Eyes-Neck Coordination Using Chaos

Boris Durán[1], Yasuo Kuniyoshi[2], and Giulio Sandini[1]

[1] Italian Institute of Technology - University of Genova,
Via Morego 30, 16145 Genova, Italy,
boris@unige.it, giulio.sandini@iit.it,
[2] University of Tokyo, Laboratory for Intelligent Systems and Informatics,
Eng. Bldg. 2. 7-3-1 Hongo, Bunkyo-ku, Tokyo, Japan
kuniyosh@isi.imi.i.u-tokyo.ac.jp,

Abstract. The increasing complexity of humanoid robots and their expected performance in real dynamic environments demand an equally complex, autonomous and dynamic solution. Our approach for the creation of real autonomy in artificial systems is based on the use of nonlinear dynamical systems. The purpose of this research is to demonstrate the feasibility of using coupled chaotic systems within the area of cognitive developmental robotics.
Using a robotic head, we demonstrate that the visual input coming into the head's eyes is enough for the self-organization of the axes controlling the motion of eyes and neck. No specific coding of the task is needed, which results in a very fast adaptation and robustness to perturbations. Another equally important goal of this research is the possibility of having new insights about how the coordination of multiple degrees of freedom emerges in human infants. We show that the interaction between body and environment modifies the inner connections of the controlling network resulting in the emergence of a tracking behavior.

1 INTRODUCTION

Most of today's humanoid platforms follow an almost 50-year-old tradition of control theory that started with the industrial automation at the beginning of the 1960s. The methodology followed by this approach is based on modeling as precise as possible both the plant and the controller; and filtering or processing as noise the different unexpected circumstances that could occur during the operation of the system. This approach has worked pretty well when the system is in a fixed framework and the environmental conditions are known and controlled; however, this will not be the case for humanoid robots of the future. It is absolutely necessary to start working on a different approach if we want to design and build systems that move and act in the same kind of dynamic environments where humans move and act. A more adaptive and flexible theory is needed in order to 'control' a device that is supposed to move within an ever-changing environment. These are our first steps towards the design and implementation of a real autonomous cognitive architecture based on nonlinear dynamical systems.

Although the study of nonlinear dynamical systems and chaos has also a long history, real applications that make direct use of chaos theory have not been fully developed. The purpose of this research is to demonstrate the feasibility of using coupled chaotic systems [1] within the area of cognitive developmental robotics. Based on the model of behavior emergence introduced by Kuniyoshi et al. [2], we study the coordination of multiple degrees of freedom in humanoid robots.

The task of tracking an object has been fully studied and many solutions presented before. Based either in position errors or velocity mismatches, some approaches try to control the activation of motors by means of robust PID controllers [3–5], while others base their controllers in fuzzy logic [6] or neural networks [7]. In any case, the common methodology in these approaches is to compute expensive Jacobian and kinematic expressions thinking in all the possible circumstances the system could encounter.

All these works comprehend the state of the art in motor control for tracking systems; therefore it would not be necessary to develop new solutions. However, the tracking problem represented the simplest test bed for the study of coupled chaotic systems, both in a simulated environment and for its implementation in a real platform. Our approach differs from previous work mainly in two aspects: first, our system does not need to deal with complex equations of kinematics and dynamics; second, the main goal behind our research is not to improve the performance of existing algorithms but, through our experiments, start building the basis of a dynamic model for motion emergence that embrace as a single entity body and environment. Following Esther Thelen and Linda Smith's suggestion that "action and cognition are also emergent and not designed" [8], another equally important goal of this research is the possibility of having new insights about how the coordination of multiple degrees of freedom emerges in human infants.

The following section contains a short introduction on chaos and coupled chaotic systems; as well as a description of the model of behavior emergence proposed in [2]. Section III describes the experimental setup and the results of our experiments from the implementation of our model when working with constant parameters. In Section IV it is presented the results of a developmental process in a five degree of freedom implementation of our approach. Finally, conclusions and guidelines for future work are summarized in section V.

2 Coupled Chaotic Systems

2.1 A Short Introduction to Chaos

The word 'chaos' has been used to represent a part of nonlinear dynamical systems theory that deals with the unpredictable behavior of a system governed by deterministic rules, [9]. One of the most common, and probably the simplest, deterministic rule that generates chaos is the logistic map (1). This second-order difference equation was studied by the biologist Robert May as a model of population growth [10]. In this equation, the parameter α controls the nonlinearity of the system. In order to keep the system bounded between -1 and 1, α takes values between 0 and 2, Fig. 1.

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

A stand-alone logistic map (internal feedback whitout external influences) stabilizes in an specific behavior depending on its initial condition and the value of α. This very simple rule can generate fixed points, Fig. 1a; periodic oscillations of period two, Fig. 1b; period four, Fig. 1c; and following the period doubling path until reaching a choatic behavior, Fig. 1d.

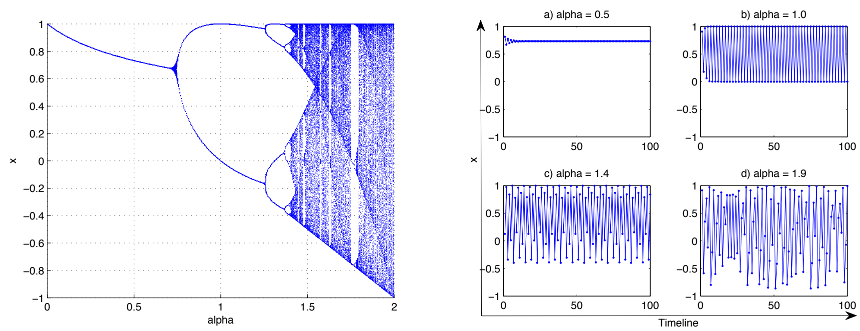

Fig. 1. Left, bifurcation plot for logistic map. Right, different outputs for Logistic Map depending on α

2.2 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 [1]. 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.

Due to the chaotic nature of the system, it is possible to see one of the main properties of chaotic systems: two slightly different initial conditions amplify their difference through time. On the other hand, the system tries to synchronize the activations of all its chaotic elements by coupling them. In between these two states of complete chaos and complete synchronization, interesting states emerge like the formation of clusters oscillating in different phases and amplitudes.

The study of dynamically varying the connections among the elements in a GCM was done by Ito and Kaneko [11, 12]. The model is described by the set of equations in (2). The first equation correspond to a GCM, where f represents a chaotic map; (2b) updates each unit's connections coming from other units in the network; and (2c) specifies the hebbian rule governing the relationship between all units.

$$x_n^i = f\left((1-\epsilon)x_{n-1}^i + \epsilon \sum_{j=1}^{N} w_n^{ij} x_{n-1}^j\right), \tag{2a}$$

$$w_{n+1}^{ij} = \frac{\left[1+\delta g\left(x_n^i, x_n^j\right)\right] w_n^{ij}}{\sum_{j=1}^{N}\left[1+\delta g\left(x_n^i, x_n^j\right)\right] w_n^{ij}}, \tag{2b}$$

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

In (2b), δ represents the degree of plasticity of the connections and ranges from 0 to 1. The weights w^{ij} in (2b) 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.

2.3 A Model for Behavior Emergence

The states of each of the elements in a GCM, or a CML, depend only on the internal dynamics of these systems; they are not influenced in any moment by an external force. When taking these concepts to robotic applications it is necessary to think in a way of including the environment within the dynamics of the system.

The model used in this project is based on the approach followed by Kuniyoshi and Suzuki [2]. Their model uses both, the local interaction (CML) and the global interaction (GCM) but with the environment as the external force influencing the internal dynamics of the network. In our case, only GCM was used since no extra benefit was seen when including local connections; nevertheless the overall approach is the same, Fig. 2.

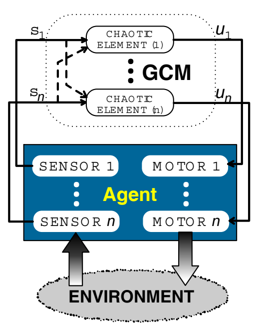

Fig. 2. Body-environment interaction through coupled chaotic fields

3 Implementation

A copy of the iCub's head, the humanoid platform of the Robotcub's project [13], was used in the present work. The head's hardware and software components will be described in the following subsections together with the implementation of the algorithms used to create a dynamic smooth pursuit.

3.1 Hardware and Software

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. DC-micromotors are used for moving the different joints; each motor contains an incremental encoder that provides the position of the joint at any time. All motors and sensors are controlled by a suite of DSP chips which channel data over a CAN bus to a computer in charge of iCub's high-level behavioral control [14].

Due to the large amount of sensori-motor information generated within the platform the iCub's software was configured to run in parallel on a distributed system of computers. An open-source framework for robotics named YARP (Yet Another Robot Platform) [15] was used for the implementation of the algorithms. It is important to mention that the focus of this project is not the extraction of saliencies from moving images, which is in itself a hard problem in computer vision. A tracking algorithm available in the YARP repository was used as the visual component in charge of providing us with the horizontal and vertical coordinates of a moving object. With this information we focus our efforts on the motor control problem.

3.2 Methodology

Each camera 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. 3. The algorithm governing the dynamics of the system is governed by (3).

$$u_n^i = f\left((1-\epsilon)s_{n-1}^i + \epsilon \sum_{j=1}^{N} w_n^{ij} s_{n-1}^j\right) \tag{3a}$$

$$\begin{aligned} m_n^i &= G_m(u_n^i + O_m) \\ s_n^i &= G_s(r_n^i + O_s) \end{aligned} \tag{3b}$$

Where m is the output applied to each motor as speed values, s and u are inputs and outputs respectively of the chaotic field block, and r is the raw value coming from the sensors. Finally, G_m, G_s, O_m, and O_s are gains and offsets of the sensors and motors respectively; these values are applied in the same magnitude to all elements in the system.

The methodology for tuning offsets was done by approximating the average of the raw output from the logistic map towards a zero average of the motor

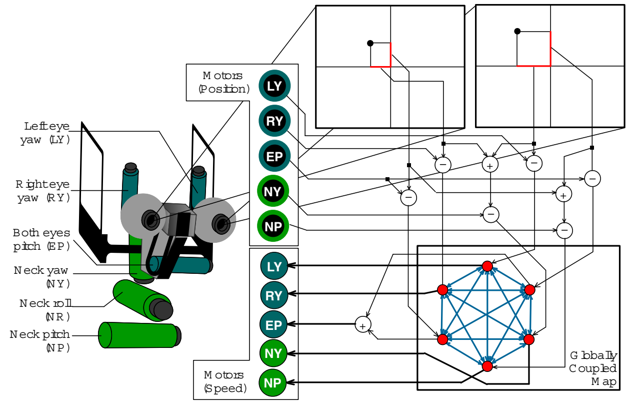

Fig. 3. iCub's sensorimotor diagram, 5dof actuation.

activation values. In other words, offsets should be chosen in such a way that the activations from the logistic map oscillate around zero. Gains G_m were chosen depending on the speed limits of the motors. The following parameters were fixed during all experiments:G_s=1.0, O_s=-0.8, $G_{LY} = G_{RY} = G_{EP}$=25.0, G_{NY}=70, G_{NP}=35, and O_m= 0.0; $\alpha = 1.9$, and $\epsilon = 0.1$.

3.3 Results

The motion of both eyes and the motion of the head is shown in Fig. 4. This plot shows the motion of the eyes relative to the head and the motion of the head relative to its fixed position. In this plot is possible to see the coordination between eyes and neck. The target was moved in random directions and at different speeds. Since the joints of the neck give approximately an extra 60 degrees on each side and on each direction, an object can be tracked in a wider space. It was also observed an increase of the tracking speed when compared to the 3dof case (2-eye tracking). The motors in the neck help the motors in the eyes to follow the object in a faster way, especially in the yaw direction.

The coordination between both eyes and between eyes and neck in each direction can be more easily appreciated in Fig. 5. Since the tracking algorithm works on independent threads in each camera, different points in space are delivered to the GCM. This 'computer vision' problem creates the errors observed during some points during the experiments.

The activations of all units grouped in yaw, Fig. 6, and pitch Fig. 6 directions show the dynamics of the system. Here is also possible to see the coordination of chaotic units since all activations are gathered along the diagonal of each plot. The nonlinearity of the chaotic units give them enough freedom to use the rest of the space when needed but always staying and returning back to this diagonal.

The development of weak and strong connections among the chaotic units depend on the level of interaction they have through time, Fig. 7. Even though all

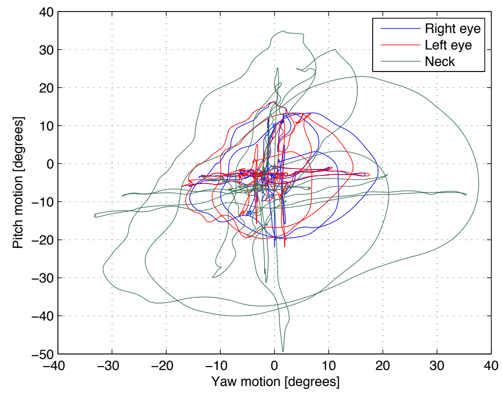

Fig. 4. Motion of both eyes and neck.

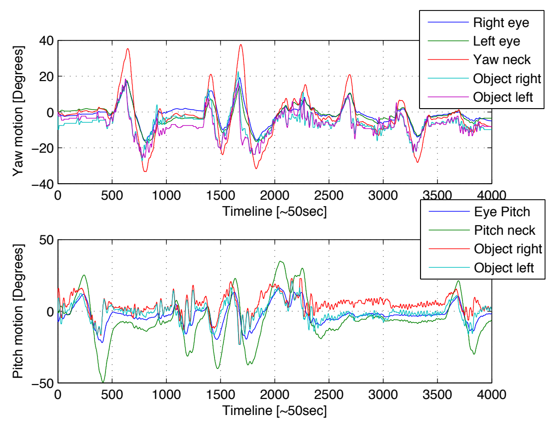

Fig. 5. Position of target w.r.t. center of eye: yaw motion, top; and pitch motion, bottom.

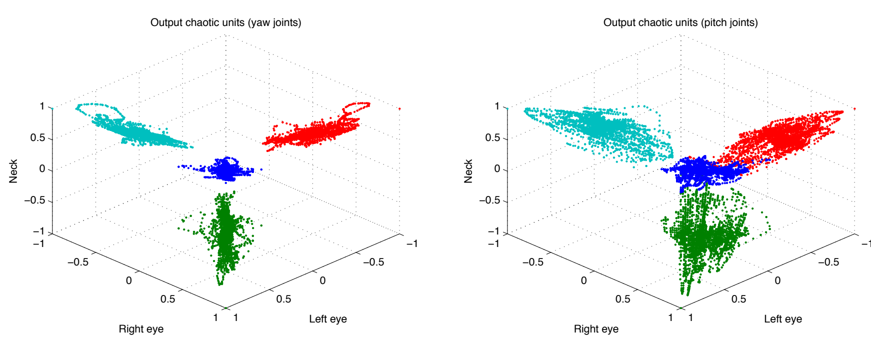

Fig. 6. Left, phase space (yaw). Right, phase space (pitch)

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.

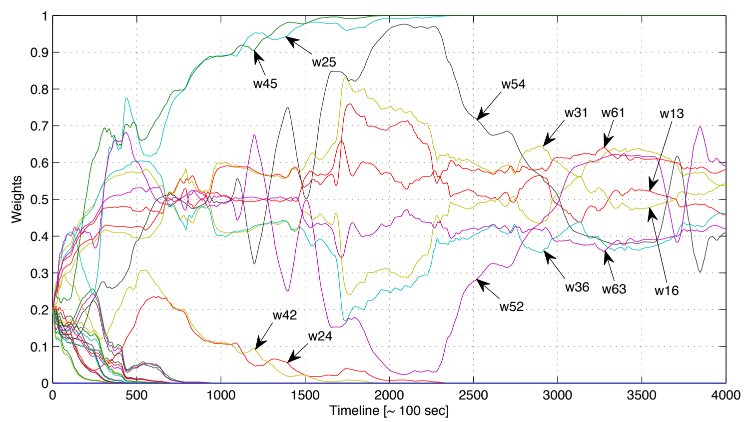

Fig. 7. Development of connections in time.

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. 8. 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 towards and from 'pitch' units; and the same happens with those units fed by pitch motions when compared to 'yaw' units.

4 Conclusions and Future work

Conclusions

A very simple experiment for demonstrating the feasibility of applying coupled chaotic systems in the area of cognitive developmental robotics has been shown in this project. Tracking an object moving in front of a camera has been solved in several ways previously, from using very simple trigonometric solutions to advanced control algorithms. However, this task represented the simplest test bed for the study of emergence of a reactive behavior in a real platform.

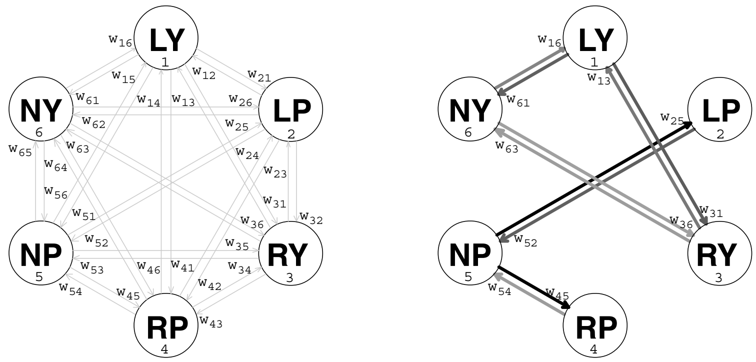

Fig. 8. Initial (left), and final (right) configurations of the GCM.

A copy of the iCub's head [13], a 6 DOF robotic platform, was used to replicate the sensori-motor configuration of a real head. The tracking algorithm used in all experiments was taken from the YARP repository [15]. The experience obtained in previous experiments with the simulation and implementation of a single eye tracking [16] gave us enough confidence to increase the complexity of our model. The present work contains the results on the development of connections in the eyes-neck coordination problem (5 DOF).

We have demonstrated that a visual input is enough for the self-organization of a globally coupled map whose outputs are used as speed values activating each of the joints of our device. No specific coding of the task is needed, which results in a very fast reactive behavior. A very simple Hebbian rule was used to study the development of connections within the core of the system, a globally coupled map. From normalized initial connections we saw them changing through time, restructuring the 'brain' according to the experiences with the environment. In the final stage, two independent sub networks were formed, one containing yaw-related chaotic units only and the other pitch-related chaotic units only. The smooth pursuit behavior emerged during this process.

Future work

The iCub's head includes also an inertial sensor which will be used in the future as another element influencing the chaotic field. Several questions should be addressed regarding the correspondences between this research and the biological counterpart; for example, if a smooth pursuit behavior emerged from the interaction of chaotic units, could it be possible to obtain other visual behaviors like vestibulo-ocular reflex (VOR), vergence or saccades in the same way?

The tracking algorithm used in all experiments does not focus on the same point in both cameras; consequently a displacement is observed when comparing the centers of both images. Therefore, this algorithm will be modified in order to visually track the same point in space.

Acknowledgments

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