A study of Adaptive Locomotive Behaviors of a Biped Robot: Patterns Generation and Classification

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Abstract. Neurobiological studies showed the important role of Centeral Pattern Generators for spinal cord in the control and sensory feedback of animals' locomotion. In this paper, this role is taken into account in modeling bipedal locomotion of a robot. Indeed, as a rhythm generator, a non-classical model of a neuron that can generate oscillatory as well as diverse motor patterns is presented. This allows different motion patterns on the joints to be generated easily. Complex tasks, like walking, running, and obstacle avoidance require more than just oscillatory movements. Our model provides the ability to switch between intrinsic behaviors, to enable the robot to react against environmental changes quickly. To achieve complex tasks while handling external perturbations, a new space for joints' patterns is introduced. Patterns are generated by our learning mechanism based on success and failure with the concept of vigilance. This allows the robot to be prudent at the beginning and adventurous at the end of the learning process, inducing a more efficient exploration for new patterns. Motion patterns of the joint are classified into classes according to a metric, which reflects the kinetic energy of the limb. Due to the classification metric, high-level control for action learning is introduced. For instance, an adaptive behavior of the rhythm generator neurons in the hip and the knee joints against external perturbation are shown to demonstrate the effectiveness of the proposed learning approach.

1 Introduction

Biological studies of animals suggest that animals' locomotion is mainly generated at the spinal cord, by a combination of a central pattern generator (CPG) and reflexes receiving adjustment signals from a cerebrum, cerebellum and the brain [1], [2], [3]. These studies were taken into account in robot's locomotion gait in order to implement such mechanism, especially on legged robots [4], [5], [6], [7], [8]. Biologically inspired walking mechanism for legged robot does not require a perfect knowledge of the robot's dynamics. Different models of neural oscillators are widely used to generate rhythmic motion [9], [10], [11], [12], [13].

Such oscillations generated by two mutually inhibiting neurons are described in a set of differential equations (e.g. Matsuoka [9]). Rowat and Selverston [14] proposed a new model of rhythmic neuron that can generate different types of patterns such as oscillatory ones. The different behaviors in the activity of these neurons can be used in robot's locomotion to achieve different tasks as well as walking. Complex task, like walking, hopping, running, and obstacle avoidance, require correct synchronization and switching between patterns [15]. In action learning approach, where learning always occurs in the space of parameters, there is a limitation to learn complex tasks, due to the dimension of this space which can drastically increases. This issue can solved by looking for a new representation of patterns. Instead of learning in the space of parameters, learning can be occur inside a new space called patterns' space. (e.g. in case of one dimensional patterns space, patterns will be represented only on one axis). Our work aims to produce a biological inspired neural controller for biped walking, based on CPG with a rhythmic neuron proposed by Rowat and Selverston [14]. According to the environment changes, the adaptation of the neurons behavior will be shown. Therefore, a new space for patterns allowing intrinsic behaviors of a joint motion will be proposed.

This paper is organized as following. Section 2 presents the principles of the neural controller based on the model of rhythmic neurons, which is able to generate CPG-like patterns. The three layers of the CPG used in bipedal control will be presented. A coupling circuitry for walking will be proposed. Next, the walk learning phase based on previous experience with a threshold of vigilance to allow extensive patterns search within a large space of parameters will be detailed in section 3. In the fourth section, a new representation of successful and failure walking patterns is proposed. This approach allows a high level control in space of patterns instead of space of parameters. The effectiveness of our learning scheme, which allows switching between bipedal patterns to achieve different locomotive tasks will be demonstrated. Moreover, an example on the adaptation behavior of the rhythm generator neurons in the hip and the knee joints against external perturbation will be shown. The last section gives a conclusion and details of further developments.

2 Neural Control of Locomotion

Physiological studies suggest that rhythmic movements in animal's locomotion system are produced by a neural network called CPG [16]. It can generate a locomotive rhythmic behaviors with neither sensory nor central inputs [17]. Sensory inputs shape the output of this locomotion system, and allow the animal to adapt its locomotion patterns to external or internal changes. Genetic studies on newborn rat and mice suggest that rhythmic limb movements during locomotion are generated by neuronal networks located within the spinal cord [18]. Matsuoka and McMillen neural oscillators are widely used as mathematical models for non-linear oscillators [9], [10]. These half-centre oscillators consist of two neurons that individually have no rhythmic behavior, but which produce rhythmic outputs when they are reciprocally coupled. This paper present another model of non-linear rhythm generator. This model is based on the fact that one neuron can generate oscillatory as well as different motor patterns [14].

2.1 Cell Model

The cell model introduced by Rowat and Selverston to modulate the gastric mill CPG in the lobster is interesting due to its ability to generate different patterns by controlling only two parameters [14]. Furthermore, such patterns can be generated with only one neuron without need for another coupled neuron as used in classical models [9], [10]. In the adopted model, the membrane currents of the neuron are separated into two classes, fast and slow, according to their time responses. The sum of all fast currents is modeled by a single fast one, and a single slow current is used to model the sum of all slow ones. This model cell has two differential equations, one for membrane potential V, derived from current's conservation, and one for lumped slow current q, derived from current's activation, see eq.(1).

$$\tau_m.\frac{dV}{dt} = -(fast(V,\sigma_f) + q - i_{inj}) \qquad \tau_s.\frac{dq}{dt} = -q + q_\infty(V) \tag{1}$$

While the fast current is supposed to activate immediately, the membrane time constant τ_m is assumed to be smaller than the slow current's time constant for activation τ_s. We have taken the ratio of τ_s to τ_m to be about 20 as in [14], $\tau_m = 0.05$, and $\tau_s = 1$ for all rhythmic neurons. The injected current is i_{inj}. An idealized current-voltage curve for the lumped fast current is given by: $fast(V,\sigma_f) = V - A_f.tanh((\sigma_f/A_f)V)$. The fast current can represent the sum of a leak current and an inward Ca^{++}. The dimensionless shape parameter for current-voltage curve is given by: $\sigma_f = \frac{g_{Ca}}{g_L}$. Where g_L is a leak conductance and g_{Ca} is the calcium conductance. $q_\infty(V)$ is the steady state value of the lumped slow current, which is given by: $q_\infty(V) = \sigma_s(V - E_s)$. $q_\infty(V)$ is linear in V with a reversal potential E_s. σ_s is the potassium conductance g_K normalized to g_L. σ_s is given by: $\sigma_s = \frac{g_K}{g_L}$. q and i_{inj} have the dimension of an electrical potential. A true current is obtained by multiplying the model current by a leak conductance g_L. V, E_s, i_{inj}, and q are given in millivolts while τ_s and τ_f are expressed in milliseconds. With different values of the cell parameters, different intrinsic behaviors can be achieved : quiescence (Q), almost an oscillator (A), endogenous oscillator (O), depolarization (D), hyperpolarization (H), and plateau (P), as shown in Fig.1. In bio-inspired locomotion, a pair of neurons

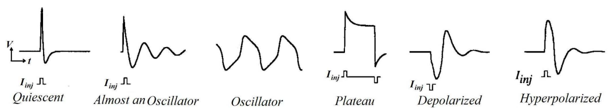

Fig. 1. The six intrinsic behaviors of the cell's model, Rowat and Selverston [14].

with mutual inhibition can be used to generate rhythmic motion in extension and flexion. A bio-inspired model for locomotion is proposed in the next section.

2.2 Locomotion Model

Studies of rhythmic movement in the animal show that local circuits in the spinal cord are able to control the timing and coordination of complex motion patterns [19]. The locomotion and rhythmic movements in mammals are organized by oscillatory spinal cord circuits called CPGs. Experimental studies show that the rhythmic patterns in cat limbs can be generated in the absence of descending control from higher centers and sensory feedback [3]. Each joint appears to have its own CPG, which can be coupled to the CPG of another joint in order to achieve complex movements such as walking, running, swimming, flying, etc. These CPGs controlling such behaviors in animals locomotion can be responsible of rhythmic movements in human locomotion [20]. Several schemes for the spinal CPG have been proposed to generate rhythmic movements: "half-center CPG" proposed by Brown [21], "half-center CPG" with more complex patterns of motorneuron activity introduced by Perret et al. [22] and "half-center CPG" with sensory input proposed by Orlovsky et al. [1]. One drawbacks of these models is the direct excitatory connection between the rhythm generator interneurons and motorneurons. Any change in the interneurons layer will affect simultaneously the motorneurons layer. A more complicated architecture is required to face the adaptation with the environment changes. Two and three levels CPGs with rhythm generation and pattern formation circuitry have been proposed by [2] and [23]. This model separates cycle timing and motoneurons activation. In order to achieve a rhythmic movement such as walking, the CPG model was implemented on a simulated biped robot using MATLAB software. Fig.2(a) shows the wiring diagram for one biped robot's joint. It can be separated into three layers: Rhythm Generation neurons (RG), Pattern Formation neurons (PF) and MotorNeurons (MN). Sensory feedback shapes the activity of these neurons. This paper focuses on the effect of descending control on the rhythm generators neurons in order to control the behavior of these neurons when external perturbation occurs during walking. In the analytical study, after observing the phase diagram of a joint and changing σ_s and σ_f in the rhythm generators neurons, different motion behaviors were observed on the joint. Fig.2(b) shows the distribution of motion patterns in space of σ_s and σ_f. Varying σ_s and σ_f in RG of a joint will change its motion pattern. The four detected basic motion patterns can lead the robot to achieve some complex tasks like walking, running, and jumping depending on synaptic circuits between joint CPGs.

2.3 Control architecture for a biped robot

Previously, the basic motion patterns obtained for one joint was shown. To achieve a complex movement like walking, synchronization between joints is needed. The complex patterns like walking and running are always composed of synchronized basic patterns. The synchronization between patterns is ensured

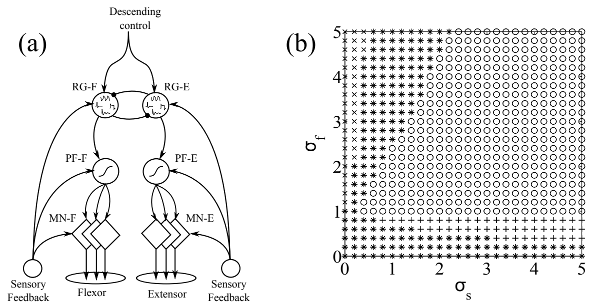

Fig. 2. Model of one joint controller and its motion patterns. (a)The model's scheme, CPG with three levels: Rhythm Generator, Pattern Formation, and MotorNeuron level. (b)The different behaviours observed on the joint for the same injected current. (x): Plateau , (*): Quiescence; (+): Almost an oscillator, and (o): Oscillatory behavior.

by coupling the CPGs for the joints. Fig.3 shows the proposed coupling circuits between the rhythm generator neurons for the hip, the knee, and the ankle joints of a simulated biped robot. Each joint is driven by a simulated servo motor. With such simple coupling, the robot can carry out walking task from basic oscillatory patterns. With different coupling circuits, another task can be achieved. In some complex circuits, the robot can walk with different gaits. A desired task can be accomplished by defining basic patterns and special coupling circuit. The principle of our proposed circuit for walking (see fig.3) is described by the activity between the CPGs which is regulated by excitatory synaptic connections. For inter-limb circuitry, rhythm generator neuron extensor in the left hip (RG-E-hipL) excites rhythm generator neuron flexor in the right hip (RG-F-hipR). Rhythm generator neuron flexor in the left hip (RG-F-hipL) excites rhythm generator neuron extensor in the right hip (RG-E-hipR). The same synaptic excitation is proposed from the right hip to the left hip. For one leg, rhythm generator extensor neuron in the hip (RG-E-hip) excites rhythm generator extensor neuron in the knee (RG-E-knee) and rhythm generator extensor neuron in the ankle (RG-E-ankle) of the same leg. Rhythm generator flexor neuron in the hip joint (RG-F-hip) excites rhythm generator flexor neuron in the knee one (RG-F-knee) and rhythm generator flexor neuron in the ankle joint (RG-F-ankle) of the same leg. As described before, the locomotion is the interaction between CPG, sensory feedback, and descending control. Sensory information is used to shape the motion and manage some perturbations and balance control [24]. Thanks to the interaction with sensory feedback, the robot can walk without a perfect knowledge of its dynamics. A static model of sensory neuron proposed by Ekberg [25] is described in eq.(2). ρ_i is the activity of sensory neuron, α is a positive constant that denotes the dynamics of the neuron, θ is the amplitude and ϕ is the input on the neuron. ϕ can be an angular position, or a contact force [26].

$$\rho_i = (1 + e^{\alpha(\theta-\phi)})^{-1} \tag{2}$$

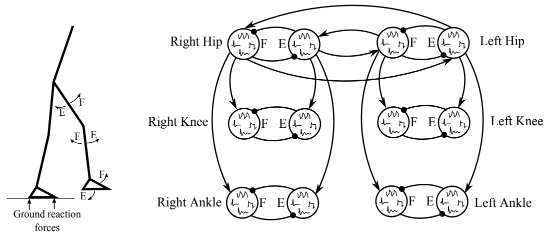

Fig. 3. Planar Biped model and proposed coupling circuitry between rhythm generator neurons for all joints. E and F are extension and flexion.

The extension and flexion sensory neurons in each joint inhibit the corresponding motorneuron for this joint. This circuitry is referred as articular reflex. Equilibrium control is achieved by the difference between the center of pressure and the projection of the center of mass. In our model, the parameter of equilibrium used as input of two neurons: falling forward and falling backward neurons. The activity of both neurons is injected in pattern formation layer at the ankle CPG. If the robot may fall forward, the corresponding neuron becomes active to excite the pattern formation neuron extensor for the ankle of stance leg. The flexor pattern formation neuron will be excited if the falling backward neuron becomes active. Once the control architecture was proposed and the model of rhythmic neurons is determined, it is time to show how the simulated biped is learning to walk on a flat terrain. As the desired task is the walking and the coupling circuit is already defined, the biped will learn basic patterns, in space of σ_s and σ_f, that lead to successful walking.

3 Success and Failure Learning

The objectives of the learning mechanism is to detect in the space of σ_s and σ_f the basic patterns which lead to successful walk. Our previous work in experience-based learning mechanism with the vigilance concept has been used here to detect successful and failure walking patterns, see [27] for more details. Walking trial occurs inside a time window of ten seconds. Successful walking is defined when the simulated biped did not fall during the time window and achieved two steps at least.

This mechanism is composed of two phases: evaluation and decision, see Fig.4. In the evaluation phase, two independent neural networks based on well-known Self Organizing Maps, proposed by Kohonen [28], are used to represent the knowledge in success and in failure. Success map learns in case of success trials, and failure map learns in case of failure ones. During learning, the two maps will be self-organized in the space of parameters that will be therefore divided into three zones: a zone of success represented by success map, a zone of failure represented by failure map, and a zone of conflict that corresponds to the interference between the two maps. The evaluation of any vector $\overrightarrow{v}$ from space

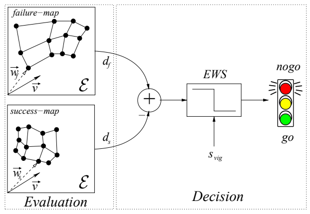

Fig. 4. Learning mechanism with evaluation and decision phases.

$\mathcal{E}$ belonging to success or failure is defined by the distance between $\overrightarrow{v}$ and each map. The distance of a vector with a map is the distance between this vector and the closest neuron in the state space (the winner neuron). For each $\overrightarrow{v}$, two distances therefore exist: one to success map called d_s, and another to failure map called d_f. In the decision phase, the comparison between the distance with success map d_s and the one with failure map d_f leads to an expected result in the case where the vector $\overrightarrow{v}$ is applied on the controller (trial). According to expected result, if it may lead to failure, then an Early Warning Signal (EWS) becomes active to avoid the trial, and the decision will be "nogo". When EWS is inactive, the decision called "go"is taken. The decision mechanism is affected by the threshold of vigilance s_{vig}, which represents the tolerance to risk. The vigilance is related to human learning approaches and decision making [29].

In order to increase the reflectivity of the vigilance threshold model proposed in our previous work [27], a modulation of the above mentioned threshold s_{vig} is introduced. This lead to get different values of it for each trial. Hence, this model increases the learning mechanism efficiency by extending the learning process to sectors of space of parameters. As an important issue, the risk behavior will change from prudence at the beginning of learning to adventure at the end. An example of vigilance threshold modulation is given as following (see Fig.5(c)):

$$y_1 \leq s_{vig} \leq y_2 \qquad \begin{cases} y_1 = a_1 - b_1 * log((x + c_1)^2) \\ y_2 = a_2 - b_2 * log((x + c_2)^2) \end{cases} \tag{3}$$

The coefficients values are ($a_1 = 0.9, a_2 = 1.47, b_1 = b_2 = 0.15, c_1 = c_2 = 20$) and were chosen after several attempts. y_1 and y_2 chosen curves ensure smooth change between the prudence and adventure above mentioned behaviors. Walking patterns are presented by success map and falling patterns are presented by failure one. With such learning mechanism, learning failure map is as important as learning success map, since falling patterns stored in failure map can be used in an adaptation approach where walking patterns are limited (ex: in case of external perturbation). Fig.5 shows success and failure maps after learning 200 trials based on the new model of the vigilance threshold. The state space is normalized between 0 and 1 and each map has 25 neurons. Weights of neuron (w_1,w_2) denote the parameters of the rhythmic neuron ($w_1 = \sigma_s$, $w_2 = \sigma_f$). Therefore, there are 25 different configurations in each map that match 25 successful walking gaits stored in success map, and 25 unsuccessful walking patterns stored in failure map. Because of the topological properties of the Self Organizing Maps, three neurons in failure map are situated in the success zone and show oscillatory behaviors ((0.39, 0.57),(0.46, 0.33),(0.17, 0.23)), see Fig.5(a). As these neurons did not represent any failure pattern, they are eliminated from the failure map.

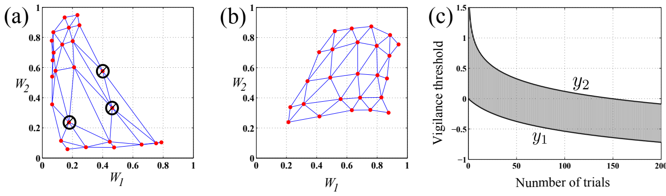

Fig. 5. Success and failure maps after learning walk on flat terrain. (a)Failure map after learning unsuccessful walking patterns. Three neurons was eliminated from the map, because they did not represent any input vector. (b)Success map after learning walking patterns. (c)New vigilance Model related to learning iterations, $y_1 \leq s_{vig} \leq y_2$. The risk behavior will change from prudence at the beginning of learning to adventure at the end.

4 Adaptive behavior for perturbation

As shown in the previous section, the walking task was achieved in the success map zone for the proposed coupling circuits. Because of the synaptic connection between rhythmic generator neurons for all joints, patterns cannot be independent. Then, the same pattern in all joints exist whenever the coupling circuitry is active. To have different patterns on different joints at a time, the synaptic connection between the CPGs must be inhibited. By having independent patterns in the hip, the knee and the ankle joints, the biped can achieve some complex behaviors. In this section, how the robot reacts to an external perturbation force is detailed.

As switching between success map neurons during walking will change the walking pattern and thus walking gait, it can also be interesting to switch between these neurons against external perturbation. The limitation of this algorithm will appear for a large perturbation force. This can be solved by switching toward failure patterns stored in failure map neurons. Inhibit the synaptic connection between CPGs is necessary to get different patterns in different joints.

The space of parameters in such case will be augmented, with a pair (σ_f, σ_s) for each joint. It increases from 2 dimensions in case of existing of coupling circuitry to 12 dimensions in case of independent patterns. To reduce dimensionality, we propose to represent all the patterns of a joint in one axis only. This will reduce the dimension by two and facilitates classification and visualization of high-dimensional data. To do so, a metric $\mathcal{E}$ which reflects the kinetic energy of one limb is introduced (eq. 4). Based on this metric, an energy based classification of the patterns can be carried out.

$$\mathcal{E} = \int_{t_0}^{t_f} \dot{\theta}^2 \, dt \tag{4}$$

Fig.6(a) shows the logarithmic scale of the energy based metric for all the motion patterns of Fig.2. Fig.6(b) shows the logarithmic scale of the energy based metric of all neurons of failure and success maps given in Fig.5. First 25 neurons belong to failure map, and last 25 neurons belong to success map. The different behaviors are separated according to the energy based metric of motion patterns. Two neurons with Plateau have the lower values for the energy based metric, then 16 neurons with Quiescent behaviors, then four neurons with Almost an oscillator, then all the neurons of success map according to the Oscillation frequency. Patterns can be classified on a new axis according to the logarithmic scale of the

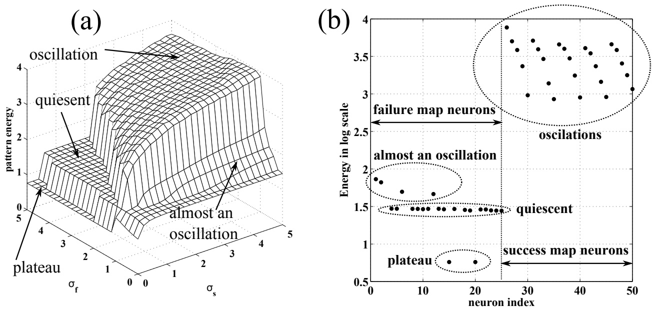

Fig. 6. The energy based metric patterns for the space of σ_s and σ_f (a), and for success and failure neurons represented on the horizontal axis (b). Neurons of success map represent oscillatory patterns with different frequency. Each neuron represent a pattern, but neurons are separated into four classes of patterns according to the energy based metric.

energy based metric. As shown in Fig.6(b) patterns can be positioned on this axis in the following order: Plateau, Quiescent, Almost an oscillator, and Oscillatory patterns from low to high oscillation frequency. All neurons in success and failure maps can be placed on the new axis according to their rhythm. Therefore, two dimensional space (σ_s, σ_f) can be represented in only one dimension axis. One axis is obviously needed for each joint. In the first step of the study, only synapses between CPGs of the hip and the knee joints are inhibited. While the connection between CPGs of the ankle and the hip joints are kept. Fig.7 shows two dimensional space of patterns for the hip and the knee joints. Walking zone in Fig.7(b) corresponds to oscillatory patterns in the hip and the knee joints. In case of external perturbation force, pattern manipulation is necessary to avoid falling. The figure shows the group of patterns in the hip and the knee joints by

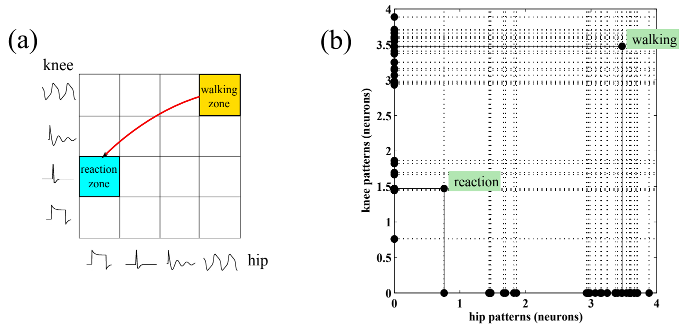

Fig. 7. The space of patterns is for hip and knee joints, with an example of switching against perturbation. (a)Patterns switch from walking by oscillatory patterns to quiescent pattern for knee and plateau for hip. (b)Neurons switch from walking zone to other neurons that represent quiescent pattern for knee and plateau for hip. Each neuron represents one pattern.

which the robot can react against the perturbation. An example for walking and reaction phases is shown in Fig.8. First, it presents the normal walking on a flat terrain without any perturbation. Next, it illustrates the fall because of external perturbation force of $45N$ applied on the back of the robot (the simulated robot mass is about 22 kg and the walking speed is almost $0.2m/s$). Fig.8(c) shows how the biped robot react correctly against the external force by adapting the behavior of the rhythm generators neurons.

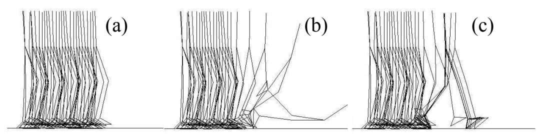

Fig. 8. Effects of adaptation mechanism on the biped to avoid falling. (a)Walking without perturbation.(b)Falling due to the perturbation. (c)Successful walking with adapation to the perturbation.

5 Conclusion

In this paper a neurobiological inspired controller for biped walking is presented. We showed how the behavior in rhythm generator neurons brings adaptation to face external perturbations. The switching between patterns was simplified by using a simple method to classify success and failure. Moreover, a technique for dimensionality reduction depending on the energy based metric patterns leads greater benefits, since the classification can be carried out over one axis only in relation to the motion patterns. Hence, establishing a space of patterns for the hip, and the knee joints. This space allows high-level control for goal directed action, thus, learning to achieve more complicated reactions. It also permits other rhythmic movement, where learning patterns replaces learning parameters. This was done by our experience based learning mechanism with this new model for vigilance threshold; we are able to explore in more efficient manner the space of parameters for new motion patterns. This mechanism was implemented on a simulated planar biped and allowed the robot to learn to walk and to react to perturbation without supervision. Our future work shall address goal directed action learning and adaptation to further changes in the environment, as well as changes in the physical parameters of the biped. This important issue will be addressed in order to apply the proposed adaptation mechanism to a humanoid prototype under development.

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