Towards a “chaotic” smooth pursuit

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***Abstract*— Real autonomous systems are very difficult to design, mainly due to the ever changing conditions of the environments where they are supposed to work. In the area of humanoid robotics these difficulties are increased not only because of the complexity of their mechanical structure, above all because they are supposed to work under the same dynamic conditions as we humans do. 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.**

In our quest towards the design and implementation of a real self-adaptive autonomous cognitive architecture, we have decided to start with a simple application that will tell us how appropriate this approach can be for humanoid robots. Once an object appears in front of a camera, we demonstrate that the visual input is enough for the self-organization of the axes controlling the motion of a single eye, both in a virtual and a real platform. No learning or 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.

I. 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], [4], [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, this 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. 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.

According to neurosciences, all behavior is mediated by the central nervous system (brain and spinal cord) which is separated but functionally interconnected with the peripheral nervous system (continuous stream of sensory information about the environment). Simply put, the major difference between voluntary and reflexive movements is the intervention or not of the central nervous system [8]. In practice, it is not possible to separate the modulation signals coming from the brain into the muscles of our eyes. But according to the results of this experiment, we could speculate that visual tracking is just a reactive behavior given a saliency in our visual field. These saliencies are the necessary modulations given by our central nervous system and its areas of emotions, experiences, needs, etc.

The next section describes the basics of coupled chaotic systems together with the model of behavior emergence proposed in [2]. In section III a description of the simulation setup used for smooth pursuit is presented together with the results. Section IV presents the physical platform and results of the implementation of this approach; and, finally, conclusions and guidelines for future work are summarized in section V.

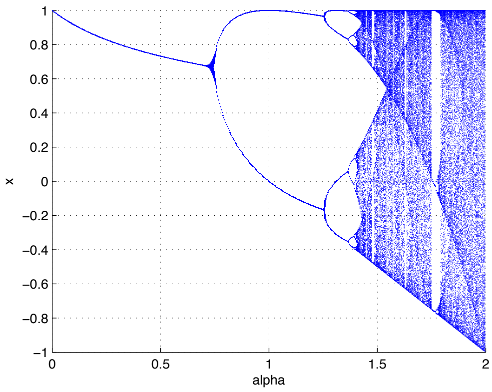

Fig. 1. Bifurcation plot for logistic map

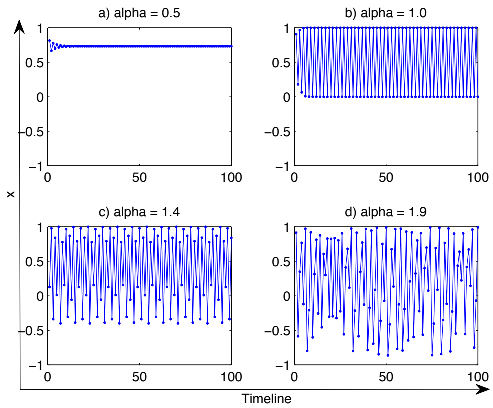

Fig. 2. Logistic map, different outputs depending on α

II. Coupled Chaotic Systems

A. 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]. It is often easier to understand what chaos is through the examples found in almost all the areas of sciences studying nature: it can be found in the way the weather changes every year (Lorentz); in the way the planets and all other celestial objects influence each other and move in space (Poincaré); in the dynamics of population grow (May); the turbulence generated in fluid systems (Libchaber); etc.

One of the most common, and probably the simplest, deterministic rule that generates chaos is the logistic map, Eq. (1). This second-order difference equation was studied by the biologist Robert May as a model of population growth. In this equation, the parameter α controls the nonlinearity of the system. In order to keep the system bounded between 0 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 without 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. 2a; periodic oscillations of period two (Fig. 2b), period four (Fig. 2c); and following the period doubling path until reaching a chaotic behavior, Fig. 2d.

B. Coupled Map Lattices (CML)

CML 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. Equation (2) describes the dynamics of CML, whereas Eq. (1) represents the logistic map used in this work.

$$x_n^i = (1-\epsilon) f(x_{n-1}^i) + \frac{\epsilon}{2}\{f(x_{n-1}^{i+1}) + f(x_{n-1}^{i-1})\} \tag{2}$$

Where x_n^i is a variable at discrete time step n and a lattice point i. x represents a set of field variables which could be temperature, position measurements, velocities, etc. There are two parameters: α controlling the level of chaoticity of the system and ϵ controlling the coupling level among neighbor elements.

C. Globally Coupled Maps (GCM)

These kinds of maps were also introduced by Kaneko and represent a network of chaotic elements with interactions among all of them. While CML interact with specific points within the lattice, each of the nodes in a Globally Coupled Map (GCM) interacts with all the others, Eq (3). Due to the chaotic nature of the system, specified by α, 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, ϵ tries to synchronize the activations of all these 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.

$$x_n^i = (1-\epsilon) f(x_{n-1}^i) + \frac{\epsilon}{N}\sum_{j=1}^{N} f(x_{n-1}^j) \tag{3}$$

During the last two decades, these two categories have been the subjects of thorough investigation with the aim of describing them both qualitatively and quantitatively. The effects of varying both, chaoticity and coupling factor, in stand-alone CML and GCM systems were studied meticulously by Kaneko's group in the late 1990's [10], [11]. Approximate phase diagrams were sketched covering the whole spectrum of synchronization among the interacting chaotic elements of a network.

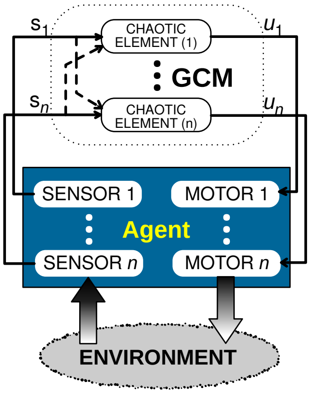

Fig. 3. Body-environment interaction through coupled chaotic fields

D. Coupled Chaotic Fields

The model used in this project is based on the approach followed by Kuniyoshi and Suzuki [2]. The main idea behind this model is to make use of the freedom given by the chaoticity of the system; and, on the other hand, the limitations imposed by the synchronization of all the elements. It is being used both, the local interaction (CML) and the global interaction (GCM). The system is depicted in Fig. 3. Each one of the blocks containing "Chaotic" elements and their relationship constitute the core of the system and it is defined by Eq. (4) and (5). The function f represents the logistic map, Eq. (1).

$$u_n^i = f\left\{ s_{n-1}^i + \epsilon_1(\bar{s}_{n-1} - s_{n-1}^i) + \epsilon_2\left(\frac{s_{n-1}^{i+1} - s_{n-1}^{i-1}}{2} - s_{n-1}^i\right)\right\} \tag{4}$$

$$\begin{aligned} m_n^i &= G_u(u_n^i + O_u) \\ s_n^i &= G_s(r_n^i + O_s) \end{aligned} \tag{5}$$

Where m is the output applied to each motor, 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_u, G_r, O_u, and O_r are gains and offsets of the sensors and motors respectively; these values are applied in the same magnitude to all the elements of the system.

III. Simulation

A. Software

To simulate the dynamics of an artificial eye, a virtual environment named Webots has been used [12]. This software is based on the Open Dynamics Engine libraries for reasonably accurate physics simulation such as the effect of gravity and friction. The time step for the simulations was fixed to 32 milliseconds and the experiments were done without the influence of gravity and with a minimum value of friction.

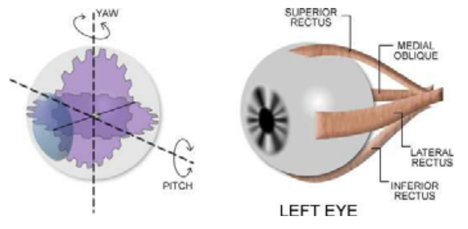

Fig. 4. Biological eye and its virtual counterpart for the experiment

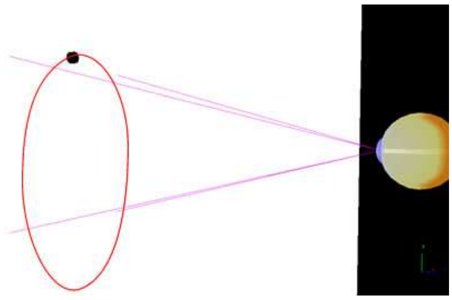

Fig. 5. Screenshot of the virtual setup

B. The setup

The virtual eye was created using two rotational joints, one perpendicular to the other in order to simulate the "yaw" and "pitch" motions of a real eye, Fig. 4. Each joint is also modeled by a spring and a damper, trying to replicate the physical characteristics of real muscles. These two motors are actuating the virtual eye in the same way as the main four muscles do in biological eyes.

A virtual camera mounted in front of the eye gives the visual input needed for modulating the chaotic field. The width and height were fixed to 32 x 32 pixels with a field of view of 0.5 radians. It is assumed that values of saliency are obtained from other visual components. One of these values to be tracked was simulated by a black circular shape moving on a white screen, Fig. 5. The initial conditions were defined by having the object out of the field of view of the eye and generating a circular motion from zero to a maximum speed, and slowing down to zero again for two cycles, then changing direction for another two cycles of zero to maximum speed and so on. This motion was used as a basic test for the robustness of the system.

The input to the system is given by the difference between the center of the observed object within the field of view and the position of the center of the eye, for both the vertical and horizontal motions. The outputs from the chaotic field are fed as speed values to the motors after applying the respective offset and gain.

The methodology for tuning the gains and offsets was done by approximating the average of the raw output from the logistic map towards a zero average of the motor activation values. In other words, offsets and gains should be chosen in such a way that the activations from the logistic map oscillate around zero. Our simulation worked with the following offsets and gains: G_u=1.0, G_r=1.0, O_u= 0.0, and G_s=-0.72, for α=1.9 and ϵ=0.1.

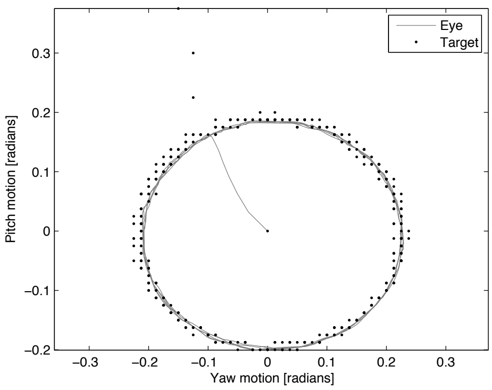

Fig. 6. Motion of the eye (α = 1.9, ϵ = 0.1)

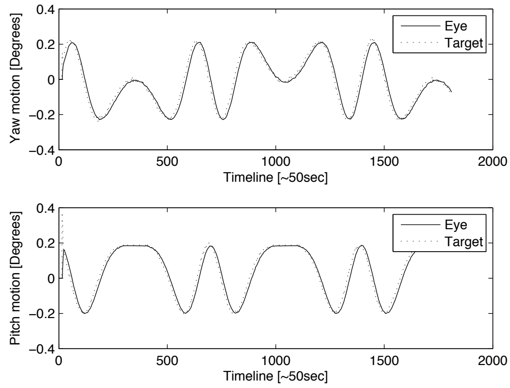

Fig. 7. Relative displacement between eye and object.

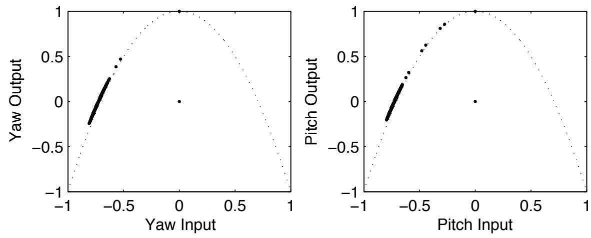

Fig. 8. Return maps for both chaotic units. The dotted line is shown as refence for the logistic map.

C. Results

As mentioned before, the outputs from our globally coupled map were treated as speeds; in other words, we wanted our system to be controlled in velocity. However, it was proven that the same configuration and parameters were enough for controlling our virtual eye either in position or in torque. The trajectory followed by our virtual eye can be observed in Fig. 6. The first reaction, once the object has entered into the eye's field of view, is to move toward the object. As we can see, the adaptation to the path of motion is immediate, there are no overshooting or oscillations.

Note that there is no way of discerning the moments where the object is not moving or moving at full speed, this tell us how adaptive the system is to changes in the environment. Even though the tracking is not accurate, the object remains inside the field of view and almost in the center of the eye throughout the simulation time.

The simulation was run over more than two cycles of increasing and decreasing the object's velocity, Fig. 7. The overshooting observed at the beginning of the plot is the result of the object entering into the field of view of the eye; in less than one second, the system adapts to the recent change in the environment. It is possible to observe those moments when the object is changing direction, its speed decreases to zero; the relative displacement of the center of the eye and the object decreases even more.

Finally, Fig. 8 represents the relationship between the input to the GCM and its output on both chaotic units, yaw and pitch. The inputs to this function are the errors in both horizontal and vertical directions after being modified by their previous states and the influence among each other. The linearity of both units is necessary for the tracking to occur.

The "smooth pursuit"-kind of motion was tested using different values of α (chaoticity factor) and ϵ (coupling factor). However the tracking behavior was found to be optimal for a high chaoticity and small coupling. When decreasing α to values smaller than the critical point for being inside the desynchronized areas ($\alpha \approx 1.34$), it was possible to see the appearance of other interesting behaviors like avoidance of the target or a sort of "boring" tracking, following the target for a short time but relaxing after a while. The motion of eye and target for the later case is showed in Fig. 9.

IV. Implementation

The results from the simulation gave us enough confidence to implement this algorithm in a real platform. The following subsections describe the experimental setup and the results of implementing the GCM algorithm for the activation of two degrees of freedom.

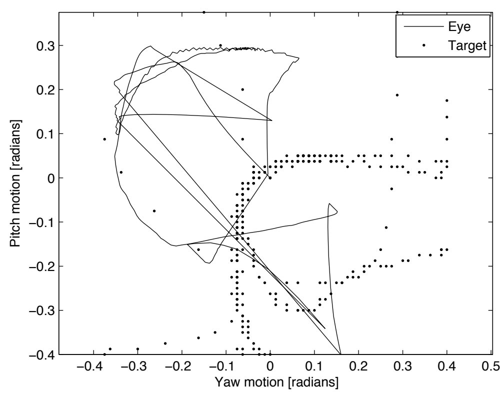

Fig. 9. A "boring"-kind of tracking ($\alpha = 1.05$, $\epsilon = 0.1$)

Fig. 10. Picture of the iCub's head

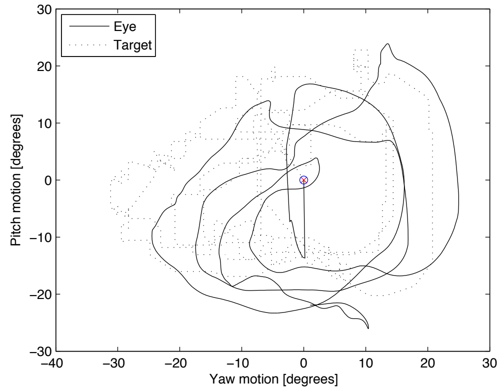

Fig. 11. Motion of the eye

A. Software

An open-source framework for robotics named YARP (Yet Another Robot Platform) was used for the implementation of the algorithms. The main features of YARP are: support for inter-process communication, image processing, and a class hierarchy to code reuse across different hardware platforms [13]. The programming language in YARP is C++; however, a set of libraries has been developed to allow other programs, like Matlab, access YARP.

As mentioned before, the focus of this project is not the extraction of saliencies from the image, 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.

B. Hardware

A copy of the iCub's head from the RobotCub project [14] was built to test this and future 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. Three Faulhaber DC-micromotors [15] are used for moving the eyes; each motor contains an incremental encoder that provides the position of the joint at any time. We invite the reader to visit the project's webpage for having more information about hardware and software. The RobotCub project has been thought to be distributed as an open platform both in hardware and software. Fig. 10 shows a picture of the platform.

Again, the difference between the center of the observed object within the field of view and the position of the center of the eye, for both vertical and horizontal motions, was the value that modified the way the chaotic system behaves. The algorithm governing the dynamics for this part of the project was the same as in the simulation; however, the gains and offsets had to be modified, Eq. (4, 5) since the values representing mass, inertia, friction and gravity are different in both frameworks. Using the same methodology for adjusting gains and offsets as before, these values were fixed to: G_u=1.0, G_s=1.0, O_u= 0.0, and O_s=-0.8; α = 1.9, and ϵ = 0.1.

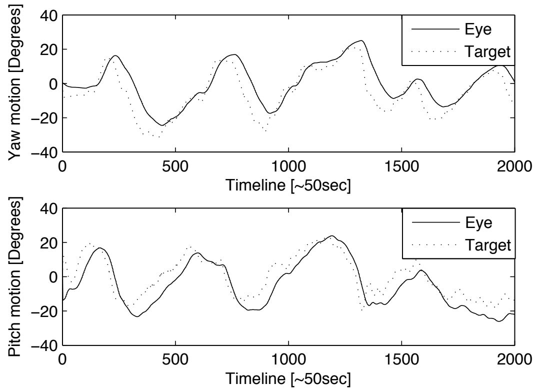

Fig. 12. Root Squared Error

C. Results

Figure 11 depicts the motion of the eye as well as the motion of the target. When analyzing these results, it is important to remember the following working conditions: first, the target was moved in all possible directions and with different speeds; second, the target was moved in several occasions into the limits of the visual field after reaching the mechanical constraints. Independently of the direction or the acceleration of the target, it remains inside the field of view within a maximum error of 10 degrees, Fig. 12.

The return maps are depicted in Fig. 13 and describe the relationship of input and output in the GCM. In contrast with the simulation, the use of a larger area in the logistic map is seen. These plots show activations in the left side of the logistic map; however, activations reaching and trespassing the top of the map were also observed in several trials. In those experiments, the target was moved at very low speed around the mechanical and visual limits of the system.

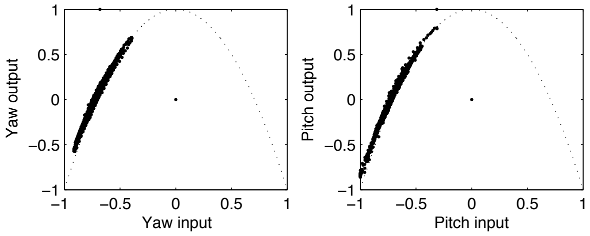

Fig. 13. Return maps for both chaotic units. The dotted line is shown as refence for the logistic map.

V. Conclusions and Future Work

A. 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, both in a simulated environment and for its implementation in a real platform.

A virtual setup consisting of only two rotational joints and a camera was created to replicate the sensori-motor configuration of a real eye. We have demonstrated that, once the object enters the field of view, this input is enough for the self-organization of the controller that generates the torques applied to each of the joints of our devices. No learning or specific coding of the task is needed, which results in a very fast reactive behavior.

By playing with the values of α (chaoticity factor) and ϵ (coupling factor) we saw that a smooth pursuit behavior can change to other 'non-tracking' patterns like following during some time and escaping from the target in some others. This very simple action tells us that other visual behaviors can be achieved without much effort from the designing part to simulate specific cognitive actions.

The implementation of this algorithm in a real platform was straight forward. A copy of the iCub's head from the RobotCub project [14] was used with only minor changes in offsets and gains. The tracking algorithm used in the implementation was taken from the YARP repository [16]. The algorithm was tested by changing both the chaoticity of the system and the coupling among its elements. In both cases, simulation and implementation, the smooth pursuit behavior emerges when the system is highly chaotic and there is a weak coupling among its elements.

The focus of the present research is the coordination of several degrees of freedom for smooth pursuit but we found that other cognitive behaviors are also possible by changing a single parameter in our system. The work reported in this article represents the ground for building a more complex architecture for sensori-motor integration and cognitive development.

B. Future work

The iCub's head has also an inertial sensor which will be included in the future as another element influencing the chaotic field. Future work involves the emergence of a coordinated motion between both eyes and finally among the motors representing the three degrees of freedom of neck (yaw, pitch and roll) and the three degrees of freedom of the eyes (left eye yaw, right eye yaw, and both eyes pitch). 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?

Acknowledgments

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