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Evolved Center-crossing Recurrent Synaptic Delay Based Neural Networks for Biped Locomotion Control

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***Abstract*—This paper combines the center-crossing condition in artificial neural networks that incorporate synaptic delays in their connections and which act as Central Pattern Generators (CPGs) for biped controllers. Recurrent synaptic delay based neural networks allow greater time reasoning capabilities in the neural controllers, outperforming the results of continuous time recurrent neural networks, the neural model most used as CPG for biped robot locomotion related behaviors. Simulated evolution is used to automatically obtain neural controllers for walking behaviors, showing the capabilities of the synaptic delay based neural networks for the temporal coordination of the biped joints in difficult surfaces.**

***Keywords*— Synaptic delay based neural networks, continuous time recurrent ANNs, center-crossing ANNs, evolutionary robotics;**

I. Introduction

Central Pattern Generators (CPGs) are neural circuits in peripheral nervous systems like the spine that can be activated to produce rhythmic motor patterns such as walking, breathing, flying or swimming. CPGs are able to operate in the absence of sensory or descending inputs that carry specific timing information. CPGs were implemented using models such as vector maps, systems of coupled oscillators and connectionist models [1]. In the neural computing community, Beer [2] introduced the model of Continuous Time Recurrent Neural Networks (CTRNN), one of the most used to represent CPGs.

Here the focus is on the control of biped robots. Bipedal walking is a difficult task due to its highly unstable dynamic behavior [3]. Legged locomotion is characterized by cyclic activity of the limbs, and the defining feature of CPGs is a high degree of recurrence, which greatly biases the dynamics of the system toward cyclic activation patterns [4].

The work of Ijspeert [1] reviews different alternatives to define CPGs and many researchers have used the CTRNNs or other NN models to obtain the rhythmic activity which characterize CPGs. For instance, McHale and Husbands [5] compared four types of neural networks to synthesize bipedal control systems: the conventional CTRNN [2], the Center-Crossing CTRNN (explained next, incorporating a center-crossing condition which facilitates that the NN provides oscillatory behaviors), the Plastic Neural Network (PNN) which incorporates run-time Hebbian adaptive network weights [6] and the GasNet developed by the authors that incorporates the effect of a neuromodulator in the neural nodes activation function. In their study, CTRNNs were shown to have advantages in most of the cases.

Many other authors used CTRNNs or adaptations of this model [7][8]. For example, Jones et al. [9] also used the CTRNN model. The authors modeled a segmented swimming organism co-evolving its nervous system and body plan morphology, where the structure of the CPGs was not predefined. They found that animats artificially endowed with proprioceptive feedback were able to evolve completely decoupled CPGs, meaning that they emerge without any connections made to neural circuits in adjacent body segments. Without such feedback however, they found that the distribution of sensory information from the head of the animat becomes far more important, with adjacent CPG circuits becoming interconnected.

Other authors used different models than CTRNNs, like the neural oscillator proposed by Matsuoka [10], used to model the firing rate of two mutually inhibiting neurons [11][12]; other models include the two neuron network oscillator to generate a core oscillation by Hein et al. [13], or the reflex-oscillators proposed by von Twickel and Pasemann [14], which rely on the sensorimotor loop and hysteresis effects, with the aim of generating effective locomotion in an hexapod robot.

In previous works, Santos and Campo [15][16] used center-crossing CTRNNs as neural controllers in biped structures, and additionally defined an adaptive methodology to improve the ability of these recurrent neural networks to produce rhythmic activation behaviors. The adaptive process, which modifies the CTRNN parameters in run-time to reach the center-crossing condition, facilitates the evolution of the networks that act as central pattern generators to control biped structures. Here the application of synaptic delay based neural networks is introduced, which incorporate synaptic delays in the NN connections. This neural structure was used in temporal pattern recognition and signal prediction applications [17]. In this work the center-crossing definition is incorporated in this type of artificial neural networks, and it is tested the integration of the center-crossing condition with the time reasoning capabilities of such networks, with the aim of obtaining neural oscillators that act as CPGs for biped walking behaviors in difficult surfaces.

II. NEURAL NETWORK CONTROLLER MODELS

A. Continuous time recurrent neural networks

Beer [2] introduced the model of Continuous Time Recurrent Neural Networks (CTRNN), one of the most used to represent CPGs. In a CTRNN, the state of a single neuron i is computed by the following equation:

$$\tau_{ci}\dot{y}_i = -y_i + \left[\sum_{j=1}^{N} w_{ji} \cdot \sigma(y_j + \theta_j)\right] + I_i \quad (1)$$

where y_i is the state of neuron i, τ_{ci} is a time constant which defines the rate of decay of the state, w_{ji} is the weight of the incoming connection from neuron j, σ is the sigmoid activation function, θ_i is the bias term or firing threshold of the node and I_i is an external input. Totally connected CTRNNs will be used, where each node follows this equation. The external input is not considered in this application.

B. Center-crossing condition

Mathayomchan and Beer introduced the concept of center-crossing in CTRNNs [18] to easily obtain neural oscillators. In a center-crossing CTRNN the null surfaces of all neurons intersect at their exact centers of symmetry. The null surface of a neuron is where the sum of the neuron bias and all the synaptic inputs is 0. This ensures that each neuron's activation function is centered over the range of net inputs that it receives.

Using a sigmoid activation function in the NN nodes, a neuron has a firing frequency of 0.5 at its null surface ($\sigma(0)=0.5$), that is, center-crossing networks have neurons that on average have firing frequencies around this value. Hence, the center-crossing condition occurs when the neuron biases of all neurons are set to the negative of the sum of the input weights divided by 2:

$$\theta_i = -\frac{\sum_{j=1}^{N} w_{ji}}{2} \quad (2)$$

This means that the bias exactly counteracts the sum of all the synaptic inputs when the connected neurons have a firing frequency of 0.5. In other words, the nodes of such type of networks should have an average firing value of 0.5, which implies that the neurons are in states of maximum sensitivity most of the time.

The importance of the network process is that now small changes in synaptic inputs around the null surface can lead to a very different neuron firing frequency. Outside this range, the change of a net input has only sparse effect on the firing frequency. Bearing in mind that the objective is to obtain neural oscillators that act as CPGs, the richest dynamics should be found in the neighborhood of the center-crossing networks in the search space of parameters. Hence, as Mathayomchan and Beer indicate [18], one would expect that an evolutionary algorithm would benefit from focusing its search there.

C. Synaptic delay based neural networks

In a synaptic delay based neural network, in addition to the weights of the synaptic connections, their length is modeled through a parameter that indicates the delay a discrete event suffers when going from the origin neuron to the target neuron through a synaptic connection.

The network consists of several layers of neurons connected as a multiple layer perceptron (MLP). Each neuron performs a summation of its inputs and passes these values through a non linear function, a standard sigmoid function. So, the only difference with a traditional MLP is that the synapses contain a delay term in addition to the classical weight term. That is, now the synaptic connections between neurons are described by a pair of values, W and τ, where W is the weight describing the ability of the synapses to transmit information and τ is a delay, which in a certain sense provides an indication of the length of the synapse, the longer it is it will take more time for information to traverse it and reach the target neuron. Figure 1 shows the neural structure, adding recurrences from the outputs to the inputs, in order to use the structure as Central Pattern Generator.

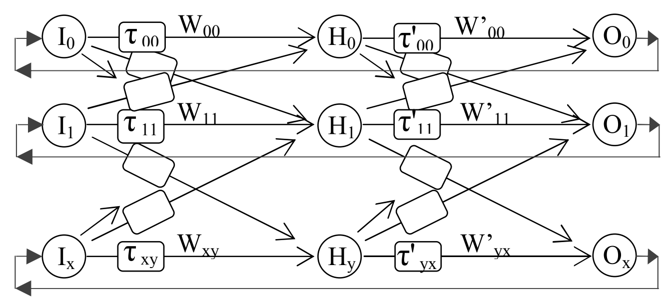

Fig. 1. Synaptic delay based neural network with feedback connections.

Taking into account the description of the network in terms of synaptic weights and synaptic delays, each neuron in a given layer can choose which of the previous outputs of the neurons in the previous layer it wishes to input in a given instant of time. Time is discretized into instants, each one of which corresponds to the period of time between an input to the network and the next input. During this instant of time, each of the neurons of the network computes an output, working its way from the first to the last layer. Thus, for each input, there is an output assigned to it.

The process is summarized in the following equation, which defines the output of a neuron k in an instant of time t:

$$O_{kt} = F\left(\sum_{i=0}^{N}\sum_{j=0}^{t} \delta_{j(t-\tau_{ik})} w_{ik} h_{ij}\right) \quad (3)$$

where F is the transfer function of the neuron (sigmoid function), h_{ij} is the output of neuron i of the previous layer in instant j and w_{ik} is the weight of the synaptic connection between neuron i and neuron k. δ represents the Kronecker Delta. The first summation is over all the neurons that reach neuron k (those of the previous layer) and the second one is over all the instants of time considered. The result of this function is the summation of the neuron outputs of the previous layer in times t-τ_{ik} (where τ_{ik} is the delay in the corresponding neural connection) weighed by the corresponding weight values.

Duro and Santos devised a training algorithm, extending and adapting the backpropagation algorithm to automatically and simultaneously train the weights and delays [17][19], using the neural model in temporal pattern recognition, prediction of temporal series or as a model of dynamic reconstruction of a time series [20]. Here the network structure is used as the biped neural controller, and the parameters (weights and synaptic connections delays) are evolved. To obtain neural oscillators that can act as CPGs a recurrent structure was used, with the feedbacks shown in Figure 1 from outputs to inputs (only recurrences from output node i to input node i, using the same number of inputs and outputs equal to the number of actuators or links of the biped). The importance of the structure is that now the incorporation of synaptic delays allows the network to obtain a model of the temporal processes required. In this sense, it is used again as a model for defining the required time series (oscillating behavior).

When the center-crossing condition is introduced in these synaptic delay based NNs, each node of the NN incorporates a bias term defined by Equation 2, facilitating the oscillating behavior in the activation of the nodes. Moreover, the output nodes will incorporate a time constant τ_c which facilitates to obtain different activation patterns, as their consideration defines a decay of the activation of the nodes through time (Equation 1).

TABLE I. ODE PARAMETERS OF THE BIPED STRUCTURE

Hip dimensions	Cylinder, length: 0.2 m., radius: 0.05 m.
Thigh and leg dimensions	Cylinder, length: 0.5 m., radius: 0.05 m.
Feet arcs	Box, length: 0.005 m., width: 0.1 m., height: 0.01 m.
Angular hip displacement	[-π/6,0.75·π]
Angular knee displacement	[-0.75·π,0]
Angular ankle displacement	[-0.25·π,0]
g	-9.81 m/s²
Time step in ODE simulation	0.01 s

III. METHODS

A. Biped model

A simulated biped previously used in [16] was employed for the experiments, implemented with the physics simulator Open Dynamics Engine (ODE) [21]. The articulated structure consists of rigid bodies connected through joints. Figure 2 indicates how the joints of the biped are controlled by a neural controller, a fully interconnected CTRNN in the Figure.

The biped has two joints, each linking a hip with a leg, containing a knee joint and an ankle joint. All the actuated joints had a degree of freedom and were simulated as torsional springs. The outputs of the neural network models were scaled to provide a velocity that can reach the angle limits of the joints. Table 1 summarizes the main parameters for the joints. Finally, the feet were composed of 6 consecutive arcs joined with fixed hinges, providing a concave structure in each foot.

Other relevant aspects concerning the simulation are: The mass of each body part was proportional to its volume, the gravity was fixed to -9.81 m/s², a time step of 0.01s was used in the ODE simulation for each iteration in the environment, and the maximum ground friction was used in the simulator to avoid the possibility of the feet sleeping.

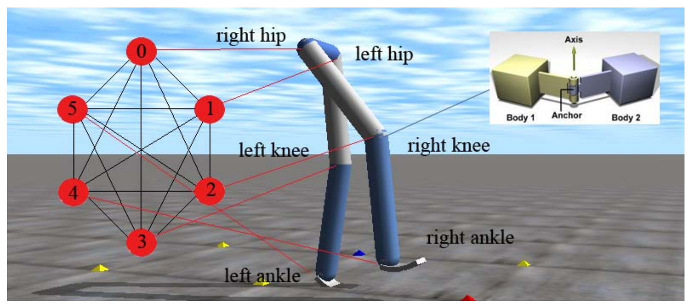

Fig. 2. Control of the biped robot by a CTRNN. The values of the NN nodes control the different joints of the simulated biped in ODE. The inset shows the hinge joint used at each of the contacts.

B. Evolutionary algorithm and NN controllers details

As in previous works [15][16], a standard genetic algorithm (GA) was used for the evolution of the CPGs. Each individual of the genetic population encoded the defining parameters of the control network, being a center-crossing CTRNN or a center-crossing recurrent synaptic delay based neural network. In the first case, the genotypes encoded the weights and time constants (τ_c), whereas the biases were set according to Equation 2 taking into account the encoded values of the weights. In the case of center-crossing recurrent synaptic delay based neural networks, the genotypes encoded the weights and synaptic delays of the NN connections, in addition to the time constants (τ_c) of the NN output nodes, whereas the biases of all the nodes were set, as in the previous case, according to Equation 2. The time constants were used only in the output nodes as it was sufficient the capacity that the time constants add in the behavior of the output nodes, which is translated to the rest of the nodes given the feedback of the output information. When a node uses a time constant (τ_c), the time step for the integration of Equation 1 was 0.1 s.

In the case of fully interconnected center-crossing CTRNNs, all the neurons were motor neurons to control each of the six joints of the biped structure (Fig. 2), so the genotypes have 42 parameters to evolve (36 connection weights and 6 time constants). Using the second possibility of center-crossing recurrent synaptic delay based NNs, with a typical configuration considered in the experiments reported later, with an input and an output layer of 6 nodes, and two hidden layers with 4 nodes, the number of encoded parameters is quite larger: 134 (64 weights, 64 synaptic delays, 6 time constants of the 6 output nodes).

In both NN models, the connection weights were constrained to lie in the range ±16 (as in [18] and [4]) and the time constants (τ_c) were constrained in the range [0.5, 5], as in [4]. For the synaptic delay based NNs, the synaptic delays (τ) were constrained in the range [0, 50] (although it will depend on the required oscillating behavior, as justified next). This means that each node can use, for each connection with a previous node of the previous layer, the current information of the input node, that is, using a synaptic delay with a value of 0 (which is the behavior of a NN without synaptic delays) or the information of the node but 50 time instants in the past. In all cases, all the parameters were encoded in the range [-1, 1] and decoded in such intervals.

A population of 100 individuals was used in the different evolutionary runs. A rank-based method was used as selection operator: Twenty-five percent of the best individuals of the population were replicated to generate the next population. As in [18], these individuals were mutated, adding a random displacement in their genes (parameters) whose magnitude was a Gaussian random variable with 0 mean and variance σ^2 (0.05). The elitist selection was included, as the best individual was copied to the new population without any change. Crossover operators were not used, given the epistasis present in these distributed connectionist structures, as Reil and Husbands pointed out with the lack of efficiency of crossover in this problem domain [4].

The fitness was defined, as in most of the previous works, as the distance traveled in a straight line by the biped in a given time (8 seconds in the experiments). To avoid the transient perturbations at the beginning of the temporal evolution of the recurrent neural networks, each network controller was iterated a given number of steps (500) before taking the control of the biped joints. Moreover, penalizations are introduced. For example, with the biped on a flat surface, to avoid grotesque movements, a penalization was introduced when the center of gravity falls below a certain threshold (90% of the robot height) or, on the contrary, when it was above (110% of the robot height). For the other locomotion behaviors considered in the next section (biped on a slope and on stairs), when the hip falls below the position of any of the feet, the evaluation of the genotype finishes, so the controller only summarizes fitness (the distance traveled) until one of such conditions occurs. This helps to refine many non-perfect oscillators to progressively obtain better evolved behaviors.

IV. RESULTS

Previous works using center-crossing CTRNNs as well as adaptive center-crossing CTRNNs controllers [15][16] successfully obtained walking behaviors for biped structures in flat surfaces. Nevertheless, in other surfaces it was difficult to obtain the required rhythmic behavior that the NN must provide. So, the center-crossing condition is introduced in synaptic delay based NNs with feedbacks, to test the capabilities of integration of the center-crossing condition, which facilitates the oscillating behavior in the neural nodes, with the time reasoning capabilities that the inclusion of synaptic delays adds in the NN processing.

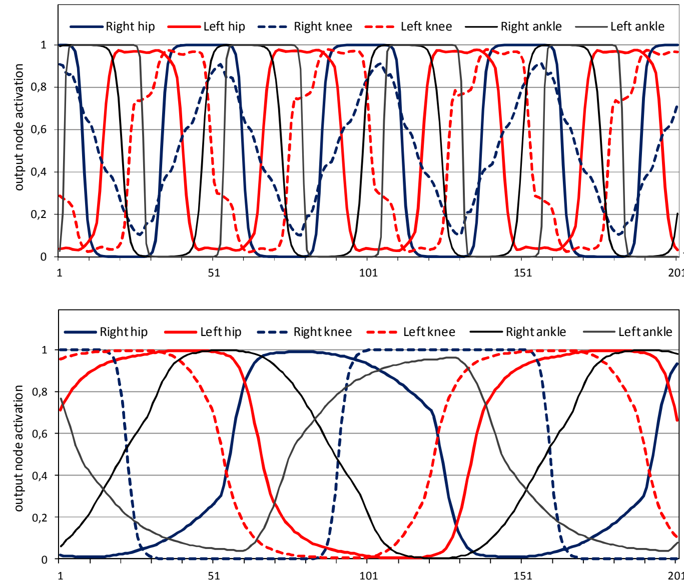

Fig. 3. Activation values in the output nodes provided with evolved center-crossing recurrent synaptic delay based NNs. Upper figure: Time constants (τ_c) in output nodes between 0.5 and 2.5. Bottom figure: Time constants between 2.5 and 5.0.

First, to show the ease of obtaining different oscillating behaviors, Figure 3 shows two oscillating patterns of evolved center-crossing recurrent synaptic delay based NNs which provide different activation frequencies for the biped joints. The evolved NNs were obtained with the robot on a flat surface. The first one (upper part of Fig. 3) provides fast movements in the legs with short steps in the walking behavior, while the second provides longer steps with slower movements of the joints (Fig. 3, bottom part). The videos of these behaviors (and the rest of this section) can be downloaded from [22].

The synaptic delay based NN had a configuration 6x4x4x6. To obtain the desired behaviors, in the first case the output nodes had time constants (parameter τ_c) between 0.5 and 2.5. That is, the GA optimized the values of these time constants in the six output nodes in such range. The range allowed for the temporal delays (parameter τ in each connection) was [0, 25], because, using four layers of nodes with three sets of connections and synaptic delays between the layers, the network output nodes can "reason" with the values of the input nodes up to 75 instants in the past, which is sufficient to cover the period of each one of the inputs. Of course, with larger values in the interval of synaptic delays, the GA can obtain a similar pattern of activation with the same period, but such interval is sufficient.

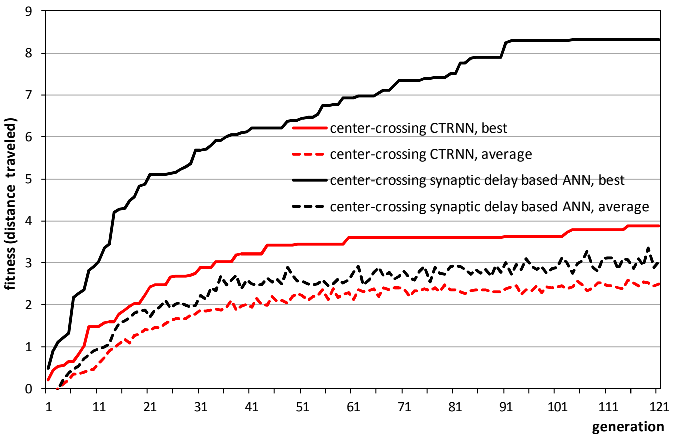

Fig. 4. Evolution of the quality of the best individual and the average quality of the population using two neural controllers for climbing a slope: center-crossing CTRNNs and center-crossing recurrent synaptic delay based NNs. Fitness is defined as the distance traveled in a straight line by the biped in a given time (8 seconds).

In the second case, the output nodes had time constants (τ_c) with greater values, between 2.5 and 5.0. This means that each output node has a greater tendency to maintain the previous value (with respect to the previous case), which generates oscillating patterns with longer periods of activation. In this second case, the range of synaptic delays in the genetic population genotypes was [0, 50], so the network outputs can consider the values of the input nodes up to 150 instants in the past, sufficient again to cover the values of an input in its whole period of activation. So, the only rule to consider the range of synaptic delays is that the network must have the possibility to select the values of an input in the interval useful to determine the output (the "Embedding Dimension" concept in Signal Processing terms [20]). With a required oscillating behavior in the outputs/inputs, such interval is clearly the period of the oscillating temporal pattern.

To show the better capabilities of the synaptic delay based NN, now two additional surfaces are used for the biped structure: A slope surface and an especially difficult one defined by stairs.

A. *CPG for a slope*

For a walking behavior of the biped on a slope, now it is tested the difficulty of obtaining neural models, by means of the evolutionary algorithm, to provide the necessary rhythmic behavior, using center-crossing CTRNNs and center-crossing recurrent synaptic delay based NNs. In the first case (CTRNNs), in the individuals of the initial populations the weights and time constants were random, whereas the biases were defined according to the center-crossing condition (Equation 2) as explained in the previous section, using the range [0.5, 5.0] for the time constants.

In the second case, the initial individuals encoded random weights, synaptic delays and time constants of the output nodes (using the NN configuration 6x4x4x6). The range for synaptic delays was [0, 50] and the range for the time constants was also

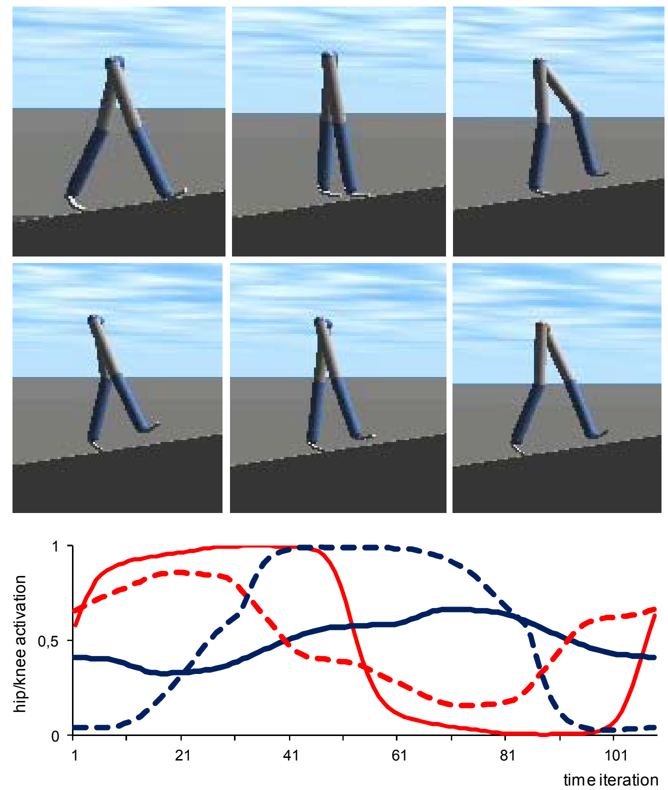

Fig. 5. Several steps in the swing and stand phases of the locomotion behavior on a slope (8.6º) with an evolved recurrent synaptic delay based NN as controller. The bottom graph shows the rhythmic activation of the nodes that directly control the hip joints (continuous lines) and knee joints (dashed lines) during the time iterations necessary for the swing of both legs.

[0.5, 5.0], so the evolutionary algorithm can obtain a great diversity of possible oscillators with different periods to select as best controllers. The biases in each node were always defined according to the center-crossing condition, in the initial genotypes or the individuals in any other generation (in both models).

Figure 4 summarizes the results of the evolutions with the GA through 120 generations. The quality evolutions were the average result of 20 different runs of the GA with different initial populations. The number of individuals was 100 for all tests (as in [18]). As Figure 4 denotes, the integration of the center-crossing condition with synaptic delay based NNs and feedbacks obtains NN controllers which acquire best fitness and in less generations. The average fitness of the best individual is more than the double of the average fitness of the best individuals obtained using a center-crossing CTRNN. The diversity of qualities in the different runs is indicated by the standard deviation of the best quality using center-crossing CTRNNs (2.53), a greater value compared with the standard deviation using center-crossing recurrent synaptic delay based NNs (1.54), which also indicates that this second type of NN is more reliable to provide the required oscillating behavior. Table II includes the basic statistical information regarding the evolution runs.

TABLE II. FINAL FITNESS VALUES IN EVOLUTIONS OF FIGURES 4 AND 6

			Average of the 20 runs	Standard deviation
Fig. 4 (Biped on a slope)	Synaptic delay based NN	Best fitness	8.31	1.54
		Average	3.03	0.71
	CTRNN	Best fitness	3.88	2.53
		Average	2.50	1.62
Fig. 6 (Biped on stairs)	Synaptic delay based NN	Best fitness	7.25	0.90
		Average	2.55	0.61
	CTRNN	Best fitness	1.47	0.42
		Average	0.94	0.27

Figure 5 shows, in the upper part, several steps of the swing and stand phases of the biped structure, using one of the best evolved recurrent synaptic delay based neural controllers with the center-crossing condition. The lower part of the Figure shows one cycle of the repetitive activation of the nodes that control the hip joints (continuous lines) and the knee joints (dashed lines), defining the swing and stand phases (the activations of the ankles are not shown for clarity). The cycle includes the time iterations that are needed for the swing of both legs. The evolutionary algorithm tries to optimize the free parameters to obtain rhythmic activations with different time phases between the hip and knee joints of both sides and to obtain the best posture that provides the maximum fitness (distance traveled). So, stable postures are obtained in the biped walking behavior, providing stable climbing behaviors and maximizing the distance traveled.

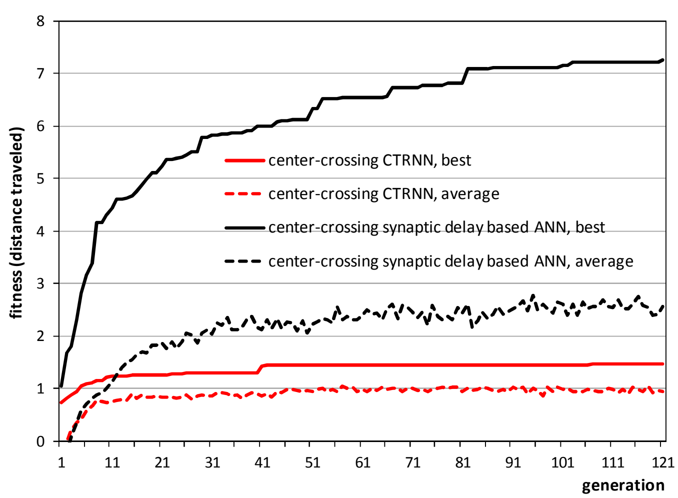

Fig. 6. Evolution of the quality of the best individual and the average quality of the population using two neural controllers for climbing stairs: center-crossing CTRNNs and center-crossing recurrent synaptic delay based NNs. Fitness is defined as the distance traveled in a straight line by the biped in a given time (8 seconds).

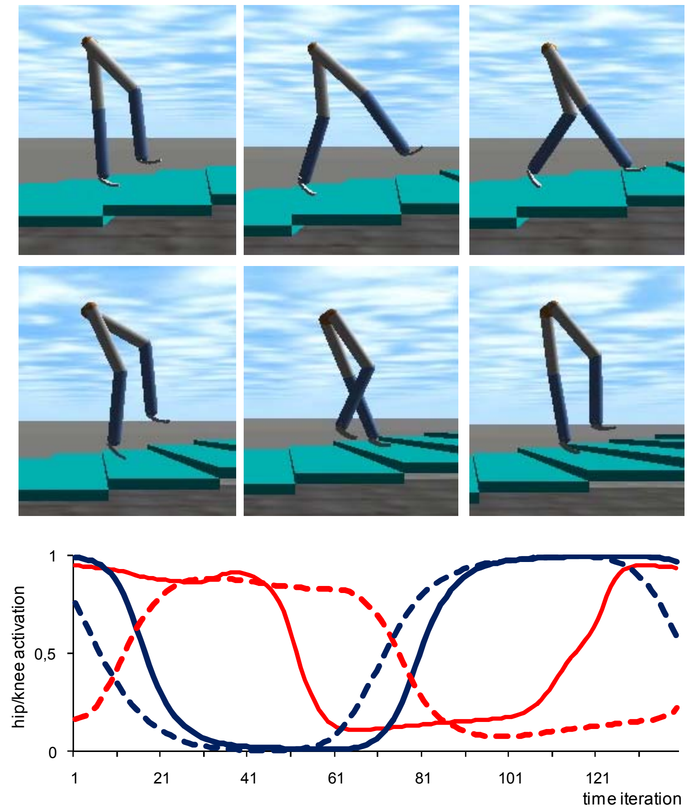

Fig. 7. Several steps in the swing and stand phases of the locomotion behavior for climbing stairs using one of the best evolved recurrent synaptic delay based NNs. The bottom graph shows the rhythmic activation of the nodes that directly control the hip joints (continuous lines) and knee joints (dashed lines) during the time iterations necessary for the swing of both legs.

B. *CPG for stairs*

The experiment was repeated with a surface with greater difficulty, defined by a stair surface (Fig. 7). Each step was defined with 0.5m. width, and each step was 0.05m. over the previous one. Figure 6 shows the comparison results using the same methodology as in the previous case, comparing both types of NNs for implementing the CPGs that provide the required rhythmic behavior.

The NN parameters were the same as in the previous case. In this case, the integration of the center-crossing condition with recurrent synaptic delay based NNs obtains clearly much better results with respect to the center-crossing CTRNN model. Again, the quality curves are an average of 20 different evolutions. The average of the best fitness in the 20 different runs (standard deviation 0.90) of the evolutionary algorithm indicates that this neural model (synaptic delay based NN) obtains oscillators to correctly climb the stairs. Even the average quality of the population using recurrent synaptic delay based NNs is greater with respect to the average of the best fitness using the center-crossing CTRNN (standard deviation 0.42). Using this last type of neural network the evolutionary algorithm did not obtain a neural oscillator so that the biped can climb several steps of the stairs. Nevertheless, the use of center-crossing recurrent synaptic delay based NNs provides a richer variety of dynamic and oscillating behaviors, so the evolutionary algorithm can progressively improve the parameters to obtain a suitable temporal pattern in the activation of the NN output nodes and to control the biped joints to climb the stairs.

Figure 7 now shows several steps of the swing and stand phases of the biped structure climbing the stairs, using one of the best evolved recurrent synaptic delay based neural controllers with the center-crossing condition (upper part). Again, the lower part of the Figure shows one cycle of the repetitive activation of the nodes that control the hip joints and the knee joints, defining the swing and stand phases. More clearly than in the previous case, the joints of both sides of the biped practically act in counter-phase to climb the stairs structure.

V. Conclusions

The capability of the integration of the center-crossing condition in recurrent synaptic delay based neural networks was tested, with the aim to automatically obtain CPGs, by means of an evolutionary algorithm, that provide rhythmic behaviors in different surfaces for a simulated biped structure. A comparison was made between the results of this model with the results using one of the neural models most used as CPG, the Continuous Time Recurrent NN model with also integrates the center-crossing condition. The first model obtained best results in terms of final quality (distance traveled). Moreover, with its use, it was easier to obtain the required temporal pattern of oscillation for controlling the biped joints, as shown in the curves of quality evolutions.

The first model takes advantage of the integration of the center-crossing condition, facilitating the change of the activation value of the nodes to obtain oscillating behaviors, with the temporal reasoning capability that the incorporation of synaptic delays adds to the NN, providing a diversity of temporal patterns which allows to easily obtain oscillating patterns for the control of the biped in difficult surfaces.

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