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A New Approach to Design of CPG Model for Stable Humanoid Locomotion Using Neural Oscillators

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Abstract

In this paper, we propose a new model using central pattern generators (CPG) for the stable motion of Humanoid robot. After that we compare the proposed model with the existing Taga's model of humanoid robot. The Matsuoka Neural Oscillators are used to generate the required signals to realize the coordinated movement of a musculoskeletal model of humanoid robot with five links. The proposed design of the CPG is verified through simulation.

Keywords: Biped Locomotion, Musculoskeletal system Central Pattern Generator (CPG), Matsuoka Neural Oscillator, Entrainment

1. Introduction

Human locomotion system has been a motivation for researchers for past decades in the field of humanoid robots. Human locomotion is characterized by smooth, regular and repeating movements of legs. The sequence of events that take place during human locomotion can be summarized as: generation of signals in the central nervous system, transmission of signals to peripheral nervous system, contraction and extension of muscles to develop forces and moments at joints to produce the resulting motion. Neurobiologists strongly believe that the animal locomotion is governed by rhythm-generating networks in the nervous system, which are called central pattern generators (CPGs). The central pattern generators are biological oscillators which consists of a number of neurons, the neurons are connected to each other in such a way that they can generate coordinated oscillations due to the membrane potentials of the neurons. Mathematically, CPGs are generally modeled as coupled nonlinear ordinary differential equations. To implement CPGs and to generate required signals a number of nonlinear oscillators have been proposed and developed by various authors, some of them are Vander Pol, Hopf, Rayleigh and Matsuoka oscillators. Matsuoka oscillators are most frequently used for movement simulation and rhythmic movement pattern generation. Because they are easy to use in comparison of other oscillators. Employing the Matsuoka neural oscillator, Taga *et.al.* placed a CPG in the feedback loop to activate rhythmic muscle contractions and extensions, where the commanded pattern is modified through sensory signals in response to changes in the environment and body mechanics. This robot model was also simulated and applied to the 3D locomotion by Miyakoshi *et.al.* Liu *et.al.* modified the design of CPG model with new interconnection coupling links and its inhibition coefficients for a CPG based controller. Many studies are also reported to expound the application of CPG based controller for biped robots, quadruped robots and hexapods. In the central nervous system the human like motion is controlled hierarchically at several levels, for example the cerebral cortex, brainstem and spinal cord. Locomotion studies have shown that the low level motion patterns such as swimming, running and walking in vertebrates are generated by the CPG mostly found in the spinal cord.

A CPG is a distributed biological neural network which can produce coordinated rhythmic signals without oscillating input from the brain or from sensory feedback. As an example, they mention that a cat exhibits a walking

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gait as soon as a simple signal is sent to its brain stem. By changing the amplitude of the signal, the cat's movements can be changed from a trotting- to a walking- and even a running gait. In this example the nervous cell in the cat's brain stem and spinal cord is the neural network forming the CPG. The nervous signals required to make the cat's leg joints produce the trajectories of the gait are the output of the neural network.

The rhythm control is a challenging task whenever the humanoid move at the terrain, because the terrain may be even or uneven which pauses threat on the movement, so the rhythm control is necessary. *K. Matsuoka (1987)* investigated rhythm control in some networks consisting of a number of neurons, these networks consists of two, three or four neurons and include various aspects in the generation of rhythms in bipeds. Generally there are four methods to control the rhythm generation:

1. Uniform alternation in the intensity of whole input.
2. Temporal alternation in the stimulus pattern of the multimode rhythm generators.
3. Change in the part of inputs.
4. Change in the synaptic weights of neurons.

The rhythm control models proposed in this paper may be used from simple to even more complicated models of the bipeds. [Kiyotoshi Matsuoka, 1987, Mechanisms of frequency and pattern control in the neural rhythm generators].

From the biological point of view, the neural circuits which are responsible for generating rhythmic output are the pacemaker model, the closed loop model and the half centre model. The closed loop model is very similar to the Matsuoka's half center model. It is proposed for the tailed newt like amphibian. Pacemaker model involves complex interaction of ionic currents, of a group of pacemaker cells. Electrical signals are generated by such cells which are responsible for controlling of heart rates. The pacemaker cells are responsible for driving flexor motor neurons and extensor motor neurons through inhibitory interconnections.

Mathematically CPGs may be described as a set of identical systems of differential equations, which are characterized as a bounded subset of the phase space to which the dynamics becomes restrict after a sufficiently long time. The periodic movement of the biped is a limit cycle attractor, since the biped returns after a fixed period into approximately the same configuration.

2. Neuron Model of Matsuoka Oscillator

Originally, Matsuoka's neural model consisted of two first order coupled differential equations, one representing the membrane potential of the neuron and the other the degree of neuron fatigue (Matsuoka et al., 1987).

$$\frac{\tau_{ri} d_{u_i}}{d_t} = -u_i + \sum{}_j^n = 1\, w_{ij} y_j + w s_i s_o - bfi + feed_i \quad (1)$$

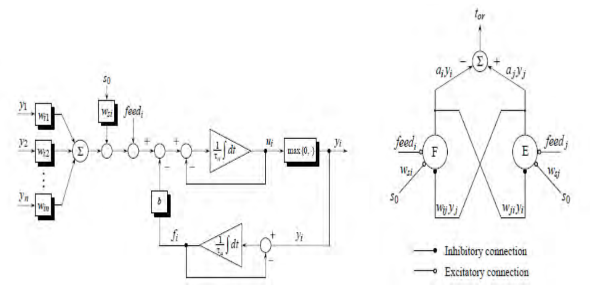
$$\frac{\tau_{ai} df_i}{d_t} = -f_i + y_i \quad (2)$$

$$y_i(u_i) = max(0, u_i) \quad (3)$$

Where the output of the neuron is nonlinear in a logic function.

The mathematical neuron model has two state variables and constant parameters but their values must be selected appropriately. The first is inner state variable u_i, corresponding to the membrane potential of the neuron.

Figure 1.1(a): General Matsuoka Neuron Model (b) One Oscillator Consisting of An Extensor and Flexor



The second state variable is f_i, representing the degree of adaptation or self inhibition in the i-th neuron, b is the adaptation constant, and yi is the output of the i-th neuron. Subscripts i, j denote the neuron number, τri is the time constant specifying the rise time when step input is given. The frequency of output is roughly proportional to $1/\tau_{ri}$. τ_{ai} is the time constant specify the adaptation time lag, w_{ij} denotes the inhibitory synaptic connection weight from the j-th neuron to the i-th neuron , w_{ij}<=0 for i!=j and w_{ij} =0 for i=j. $\sum w_{ij} y_j$ represents the total input from neurons inside a neural network, S_0 is constant drive input, and w_{si}

denotes a drive input connection weight. Feedi is an input feedback sensor signal to the i-th neuron representing internal sensory information and interaction between the robot and its environment, and it is used mainly in a closed loop CPG model or else is set to zero. Input $feed_i$ may be any number of inputs applied to the i-th neuron model, which may be either proprioceptive signals or signals from other neurons. Note that time constants τ_{ri} and τ_{ai} change frequency and that constant input S_0 changes amplitude.

Figure 1.1(a) shows the general Matsuoka neuron model described by equation (1), (2) and (3).

Assuming that the Matsuoka oscillator consists of two neurons with four state variables, two variables represent the inner state of each neuron u_i and u_j, and the other two state variables represent the degree of adaptation for each neuron, f_i and f_j, these neurons linked reciprocally, alternately inhibit and excite each other to produce oscillation as output. Such activity accounts for the alternating and mutually inhibition of the flexor and extensor muscles at joints during walking. The extensor and flexor are physiologically driven based on the output of each neuron. Self inhibition is governed by bfi and bf_j connections and mutual inhibition by $w_{ij}y_j$ and $w_{ji}y_i$ connections. Oscillator output is $t_{or} = a_j y_j - a_i y_i$, representing the algebraic sum of the weighted output signal from each neuron, where a_i and a_j denote constant gains. t_{or} may be used as a motor command to drive a 1-DOF joint, where tor > 0 implies extensor neuron activity, and $t_{or} < 0$ implies flexor neuron activity(Liu et al., 2007).

Conventionally, the output of oscillator tor is used in the framework of feed forward control, where it is directly regarded as any manipulated quantity, such as torque, rate of angle, angle, etc., for each active joint in a robot. Here the two neurons of each oscillator generate torques in opposite directions, i.e., the direction of flexor and extensor contraction. The algebraic sum of torques at each neural oscillator is proportional to the torque at the joint during biped walking.

In a simplified Matsuoka oscillator model representing an extensor neuron and a flexor neuron (Figure 1.1(b)), the neural oscillator causes attraction if provided with an input having a frequency similar to its natural frequency. τ_{ri}, τ_{ai}, b, and w_{ij} of both neurons must be optimized to achieve regular, sustainable oscillation generating stable rhythmic patterns.

3. General Model of Information Flow in Bipedal Locomotion System

The general model gives the idea about the control of locomotor system in the real environment. It is comparable with the human being or other biped exists in the real environment.

Figure1.2: The General Model of Information Flow in Bipedal Locomotion Control System.

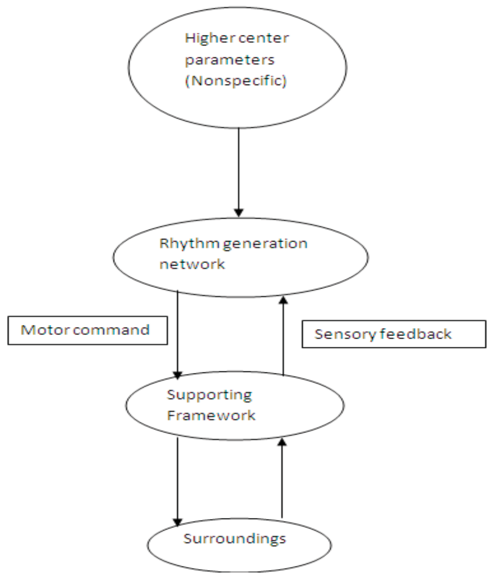


Figure shows the information flow by arrows in our model of bipedal locomotion, the higher center parameters is comparable with the human brain which is responsible for generating the control signals to control overall body of the human being or bipeds, quadrupeds, hexapods and other living things exist in the real world. The rhythm generation network is described by a system of differential equations of coupled neural oscillators. The supporting framework, we may also call it musculo-skeletal system is defined by a set of Newton-Euler equations.

4. Design of Central Pattern Generator

In robotics, the CPGs consist of networks of oscillator circuits coupled to the joints of the robot. CPG models are built by hypothesize that each joint receives signals by the oscillator which consists of two neuron. According to this hypothesis we know from the biological literatures that the real joints have two muscle groups, flexors and extensors, which control most joints. The use of CPGs to control bipedal locomotion has the advantage of being biologically inspired and adaptive to changes in the surroundings. In this work we use six Matsuoka oscillatory units; each oscillatory unit consists of two neurons.

In our model we consider the body above the heap as a point mass. Each oscillatory unit generates a torque to actuate the joints of the biped. Each oscillatory unit can be mathematically represented by the following differential equations. *(Matsuoka et al., 1985)*.

$$\tau \dot{u}_1 = -u_1 - w y_2 - \beta v_1 + u_0, \quad (4)$$

$$\tau \dot{u}_1 = -u_1 - w y_1 - \beta v_2 + u_0, \quad (5)$$

$$\tau' \dot{v}_1 = -v_1 - y_1, \quad (6)$$

$$\tau' \dot{v}_2 = -v_2 - y_2, \quad (7)$$

Where u_i is the inner state of the i-th neuron; y_i is the output of the i-th neuron; v_i is a variable representing the degree of the adaptation or self inhibition effect of the i-th neuron; u_o is an external input which is supplied with a constant rate; w is a connecting weight; and τ and τ' are time constants of the inner state and the adaptation effect respectively.

As shown in Figure 1.3, the cells 1 and 2 send signals to the right hip joint, the cells 3 and 4 send signals to the left hip joint, cells 5 and 6 send signals to the right knee joint, the cells 7 and 8 send signals to the left knee joint, cells 9 and 10 send signals to the right ankle and cells 11 and 12 send signals to the left ankle joint.

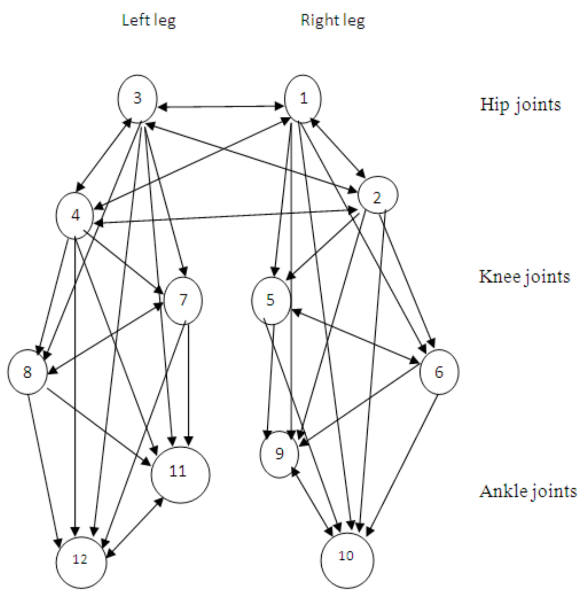
In the existing Taga Model we add some new interconnections and verify through simulation that the proposed model is better for the higher speeds and show the stable and competent movement.

5. Simulation of Central Pattern Generator

In this section we simulate our model using MATLAB software and show the results of the simulation accordingly. We use fourth order Runga-Kutta method to solve the differential equations of neural rhythm generator, The ODE113 tool of the MATLAB software will be used to solve the equations through Runga Kutta method.

We show the following results of our model one by one

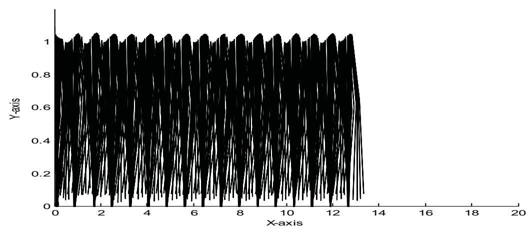
Figure 1.3: Proposed CPG Model for Locomotion in Bipeds



5.1. Simulation for the Generation of Walking Pattern

We show the model of bipedal locomotion through stick diagram which is traced for 10 second. The stick diagram clearly shows the stable walking of the biped model.

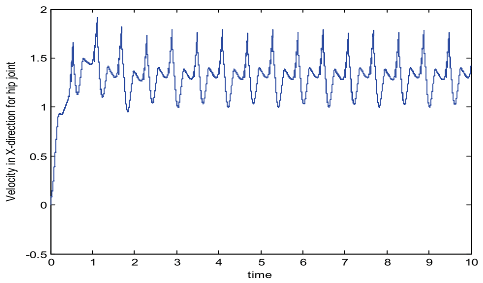
Figure 1.4: The Stick Diagram of Walking Movement of Proposed Model



5.2. Simulation for the Velocity of hip Joints in the X-direction:

The Figure shown below shows the velocity of hip joint in the proposed model, the Figure shows the stable walking movement of the biped.

Figure 1.5: The Velocity of the Hip Joint in the X-Direction



5.3. Simulation of the Activity of Neurons for Inner State

The following diagrams show the inner state activity of each neuron (denoted by u_i) implemented in the oscillators. The graph shows the repetitive or rhythmic activity of each neuron in order to generate the rhythms in bipeds.

Figure 1.6(a): The Inner State of Neuron 1

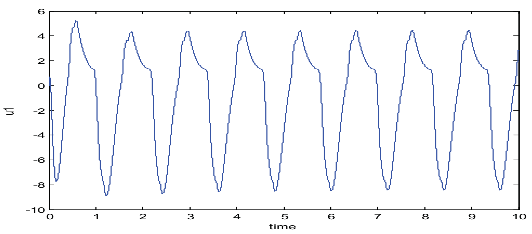
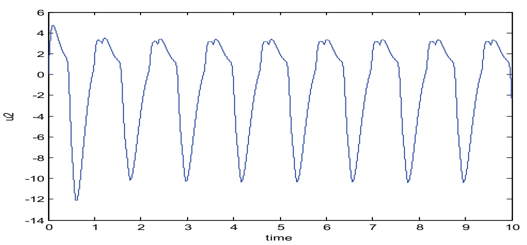


Figure 1.6(b): The Inner State of Neuron 1



5.6. Simulation for the Output of Neurons

The output of each oscillator as we know is used to actuate the joints of the bipeds and each oscillator consists of two neurons one is called the extensor and the other is called flexor neuron. The extensor neuron have the capability to cover more area when activate and the flexor have the capability to bend very similar to the human muscles.

The Figures shown below show the output of each neuron implemented in the proposed model. The graph shows the rhythmic activity of each of the neuron. The output is denoted by y_i in the proposed model.

Figure 1.7(a): The Output of Neuron 1

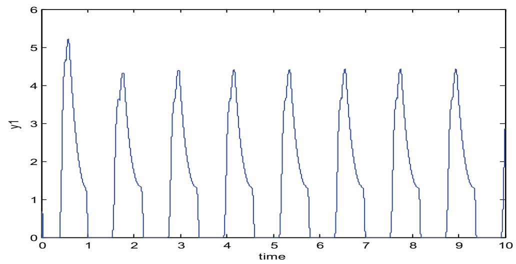
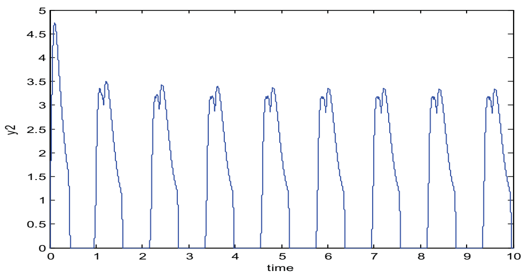


Figure 1.7(b): The Output of Neuron 2



5.7. Simulation for the Torque Generated at Each Joint

The torque generated at each joint is used to actuate the joints of the biped. There is a total of six joints exist in the proposed model out of which two joints are at hip, two at knee and two at ankle for left and right positions. We can show this by using the graphs generated in MATLAB.

The graphs generated show the rhythmic activity so the structure repeats itself and it gives the idea that the biped move in a stable manner.

Figure 1.8(a): The Torque Generated at Joint 1

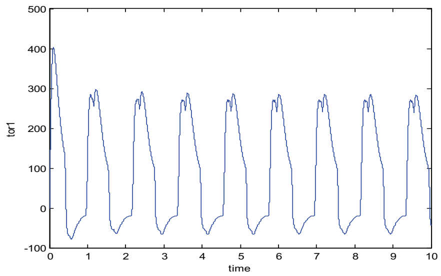
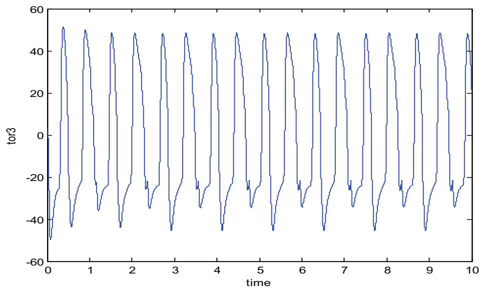


Figure 1.8(b): The Torque Generated at Joint 2



6. Comparison between TAGA Model and Proposed Model

In this section we compare the existing Taga model with the model which we have proposed. The basis for the comparison is the value of non specific parameter (u_0) of the higher center; we consider the values of u_0 ranging from 5.5 to 7.0 and show by graphs that the proposed model is best suited for the higher values of u_0 and approximately same for the lower values of u_0. Basically u_0 is concerned with the speed of the biped. The higher value of u_0 indicates higher speed.

We show the results by using stick diagrams and compare by using tables.

Now we summarize the results by using Table 1.1 and Table 1.2 for showing the stability for different values of nonspecific parameter. First we show the stability and instability of the two models after that we show the results in terms of distance travelled and time taken by both of the models.

Table 1.2: Comparison Between Taga and Proposed Model for Different Values of u0

(Distance travelled in 10 sec.)

	External Drive Input (u_0)			
	u_0 = 5.5	u_0 = 6.0	u_0 = 6.5	u_0 = 7.0
Taga Model	Dist. = 13.50 m	Dist. = 14.20 m	Dist. =17.10 m	Unstable after 3.0 m distance
Proposed Model	Dist. = 13.50 m	Dist. = 14.20	Dist. = 14.80	Dist. = 15.20 m

For all of these results and experiments we use the Intel core2 Duo processor (T 6670@2.20 GHZ, 1.18 GHZ) machine with 1.96 GB of RAM.

7. Discussion and Conclusion

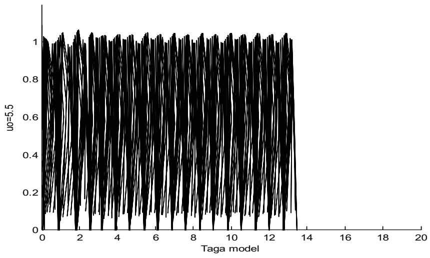
The outcome of the examinations and experiments described in this paper fulfilled the intended goal, i.e. to generate robust bipedal gait for a simulated robot by means of structural evolution of CPG networks.

Robots are used in different fields. 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. A new approach to biped locomotion is CPG. A problem of the CPG approach is too many parameters to set for CPG. Evolutionary computation methods are often used to find the parameters of the CPG.

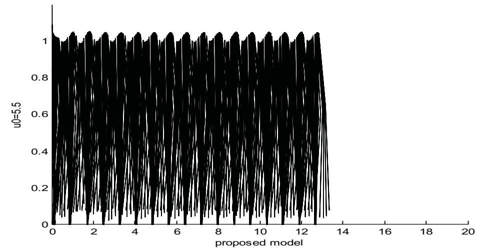
Through the results of the simulation we show that whenever we increase the value of nonspecific parameter (higher center parameter) than at a level the Taga model show the unstable walking pattern, and our model shows the stable walking pattern at these values. Results of the simulation experiments have also shown that interconnection coupling links newly added to the CPG with its inhibition coefficients ensured the generation of dynamic, stable, sustained rhythmic human like movement with robust gait for bipedal robots at different walking speeds.

The following points demonstrate that what we have done in the simulation experiments and the meaning of outcome of the experiments.

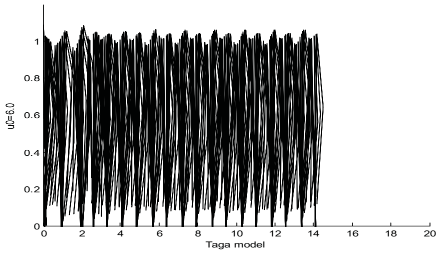
Figure1.9: Comparison between the Taga Model and the Proposed Model for Different Values of u_0



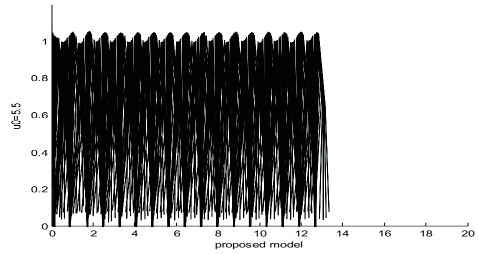
Walking trajectory of Taga model when u_0=5.5



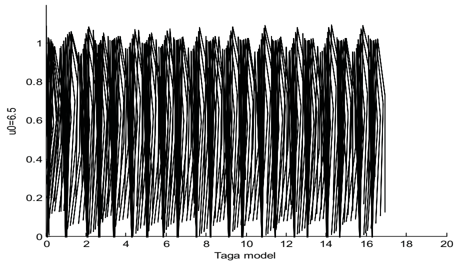
Walking trajectory of Proposed model when u_0=5.5



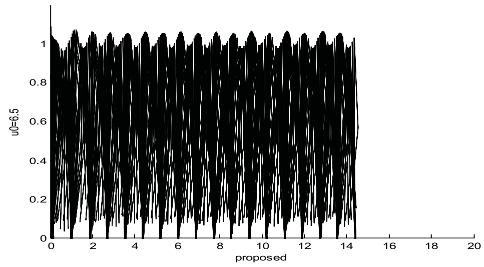
Walking trajectory of Taga model when u_0=6.0



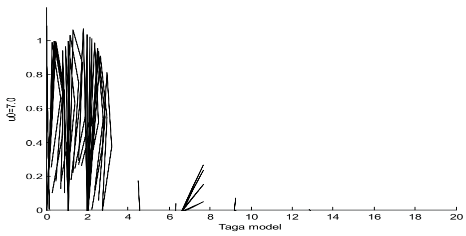
Walking trajectory of Proposed model when u_0=6.0



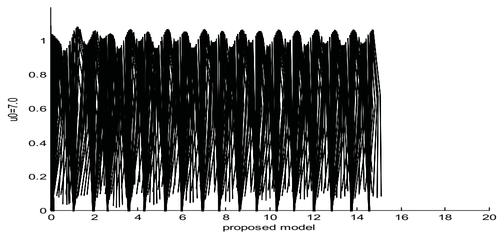
Walking trajectory of Taga model when u_0=6.5



Walking trajectory of Proposed model when u_0=6.5



Walking trajectory of Taga model when u_0=7.0



Walking trajectory of Proposed model when u_0=7.0

1. First, we generate a walking trajectory by simulating our model in the MATLAB. It shows the stable walking for 10 s simulation for u0 =6.0.
2. We show the velocity of the hip joint in the x-direction. The graph generated shows the stable walking.
3. We show the inner state of each neuron by graph. The graphs show the stability and the repeatability of the steps.
4. The Figure 1.7(a-l) shows the oscillator output. The graph generated shows the stable, rhythmic and sustained oscillations in the proposed model.
5. The Figure 1.8(a-f) represents the torque generated at each joint of the proposed model. The torque generated is used to actuate the joints of the humanoid robot. The graphs show the repetitive activity of the neural oscillators which can produce stable, rhythmic and sustained oscillations.
6. We compare the results of our proposed model with the existing Taga model for different values of higher center parameter which is denoted by u_0. We see that the proposed model shows the stable walking pattern in a range of values (5.5 to 7.0) and the existing Taga model show unstable walking whenever the value of u_0=7.0 so the proposed model is best suited whenever the values of higher center parameter is high and approximately same for lower values of u0. The results are shown in Figure 1.9 (Comparison between Taga Model and Proposed model for different values of u_0). Table 1.1, 1.2 shows the clear distinction between the two models.

8. Future Work

There is no systematic method to find out the values of different parameters till date. So our next work thus is to focus on applying appropriate learning algorithms to optimize the parameters of neural oscillators toward reconfiguring the coupling mechanism in real time.

We can also propose the models that have higher number of links or higher number of degrees of freedom and implement these models to generate the stable walking trajectories in such a way that the implementation is also physically possible.

References

1. Vaughan, C. L (2003). Theories of bipedal walking: An odyssey. *Journal of Biomechanics*, 36(4), 513-523.
2. Cohen, A. H., Holmes, P. J. & Rand, R. H. (1982). The nature of coupling between segmental oscillators of the lamprey spinal generator for locomotion: a mathematical model. *Journal of Mathematical Biology,* 13(3), 345-369.
3. Giszter, S. F., Moxon, K. A., Rybak, I. A. & Chaplin, J. K. (2001). Neurobiological and neurorobotic approaches to control architecture for a humanoid motor system. *Journal* of *Robotics and Autonomous System*, 37(2), 219-235.
4. Dimitrijevic, M. R., Gerasimenko, Y. & Pinter, M. M. (1998). Evidence for a spinal central pattern generator in humans. *Annals of the New York Academy of Sciences,* 860, 360-376. doi: 10.1111/j.1749-6632.1998.tb09062.x
5. Matsuoka, K. (1985). Sustained oscillations generated by mutually inhibiting neurons with adaptation. *Biological Cybernetics,* 52, 367-376.
6. Matsuoka, K. (1987). Mechanisms of frequency and pattern control in the neural rhythm generators *Biological Cybernetics*, 56, 345-353.
7. Taga, G., Yamaguchi, Y. & Shimizu, H. (1991). Self-organized control of bipedal locomotion by neural oscillators in unpredictable environment. *Biological Cybernetics*, 65, 147-159.
8. Miyakoshi, S., Taga, G., Kuniyoshi, Y. & Nagakubo, A. (1998). *Three-dimension bipedal stepping motion using neural oscillators-towards humanoid motion in the real world.* In Proceedings of IEEE/RSJ International Conference on Intelligent Robot and Systems, 84-89.
9. Liu, G. L., Habib, M. K., Watanabe, K. & Izumi, K. (2007). The design of central pattern generators based on the matsuoka oscillator to generate rhythmic human-like movement for biped robots. *Journal* of *Advanced Computational Intelligence and Intelligent Informatics*, 11(8), 946-954.
10. Ijspeert, A. J. (2008). Central pattern generators for locomotion control in animals and robots: A review. *Neural Networks,* 21(4), 642-653.
11. Yang, W., Chong, N. Y., Ra, S., Kim, C. H. & You, B. J. (2008). *Self-stabilizing bipedal locomotion employing neural oscillators.* In Proceedings of 8^{th} IEEE-RAS International Conference on Humanoid Robots, December, 1-3, 8-15.