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A System for Learning to Locomotion Using Adaptive Oscillators in the Humanoid Robot

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Abstract—**This paper proposes a central pattern generators based control architecture using a frequency adaptive oscillator for learning to locomotion of humanoid robot. Central pattern generators are biological neural networks that can produce coordinated multidimensional rhythmic signals, under the control of simple input signals. They are found both in vertebrate and invertebrate animals for the control of locomotion. In this article, we present a novel system composed of adaptive nonlinear oscillators that can learn arbitrary rhythmic signals in a supervised learning framework, and apply it to control a simulated humanoid robot with up to 22 degrees of freedom. A key feature of the proposed architecture is that the learning is completely embedded in to the dynamical control, and does not require external optimization algorithms. As a test bed, we chose Robocup 3D soccer simulation environment (spark). Experimental results show that learn to walk of the robot could be successfully performed, thus allowing the biped robot to walk fast, stable and straightly.**

I. Introduction

In more and more scientific projects we can see scenarios where robots are placed in a home environment helping humans, in particular elderly or disabled persons. Robots that are supposed to work in places where humans live (e.g. service robots) have to meet additional constraints. The environment in which they act is very complex: A world designed by humans, for humans.

The ability to efficiently move in complex environments is a key property of animals. It is central to their survival, i.e. to avoid predators, to look for food, and to find mates for reproduction. Similarly, providing good locomotors skills to robots is of primary importance in order to design robots that can carry out useful tasks in a variety of environments.

There exist a number of approaches to biped locomotion. Among the most successful ones is trajectory tracking methods that are based on precompiled trajectories of the legs or the Zero Moment Point (ZMP). The ZMP is the point on the ground where the total moment generated due to gravity and inertia equals zero [1].

A completely different approach to walking is that of passive dynamic walkers. These use the inherent machine dynamics for walking and thus are very efficient in energy. Most of them walk without actuation or control. McGeer [2] first introduced the notion of passive dynamic walking and showed that unsaturated and uncontrolled planar walking down a slope is possible.

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Studying bipedal locomotion in animals and in particular humans, gives us a good idea on how their gait could be modeled. Although bipedal locomotion has been studied by scientists of different domains, this problem has not been completely solved yet [3].

Studies in animal locomotion suggest that gait patterns are generated by rhythmic pattern generators. Following those observations, simple neural oscillators have been designed to work as CPG. CPGs generate trajectories for the joints by using nonlinear oscillators.

In order to represent the CPG and generate the required signals, several nonlinear oscillators that are coupled together have been developed, such as the Hopf, Rayleigh, Van del Pol, and Matsuoka oscillators, etc.

The oscillator model used in this work has been first studied by Matsuoka [10] and is widely used in many researches on robotics and CPGs [3][5] thus we selected it in our project. Models of CPGs have been used to control a variety of different types of robots and different modes of locomotion. For instance [5], models of CPG are also increasingly used for the control of biped locomotion in humanoid robots, Examples of CPG-controlled biped locomotion [6, 7, 8, 9].

One drawback of the CPG approach is too many parameters to set for CPG and there is no methodology for it. Therefore, evolutionary computation methods are often used to optimize the parameters [8].

However, when the evolutionary method is applied to find CPG parameters, learn to walk is very slowly and time-consuming for instance [12].

In this work we combined a learning rule [4] With the Matsuoka oscillator, and we have made an adaptive oscillator that can learn arbitrary periodic signals in a supervised learning framework very fast and it is completely embedded into the dynamical system, and does not require any external regression or optimization algorithms, or any preprocessing of the teaching signal. Then, we used a CPG with this adaptive oscillator for learning to walk a humanoid robot.

The rest of the paper is organized as follows. Section 2 describes our model and simulator to simulate the locomotion of the humanoid robot. Section 3 describes the details of the CPG architecture. Section 4 presents the results of the experiments.

II. Biped Model and Simulator

We decided to use a simulation for this project. Having a simulated robot has many advantages besides the price lower than a real robot. First a simulation is infinitely more flexible than a real robot. In the simulation we have the complete control over the robot's model: Its shape or its weight can be easily changed or adapted to fit our needs. That would be almost impossible with a real robot.

We used the simulator of the RoboCup 3D Simulation League. The RoboCup 3D Simulation League uses a simulator program, called the server, which uses the Open Dynamics Library (ODE) to simulate a football game [11]. The dynamics of the simulation include realistic, Newtonian physics such as gravity, friction and collisions. In the ODE implementation, a motor is associated with each joint. The physics engine is implemented in such a way that the motors can be controlled by simply setting a desired position angle.

The robots used in the 3D Simulations are models of humanoid robots. It is based on the NAO robot and has realistic sizes, weights, et cetera. Figure 1 shows the simulated agent in the football field along with his joints that make up its Degrees Of Freedom. It is a real humanoid Robot with two arms, two legs and a head. This robot weighs 4.5kg, stands 57cm high and has 22 degrees of freedom (DOF). There are six DOFs in each leg; two in the hip, two in the ankle and one at the knee. An additional DOF that exists at each leg's hip for yaw causes the legs to rotate outward and inward.

III. Central Pattern Generators

Studies made on the vertebrates' neural system tend to show that every degree of freedom in the animal's body corresponds to a single neural oscillator. To achieve locomotion the neural system generates rhythmic signals by neural oscillators that are sent to the muscle-skeletal system in order to produce torques on the different joints of the animal. So, once again in this project we will inspire our self from the biology and we will use one neural oscillator for each robot's degree of freedom. The output signals of neural oscillators are used as the target angles of corresponding joints.

The CPG found in the vertebrates are made of neural oscillators. Thus if we want to simulate a CPG, we first have to simulate one of these neural oscillators. One approach could be to build a model as close as possible to the behavior of the real neurons. But that's not what we decided to do, for two major reasons: First, the real neurons have very complex behaviors and are far from being fully understood by the biologists. Second, such a model would be pretty complicated and there for it would be difficult to embed it on a real robot.

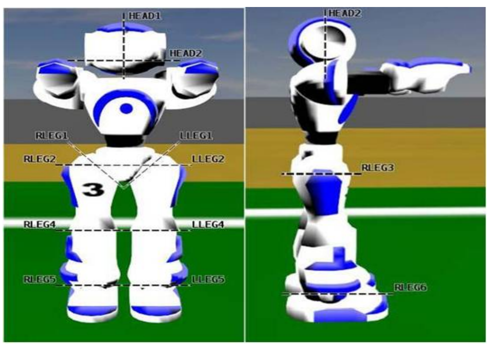


Figure 1: The NAO robot in the football field along with his joints

In order to represent the CPG and generate the required signals, several nonlinear oscillators that are coupled together have been developed, such as the Hopf, Rayleigh, Van del Pol, and Matsuoka oscillators, etc. We selected Matsuoka oscillator in our project.

In this section, first, we present the learning rule for oscillators which adapts their frequency to the frequency of any input signal briefly. It introduced in the [4] completely and then we descript Matsuoka adaptive oscillator with one example. In continue, we present a control based CPG using a frequency adaptive Matsuoka oscillator for learning to locomotion of humanoid robot**.**

A. *A generic rule for frequency adaptation*

We consider general equations for an oscillator perturbed by a periodic driving signal.

$$\dot{u} = f_u(u, v, w) + K \cdot F(t) \tag{1}$$

$$\dot{v} = f_v(u, v, w) \tag{2}$$

Where f_u and f_v are functions of the state variables that produce a structurally stable limit cycle and of a parameter ω that has a monotonic relation with the frequency of the oscillator when unperturbed, K = 0 (we do not require this relation to be linear). F (t) is a time periodic perturbation and K > 0 the coupling strength.

In order to make the oscillator learn the frequency of F (t), we transform the ω parameter into a new state variable that will have its own dynamics. The generic rule that allows us to transform this oscillator into an adaptive frequency one is as follows.

$$\dot{\omega} = \pm K \cdot F(t) \frac{v}{\sqrt{u^2+v^2}} \tag{3}$$

Where the sign depends on the direction of rotation of the limit cycle in the (x, y) plane.

B. *Matsuoka adaptive oscillator*

We use the neural oscillator model proposed by Matsuoka [10]. The neural model is a half-center oscillator which consists of two (extensor and flexor) neurons, having mutual inhibitory interactions. We According to the generic rule for frequency adaptation modified it. The model can be described by the following set of differential equations.

$$\tau_1 \dot{u}_e = u_{0e} - u_e - \beta v_e - w_{ef}[u_f]^+ + K \cdot F(t)/2 \tag{4}$$

$$\tau_2 \dot{v}_e = -v_e + [u_e]^+ \tag{5}$$

$$\tau_1 \dot{u}_f = u_{0f} - u_f - \beta v_f - w_{fe}[u_e]^+ + K \cdot F(t)/2 \tag{6}$$

$$\tau_2 \dot{v}_f = -v_f + [u_f]^+ \tag{7}$$

$$y_i = [u_i]^+ = \max(u_i, 0)\ ,\ [u_i]^- = \min(u_i, 0), \quad i = \{e, f\} \tag{8}$$

$$y_{out} = y_e - y_f \tag{9}$$

$$\dot{\tau}_1 = -K \cdot F(t) \frac{(v_e - v_f)}{\sqrt{{y_{out}}^2 - (v_e - v_f)^2}} \tag{10}$$

$$F(t) = Q_{learn}(t) - y_{out}(t) \tag{11}$$

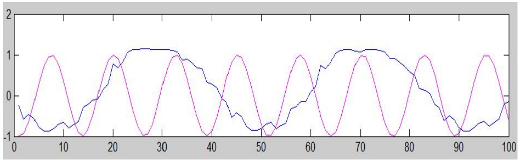
$$\tau_2 = \tau_1 / 0.5 \tag{12}$$

Where u_e, v_e, u_f, and v_f are the internal states of the oscillator. y_{out} is the output of the oscillator. β is the adaptation coefficient.

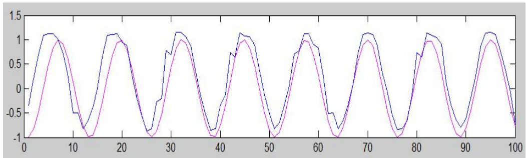
With this generic architecture, we are able to learn any periodic input signal. We just have to provide Q_{learn} the periodic trajectory we want to learn as input and integrate the system of equations. After convergence, we can set $F(t)$

= 0.

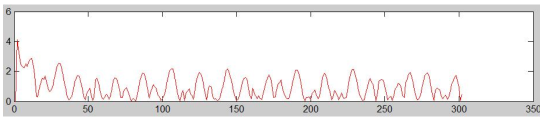
We performed simulations to confirm whether the frequency adaptive oscillator can adapt its phase to an input signal with varying frequency. We set the parameters of the oscillator as follows: τ1initial= 0.3, R = 0.5, β = 2.5, wef = w_{fe} = 2.5, $u_{0e} = u_{0f}$ = 5.0.The input signal is represented by a sinusoidal function sin 5t. After learning, the periodic signal is encoded in the network of oscillators, as can be seen in Figure2.



(a). plots of the oscillations (blue line) and of the input signal F (red line), before adaptation.



(b).plots of the oscillations (blue line) and of the input signal F (red line), before adaptation.



(c). plot of the error, defined by $error = |y_{out} - Q_{learned\_}|$.
Figure 2: Adaptive Matsuoka oscillator

C. Application to Bipedal locomotion

In this section we show how, given a sample trajectory, we can use our generic CPG architecture to control bipedal locomotion on a simulation of the NAO. First, we present the controller architecture made of several Matsuoka adaptive oscillator one for each DOF.

It is found that 6 DOFs (three for each leg) are more important than other DOFs in fast walking. These are DOFs of hip; knee and ankle DOFs which move on the same plane of forward-backward. Although other DOFs are effective in walking behavior, but in fact, their role is more in smoothing the robots walking motion. So here, it's preferred to ignore them to decrease learning search space [12]. Therefore, in our controller architecture, we control 6 of the 22 DOFs of the robot. Figure 3 shows a schematic view of the controller architecture.

IV. Experimental And Results

In this section we present experiments we did with the CPG we presented. We did this experiment with the simulator of the RoboCup 3D Simulation League. The

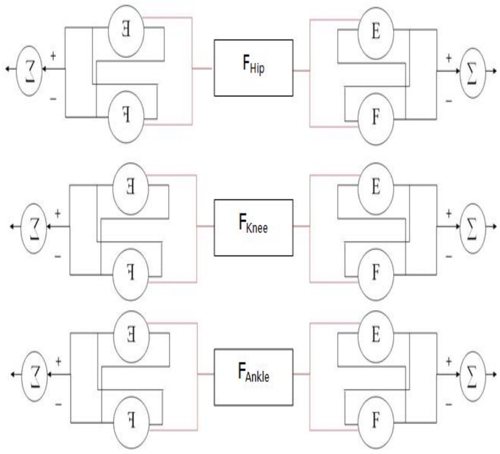


Figure 4: Structure of the CPG for the humanoid

robots used in the 3D Simulations are models of humanoid robots. It is based on the NAO robot and has realistic sizes, weights, et cetera.

With this control architecture is introduced, we are able to learn any locomotion. We just have to provide Q_{teach} the periodic trajectory we want to learn as input and integrate the system of equations. After convergence, we can set $F(t)$ = 0 (no more input nor feedback loop) and the periodic signal stays encoded into the network of oscillators. The learning process is embedded in the equations, there is no need of any external optimization or learning algorithm.

We trained the Matsuoka adaptive oscillator with sample trajectories of walk motion of the NAO provided by a player of the Nexus team in 2009 ROBOCUP competition. Each trajectory was a teacher signal to the corresponding CPG controlling the associated DOF. All the control parameters of the CPGs converged correctly and, after learning, the sample trajectories are encoded in the controller as can be shown in Figure 4.

K is a coupling constant in the rule of the frequency adaptation (equation 3). We changed the value of k according to error. The initial value of K was 0.9. We

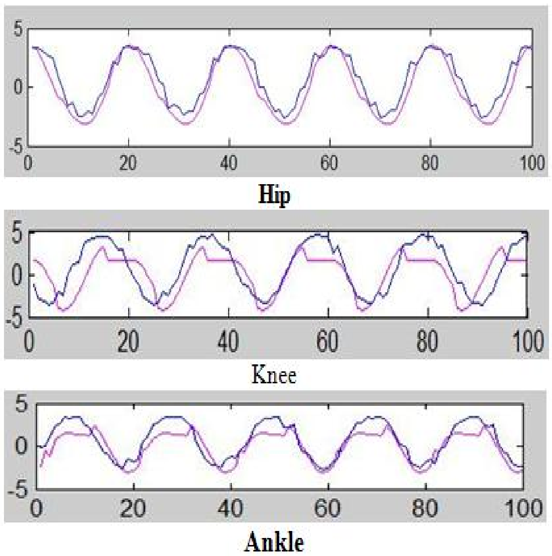


Figure 3: Result of training of the generic CPG. We plotted the 3 controlled DOFs, the blue line corresponds to the output of the CPG for each DOF, and the red line corresponds to the sample trajectory.

defined a threshold for the error value. We multiplied 0.5 in the K when the error is less than threshold and we reduced the threshold value. We used equation 13 to obtain the error.

$$error = \|The\ out\ put\ of\ osillator - \text{Input}\| \qquad (13)$$

Recently, Shafi [12] proposed a method base on evolution algorithm but his method is too slow. The NAO robot could walk after 9 hours in the [12] but the time of adaptation was 1.5 hours in our experiment.

Our NAO robot could walk similar to the virtual NAO robot of the Nexus team (figure 5). Our NAO robot could walk 25 m in 27 s with average body speed of around 0.92 m/s.

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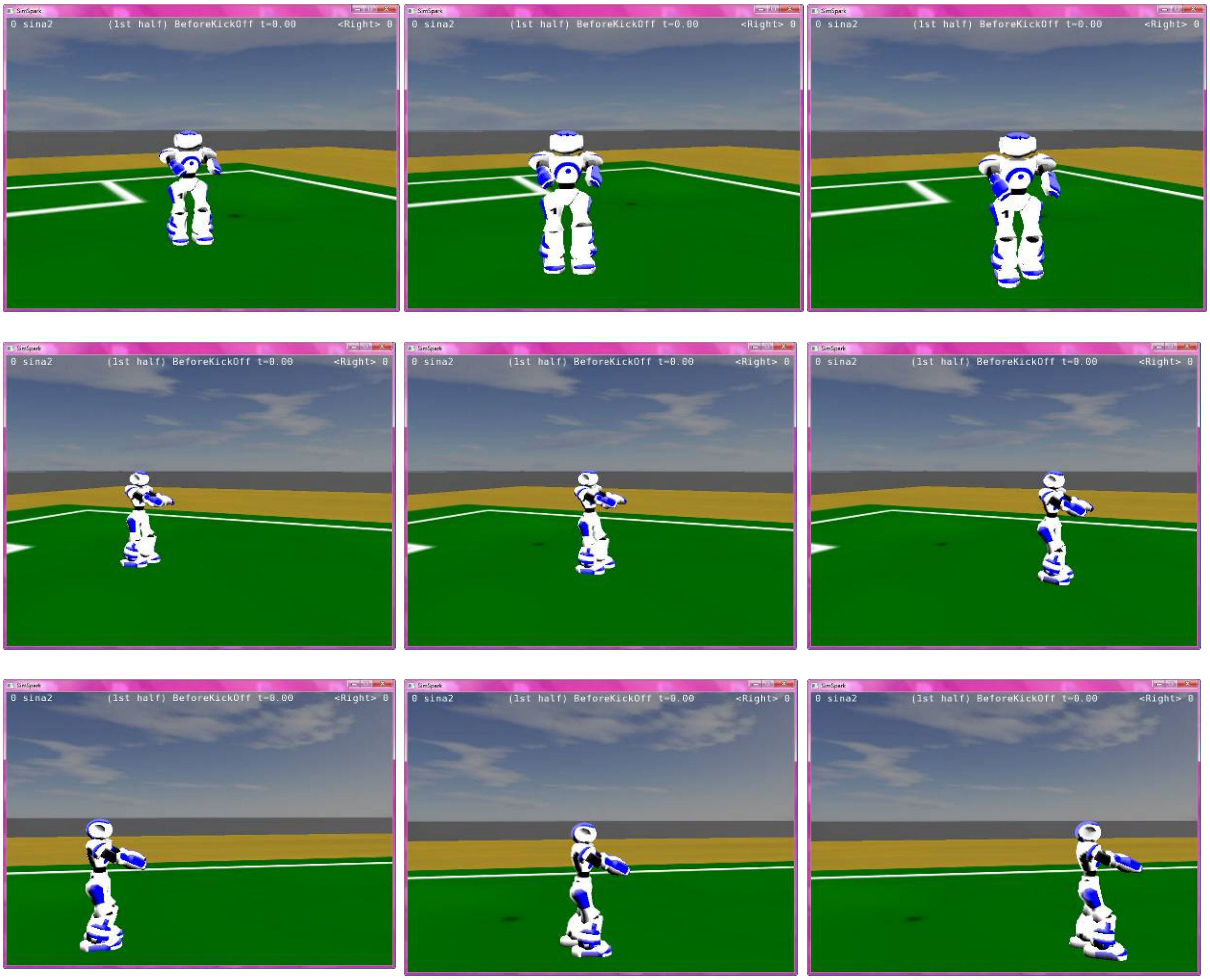

Figure 5: Snapshots of the robot while walking.