the qualitative and quantitative changes in selection of winners in a recurrent neural networks which represent a Lotka-Volterra system showing a Winnerless competition behavior. In the next section, it is summarized the properties of such "Winnerless competition" solutions to the dynamic equation of neural activities and why these systems are interesting in the robotic engineering field.

4 Winnerless Competition for Computing and Interests in Robotics

If our aim is to realize how architectures for intelligent systems trying to emulate living beings, it should be included mechanisms to generate adaptive behaviour, robustness, great encoding capacity, etc. in a similar way how insects do to implement in an artificial framework. There are some computational proposals that show the way in which a simple dynamical system can resolve in an acceptable way an adaptive problem of simple election. But in general, the current models still do not reflect the complexity and heterogeneous nature of many of the empirical and realistic results that are known.

1. Some features of the Winnerless competition system seem to be very promising if we propose 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 excitation/inhibition relations [14]. These systems have:
   - Large Capacity: The capacity of the network, indicates the number of different items which the network may thus encode through its activity.
   - Adaptive patterns: the instability inherent to the nonlinear movements helps the system to adapt rapidly going from one pattern to another if the environment is changed [1].
   - Sensitivity (to similar stimulus) and, simultaneously, capacity for categorization: The neural systems can be, at the same time, sensitive (very discriminatory) and strong against perturbations.
   - 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).

2. In the other hand, in the work of [12], is described a very simple system, based in a system of coupled oscillators, that shows in a lower level description, a complex and fruitful adaptive behavior. In [12], the interaction among the activity of elements in the model and external influences give rise to an emergence of searching rules from basic properties of nonlinear systems as a whole (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 all by itself, 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.

Why are we interested in building such a kind of bio-inspired systems? Because of its features. Evolution has chosen the nonlinear dynamical phenomena as the basis of the adaptive behaviour patterns of the living organisms [9]. 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). The capacity of both systems are much larger than that of most traditional network structures, and adaptive rules emerge without designing them and we are interested in reproduce the same characteritics in artificial intelligent architectures.

5 Summary and Conclusions

We have proposed a RNN framework for codying and to build a memory inspired in the brain of insects (a class of models whose stimulus-dependent dynamics reproduces spatiotemporal features observed in higher brain centres of insects [10]. 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.

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