Toward a 'chaotic' cognitive architecture

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Abstract. The increasing complexity of humanoid robots and their expected performance in real dynamic environments demands an equally complex, autonomous and dynamic solution. The goal of this project is the design and implementation of a cognitive architecture based on the *enactive* paradigm of cognition. The core of this architecture will make use of tools from Nonlinear Dynamical Systems Theory, and especially coupled chaotic systems. Previous feasibility studies with these kinds of systems showed interesting results and motivated the proposed ideas. This paper will present a theoretical background for understanding the proposed architecture and some of the results that encouraged our present and future work.

1 Introduction

Research in humanoid robotics dates back approximately 30 years and was founded on a strong dualist view of human nature. In one hand, the body of an agent[1] has been controlled by using a 50-year-old tradition of control theory that started with industrial automation at the beginning of the 1960s. And in the other, its mind has been treated independently of its body by using the *cognitivist* approach, which was a very promising area of research that gave birth to what it is known as *artificial intelligence*.

Cognitivism is one of the two main paradigms of cognition and has been relatively successful in solving task specific problems. This approach sees cognition as a set of computations defined over symbols or representations of the world; these representations are pre-designed by a human programmer [36]. The main problems this approach has been and is still facing are due to its dependency on the programmer's knowledge of the world: the symbol grounding problem, the frame problem, and the combinatorial problem (Vernon08).

In our proposal we will focus in the development of a cognitive architecture based on the *enactive* paradigm of cognition. This paradigm sees cognition as a process of co-determination between the environment and the agent. In other words, the agent constructs its reality through the interaction with the world [35]. Therefore, in contrast with the *cognitivist* approach, the mind can not be

[1] The term *agent* will represent in this paper an artificial entity used for the simulation of human behavior

independent of the body and the knowledge about the world is not predefined by the designer[2].

The design of the proposed cognitive architecture will be based on the strategic use of tools provided by nonlinear dynamical systems theory, and specially chaotic dynamics. By using this theory, neither the agent nor the environment require to be modeled since both entities are seen as nonlinear systems; moreover, the way of solving a task is not specified in advance, as compared with the traditional control approach where the agent is told the steps to follow for solving the task or for overcoming certain problems. In short, if both approaches still need to know what to do, nonlinear dynamical systems theory will free us from knowing how to solve a task; thus overcoming the slow reactions found in traditional control models.

After more than one hundred years of the empirical definition of Chaos and almost fifty years of its formal study, it has been only in the last 10 years that we have witnessed its use in practical applications like telecommunications, economics, sociology, motor control, etc. However, our main interest in this theory has to deal with the evidence found by several researchers in the areas of neurophysiology and developmental psychology.

1.1 Related work

Based on experimental results, several groups have suggested the presence of chaos in the brain [7, 16, 2]. With little differences on the exact role of chaos, these results show a dynamic link between perception and memory built within a nonlinear dynamic (chaotic) space. Even though the different models derived from these studies have reported great improvements when compared to conventional neural networks, a final mechanism of actuation in the same dynamic terms is missing in all of them. In other words, only perception and memory are being addressed in these models, but they do not consider motor outputs as part of these dynamic systems; in some cases they discretize the output space [10], thus loosing the efficiency gained before.

On the other hand, several groups have focused their research in the reflexive part of their agents [22, 19, 18, 27, 6]. In these models actuation is performed without considering the history of the agent. These and other groups have developed remarkable advances in adaptive behavior but, in contrast with the previous group, only perception and actuation is being addressed; thus leaving memory out of sensorimotor loop.

There is no cognitive architecture among the current models of cognition that makes direct use of nonlinear dynamical systems theory. Most architectures belonging to the enactive paradigm of cognition use modular versions of feedforward neural networks for classification and regression [3, 28, 4, 17]. This type of networks are nonlinear static networks, i.e., a given input is associated with a given output and remains in a steady state as long as the input remains the same. This leads to a reduced memory capacity and a great dependence to the quality

[2] Read [36] for a thorough study on cognitive systems.

of the training datasets. Other architectures like the Self-aware and Self-effective (SASE) cognitive architecture [20], use statistics in the form of Markov Decision Processes. Here again it is necessary to find other ways of saving, addressing and retrieving memories which results in expensive computation processes.

1.2 Objectives

The main goal of our research is to create a cognitive architecture that, using the mathematical tools from nonlinear dynamical systems theory, integrates the information coming from sensors with the information coming from an internal space (memory), and that finally modulates the motor outputs inside a reflexive physical layer. The major contribution of a system like the one proposed here is the possibility of having a dynamic sensorimotor loop that includes history as a modulator in the decision making step for the final motor behavior.

Among other advantages of working in specific chaotic regimes like *chaotic itinerancy* [33], with respect to non-recurrent neural networks, it is possible to mention the dynamic retention of information, increased learning capabilities, improved patter recognition, efficient search of memories, memories can be represented by dynamic processes and not only as static patterns, simultaneous process of learning and recalling [32].

Section 2 introduces the methodology followed in our current work and which also serves as road map for achieving the goals proposed in this paper. Some of the most interesting results from previous experiments on the implementation of coupled chaotic systems will be presented in Section 3. Finally, ...

2 Research methodology

Any human behavior could be described by the integration of three big components interacting continuously among them. An input block: Different kinds of information are acquired through specific types of sensors installed in the physical layer (hardware) of an agent. An output block: Constitutes the set of devices, also part of the physical layer, used by the agent for the generation of specific actions within the environment; i.e. motors, displays, speakers. And finally, a 'mind' block: A more complex system made up of several parts but all belonging to a software layer (mindware); i.e. short and long term memories, emotions, attention cycles, decision making.

The methodology for the study of mindware is based, as mentioned before, in the concepts of nonlinear dynamical systems theory. The main components of this block are the different stages in the creation, association, searching and retrieval of memories. Different models of dynamic memories will be studied, specially those proposed by Tsuda [33, 34], Freeman [10] and Molter [21]. All of these approaches handle information with chaos always in the background and make use of recurrent neural networks for their implementation.

A cognitive developmental autonomous system can not be achieved by considering a good reactive physical layer and a dynamic way of saving and retrieving memories only. For an agent to be considered autonomous, a way of switching between different cycles of attention, mental and/or physical rehearsal, and correct retrieval of previously learned sensorimotor information will be developed.

3 Previous experiments

3.1 Coupled Maps with Adaptive Connections

Coupled Map Lattices (CML) and Globally Coupled Maps (GCM), were introduced by Kunihiko Kaneko in the middle of the 1980's as an alternative for the study of spatiotemporal chaos [15]. In short, this kind of dynamical systems use discrete partial difference equations to study the evolution of a process described by discrete steps in space and time but with continuous states. Two parameters control the dynamics of these maps: a chaoticity factor and the strenght of connections among their elements.

The study of dynamically varying the connections among the elements in a GCM was done by Ito and Kaneko [14, 13]. The model is described by the set of equations in (1). The first equation correspond to a GCM, where f represents a chaotic map; (1c) updates each unit's connections coming from other units in the network; and (1d) specifies the hebbian rule governing the relationship between all units. The classic version of the logistic map (1b) is used as transfer function in all experiments.

$$x_n^i = f\left((1-\epsilon)x_{n-1}^i + \epsilon\sum_{j=1}^{N} w_n^{ij} x_{n-1}^j\right), \tag{1a}$$

$$f(x_n) = 1 - \alpha x_{n-1}^2 \tag{1b}$$

$$w_{n+1}^{ij} = \frac{\left[1+\delta g\left(x_n^i, x_n^j\right)\right] w_n^{ij}}{\sum_{j=1}^{N}\left[1+\delta g\left(x_n^i, x_n^j\right)\right] w_n^{ij}}, \tag{1c}$$

$$g(x,y) = 1 - 2\left|x-y\right| \tag{1d}$$

In (1c), δ represents the degree of plasticity of the connections and ranges from 0 to 1. Weights w^{ij} in (1c) refer to the influence from unit j going into unit i. All self-connections were set to 0; and the initial condition for all remaining connections are equal to $1/(N-1)$, N being the number of chaotic units.

3.2 Methodology

A copy of the iCub's head, the humanoid platform of the Robotcub's project [25], was used in previous experiments. The head has six degrees of freedom: yaw, pitch and roll for the neck, a single pitch motion for both eyes and independent yaw motors for each eye. Each eye has a camera that provides two quantities: the position of the target in vertical and horizontal directions. These values modify the position of each motor; thus generating a coupled chaotic system with 6 logistic maps, Fig. 1.

Fig. 1. iCub's sensorimotor diagram, 5dof actuation.

3.3 Results

The development of weak and strong connections among the chaotic units depend on the level of interaction they have through time, Fig. 2. Even though all connections start with the same value, the system takes only a few time steps to separate in groups of strong and weak connections. A very interesting observation from this plot is that after approximately 500 steps, the connections arriving to any unit oscillate around the middle of the permitted strength. Extreme cases are with pitch units in each eye LP and RP which develop a very strong influence from the pitch motion of the neck NP but a zero influence from one to another. Yaw units develop a more balanced influence in their network, oscillating always around 0.5.

At time step 3500 the system has entered in an almost fully developed state where its internal connections vary very little. In the end, each unit is influenced by no more than two other units within the whole network, Fig. 2. As expected, two independent sub networks emerge after approximately 20 seconds. In one side all chaotic units fed by yaw motions strengthen their connections while weakening those toward and from 'pitch' units; and the same happens with those units fed by pitch motions when compared to 'yaw' units.

4 Discussion

Modern and classical control theories have been the two frameworks applied for controlling any kind of autonomous system. They have proved to be very accurate and efficient inside industrial environments where machine and environment can be modeled precisely since they work within fixed spaces. Even though mobile and specially humanoid robotics are pushing us to reconsider the usefulness of this approach in dynamic an unpredictable environments, several state-of-the-art platforms keep using the traditional tools of control theory. Albeit the exponential growth of computational power has helped to deal with the

Fig. 2. Top: Initial (left), and final (right) configurations of the GCM. Bottom: Development of connections in time.

expensive treatment of inverse kinematics/dynamics and environment modeling of these systems, they fail every time they find a situation that demands fast reactions or motions that were not coded by the programmer.

A dynamic, flexible and autonomous cognitive architecture is needed today more than ever to get a better understanding of human nature. A system based on nonlinear dynamical systems theory would be of great importance for the study of areas such as epilepsy [12, 29], developmental psychology [31, 1, 30], psychotherapy [24, 23], motor control [9, 5, 11], neurosciences [8, 26, 32], and many others. At the same time, a cognitive architecture like the one proposed here will be of great use for, but mainly will try to integrate several areas of scientific research like human-robot interaction, imitation, motor control, computer vision, and machine learning. Each one of them has demonstrated to be a complex subject and integrating them will be a challenge on its own.

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