Central Pattern Generators Based on Matsuoka Oscillators for the Locomotion of Biped Robots

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Abstract

Biologically inspired control approaches based on central pattern generators (CPGs) with neural oscillators have been drawing much attention to generate rhythmic motion for biped robots that resemble human-like locomotion. This paper describes the design of a neural oscillator based gait rhythm generator using a network of Matsuoka oscillators to generate a walk pattern for biped robots. This includes proper consideration of oscillator's parameters, such as a time constant adaptation rate, coupling factors for mutual inhibitory connections, etc., to obtain a stable and desirable response from the network. The paper examines the characteristics of a CPG network with six oscillators and the effect of assigning symmetrical and asymmetrical coupling coefficients among oscillators within the network structure under different possibilities of inhibitions and excitations. The kinematics and dynamic of a five-link biped robot has been modeled and its joints are actuated through simulation by the torques output from the neural rhythm generator to generate the trajectories for hip, knee, and ankle joints. The parameters of the neural oscillators are tuned to achieve flexible trajectories. The CPG based control strategy are implemented and tested through simulation.

1 Introduction

Recent studies on the biped locomotion enabled humanoid robots to navigate real environments [1]. ZMP (Zero Moment Point) based control approaches are used to describe the stability and control of biped robot systems by following a targeted trajectory [2]. These approaches have focused on the ability of executing planned movements at any instance by ensuring surface contact between the sole and the ground. In general, the developed ZMP based control algorithms for bipedal locomotion have been shown to be effective to achieve bipedal locomotion in legged robots with flat feet. However, they require precise modeling and precise joint actuation with high control gains. From the biological point of view, locomotion of human and animals do not require such precision, and it is quite different from that of current biped robots. There are evidences showing the existence of various oscillatory or rhythmic pattern generation activities within the neural circuitry in almost every animal, and most of them are produced without receiving any particular extrinsic oscillatory stimulus [3]. The fundamental mechanisms of animals, rhythmic biological movement, such as locomotive motion of quadrupeds, flapping of bird wings, swimming of fish, crabs, etc. are typical examples of oscillatory activities that have been studied both in biological science and in engineering.

Neurobiological studies revealed that rhythmic motor patterns are controlled by neural oscillators referred to as CPGs which generate oscillatory signals [4]. It has been also suggested that sensory feedback plays an important role in stabilizing rhythmic movements by coordinating the physical system and the CPGs [5]. In contrast to off-line trajectory planning, biologically inspired control approaches based on CPGs with neural oscillators have been drawing much attention to generate rhythmic motion for biped robots that featured with self-adaptive properties to cope with change in their environment [6-8]. The neural oscillator proposed by Matsuoka [3] is widely used to model the firing rate of two mutually inhibiting neurons described in a set of differential equations. This model is used in robotic applications to achieve designated tasks involving rhythmic motion which requires interactions between the system and the environment. However, it is very difficult to determine the CPG parameter values for various robots and environments, since there is no design principle to determine the parameter values.

This paper describes the design of an oscillator-based gait rhythm generator using a network of Matsuoka oscillators to generate a walk pattern for biped robots. This includes proper consideration of oscillator's parameters such as a time constant, coupling factors for mutual inhibitory connection, etc., to obtain a stable and desirable response from the CPG network. The paper examines the characteristics of CPG network with six oscillators and the effect of assigning symmetrical and asymmetrical coupling coefficients among oscillators within the network structure under different possibilities of inhibitions and excitations.

2 The CPGs and Neural Oscillator Model

Almost all species developed completely different form of locomotion perfectly suited to its morphology and environment to ensure its survival. To achieve locomotion, the neural system generates rhythmic signals that are sent to the musculo-skeletal system in order to produce torques on the different joints of the animal. There are some evidences showing that the locomotion patterns in human are generated at the spinal level, and as such, it has been considered that humans use a system that is comparable to a CPG for their locomotion. CPGs are neural networks that can produce rhythmic motor patterned outputs without rhythmic sensory or central input.

Bipedal locomotion seems to be more complicated than the mentioned process as the balance is much important and critical with only two legs, while it makes the control extremely crucial. CPG based approach is directly inspired from biological considerations and can be represented by different mathematical models such as oscillators, artificial neurons, vector fields, etc. Each CPG usually represents one degree of freedom (DOF). Oscillator based CPGs use the concept of limit cycles which are very convenient in the case of locomotion as they can return to their stable state after a small perturbation and they are almost not influenced by a change in the initial conditions. Different models could be used to represent the interaction between the CPG and the reflex system that represents the type of the feedback mechanism from internal sensory information and the interaction with robot environment. In order to represent the CPG and generate the required signals several nonlinear oscillators that are coupled together have been developed, such as, Hopf, Rayleigh, Van del Pol, Matsuoka, etc. oscillators.

Due to its simplicity and effectiveness, Matsuoka oscillator is widely used in many researches on robotics and CPGs [3, 9]. It is based on the mutual inhibition of two artificial neurons that generate a periodic signal as output. The model of each neuron has represented by two equations with two state variables as below,

$$\begin{aligned}
\tau_{ri}\frac{du_i}{dt} &= -u_i + \sum_{j=1}^{n} w_{ij}y_j + w_{s_i}s_0 - bf_i \\
&\quad + feed_i \qquad (1)\\
\tau_{ai}\frac{df_i}{dt} &= -f_i + y_i \qquad (2)\\
y_i(u_i) &= \max\{0, u_i\} \qquad (3)
\end{aligned}$$

The first state variable is u_i that corresponds to the membrane potential of the neuron body, and the second state variable is f_i that represents the degree of fatigue or adaptation (self-inhibition) in the neuron, while y_i is the output of the neuron. The subscripts i, j denotes the neuron number, τ_{ri}, is the time constants that specifies the rise time when given step input. The frequency of the output is roughly proportional to $1/\tau_{ri}$. In addition, τ_{ai}, is the time constant that specifies the time lag of the adaptation effect. w_{ij}, denotes inhibitory synaptic connection weight from the jth neuron to the ith neuron; $w_{ij} \leq 0$ for $i \neq j$, and $w_{ij} = 0$ for $i = j$. $\sum(w_{ij}y_j)$, represents the total input from the neurons inside a neural network. s_0 is a driving input and w_{s_0} denotes a connection weight of the driving input, and $feed_i$, is an input feedback sensor signal to the neuron and represents the internal sensory information and interaction between the robot and its environment ($feed_i$ has been added to the neuron model of Matsuoka to represent the feedback sensory information [8]), and it is used mainly with a closed-loop CPG model.

Figure 1(a) shows the general Matsuoka neuron model described by equations 1, 2 and 3. Matsuoka oscillator consists of two neurons that are linked reciprocally while inhibit and excite each other alternatively to produce an oscillation as output. Such activity is used to account for the alternating activities of flexor and extensor muscle at each joint during walking. The self-inhibition is governed by the bf_i connections while the mutual inhibition is done through the $w_{ij}y_j$ and $w_{ji}y_i$ connections. The output torque will equal to $\tau_r = y_j - y_i$. Figure 1(b) shows two coupled neurons of the Matsuoka oscillator.

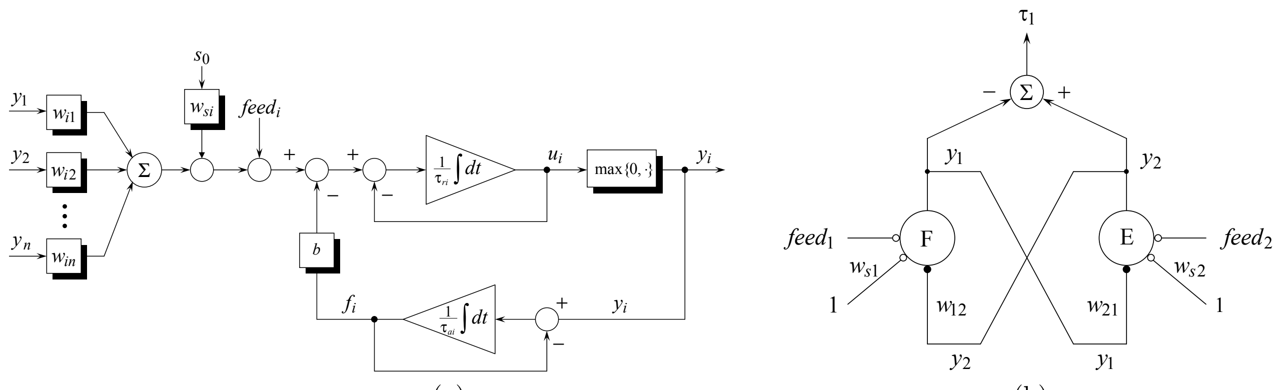

Figure 1: (a) General Matsuoka neuron model; (b) One oscillator consisting of an extensor and a flexor

3 Biped Robot and Neural Gait Rhythm Generator

3.1 The general control strategy for gait generation

Figure 2 introduces the adopted general control strategy for the bipedal robot aiming to generate flexible rhythmic walking gait, and it includes three parts. The first part consists of two major elements. The first element represents the high level activity coordinator that can set and activate the relevant neural rhythmic motion based on external and internal sensory information. The second element within the first part represents the network of coupled neural oscillators aiming to generate synchronized rhythmic signals. The locomotor movement results from torques generated by the neural rhythm generator and acting at each joint of the robot. The second part of the control strategy includes the model of the musculo-skeletal system along with the mathematical formulation of the dynamic equations of motion using Newton-Euler method. The last part represents the feedback signals that aim to establish a closed-loop to enable real time adaptation for the walking gait.

3.2 The bipedal musculo-skeletal model

Figure 3 shows the simple model for simulating a bipedal musculo-skeletal system that has been considered in this paper. It has five joints and two identical legs each with three DOFs corresponding to hip, knee and ankle joints. Each leg is composed of a thigh (links 2 and 3), and a shank (links 4 and 5). In the dynamic model of the bipedal musculo-skeletal system, the links are considered to be of uniform rectangular shape with

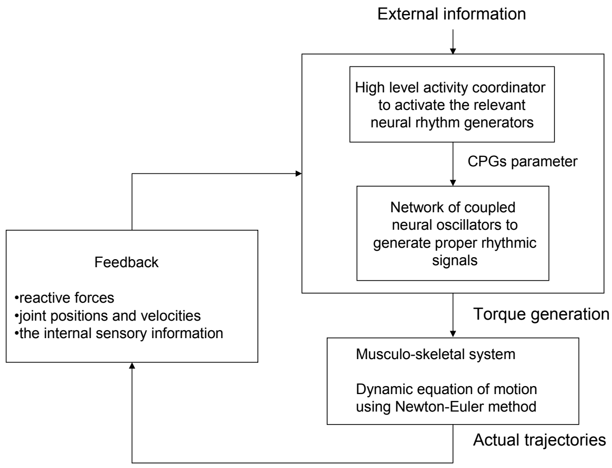

Figure 2: The general control strategy for the bipedal robot

mass at its center. A point mass is used to represent the remaining part of the body and it is described by link 1 at the hip. Both legs are integrated at link 1 while assuring suitable detachment. The joints are numbered as Joints 1, 2, 3, 4, 5 from the side of the body, where Joint 1 is the hip joint, Joints 2 and 3 are knee joints, and Joints 4 and 5 are ankle joints.

Due to their low inertia, a point foot has been considered into the dynamics during the support phase, and contact with the ground has been represented by two dimensional spring and damper. Vertical and horizontal ground reaction forces are modeled and calculated each time the ankle first makes contact with the ground respectively. A slippage model is established by using a condition that manages the relation between both reactive forces and the static friction coefficient of the ground. In addition, the described model

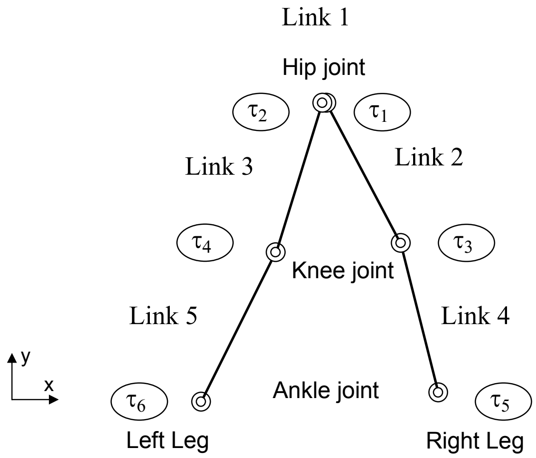

Figure 3: Five link model for a biped locomotion

is bounded to move within the sagittal plane, and the torques acting at the joints to realize the walking gait are assumed to be generated by the neural gait rhythm generator.

3.3 The mathematical motion formulation of the model

By using the Newton-Euler dynamic formulation, the general form of equations of motion for the bipedal musculo-skeletal are derived as below [8],

$$\ddot{\boldsymbol{x}} = P(\boldsymbol{x})F + Q(\boldsymbol{x}, \dot{\boldsymbol{x}}, T_r(\boldsymbol{y}), F_g(\boldsymbol{x}, \dot{\boldsymbol{x}})) \qquad (4)$$

where $\boldsymbol{x}$ is a (14×1) vector of the inertial positions of 5 links and the initial angles of 4 links; P is a (14×8) matrix; F is a (8×1) vector of constraint forces; Q is a (14×1) vector; T_r is a (6×1) vector of torques; F_g is a (4×1) vector of forces on the ankle which depends on the state of the terrain; and $\boldsymbol{y}$ is a (12×1) vector of the output of the neural rhythm generator.

From the model, the equations of the kinematic constraints are formulated, and hence the acceleration can be obtained by differentiating these equations twice with respect to time. The yielded equations can be written in the following compact form,

$$C(\boldsymbol{x})\ddot{\boldsymbol{x}} = D(\boldsymbol{x}, \dot{\boldsymbol{x}}) \qquad (5)$$

The constraint forces can be obtained by substituting equation (4) into equation (5), and to get the required accelerations without the use of the constraint forces, the yielded equation of forces is substituted into equation (4). Hence, the compact form of the acceleration equations that represents the motion of the bipedal musculo-skeletal is,

$$\begin{aligned} \ddot{\boldsymbol{x}} &= P(\boldsymbol{x})[C(\boldsymbol{x})P(\boldsymbol{x})]^{-1}[D(\boldsymbol{x}, \dot{\boldsymbol{x}}) \\ &\quad - C(\boldsymbol{x})Q(\boldsymbol{x}, \dot{\boldsymbol{x}}, T_r(\boldsymbol{y}), F_g(\boldsymbol{x}, \dot{\boldsymbol{x}}))] \\ &\quad + Q(\boldsymbol{x}, \dot{\boldsymbol{x}}, T_r(\boldsymbol{y}), F_g(\boldsymbol{x}, \dot{\boldsymbol{x}})) \end{aligned} \qquad (6)$$

To solve the motion equations, the $\boldsymbol{y}$ values are provided as an output from the neural rhythm generator that is proportional to the torque. In addition, the feedback signal from the bipedal robot to the neural rhythm generator is represented by the joint positions and velocity of different moving parts of the body, and the contact forces with the environment.

3.4 The model for the neural rhythm generator

The neural oscillators are the main elements that compose the model of the neural rhythm generator. The simplest model of the neural oscillator consists of two mutually inhibited neurons with the self adaptation in each of them. Each neural oscillator has 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), respectively. Six of the neural oscillators have been used to model the neural rhythm generator for the bipedal robot. Two oscillators have been used at the left and right side of the hip and one oscillator has been used at each of the knee and ankle joints. Figure 4 illustrates the arrangement of the neural oscillators in relation to the adopted bipedal musculo-skeletal system. The odd number oscillator represents flexor (F) and the even number oscillator represents the extensor (E), while τ_1 to τ_6 represent the output torques from the oscillators. The configured neural oscillators have inhibitory connections. The two neurons of each oscillator generate torques in opposite direction, i.e., the direction of contraction of flexor and extensor muscle. The algebraic sum of the torques at each neural oscillator is proportional to the torque at the relevant joint during bipedal walk. The inhibitory connection between the hip oscillators produces alternate excitations to give the alternation between the movements of the two legs.

The parameters for each neural oscillator and the interconnection between the oscillators are tuned experimentally to achieve the generation of a consistent pattern that assembles human biped motion. The feedback signal from the bipedal robot to the neural rhythm generator is represented by the joint positions and velocity of different moving parts of the body, and the contact forces with the environment. In case of a physical biped robot, the feedback sensory information are sensed through different internal and external sensors.

4 Simulation and Results

In order to produce a suitable relative phase at the joints of each side of the bipedal, the interconnection between the neural oscillators at each side of the bipedal has been chosen in the way that the flexor and extensor of the hip oscillators can inhibit the extensor neurons of the knee and ankle oscillators as illustrated in Figure 4 and we can call this model as one-rank model. The simulation result of the walking gait for bipedal robot is shown in Figure 5. Based on this model, both of the knees' oscillators have been chosen to inhibit the ankles' flexor neurons as shown in Figure 6 and we can call this model as two-rank model. The simulation result of this case is shown in Figure 7. The total time is 2 seconds and the ground is level.

5 Conclusions

This paper has presented a CPG based control approach composed of a network of coupled neural oscillators to generate proper rhythmic motion for bipedal robot. This approach avoids the need to have a perfect knowledge of the robot's dynamics as compared to the trajectory based methods. In addition, it is a more general and adaptive to design controllers for bided robots. Moreover, reflexes that are produced by the robot's feedback sensors are used to manage external effects within the robot environment and balance control. However, currently there is no systematic design principle that can determine the parameter values for the oscillators and assigning efficient coupling between oscillators. Hence, the next step of this work will focus on adapting the parameters of each neural oscillator with the possibility of reconfiguring the coupling mechanism between oscillators in real time through learning paradigm.

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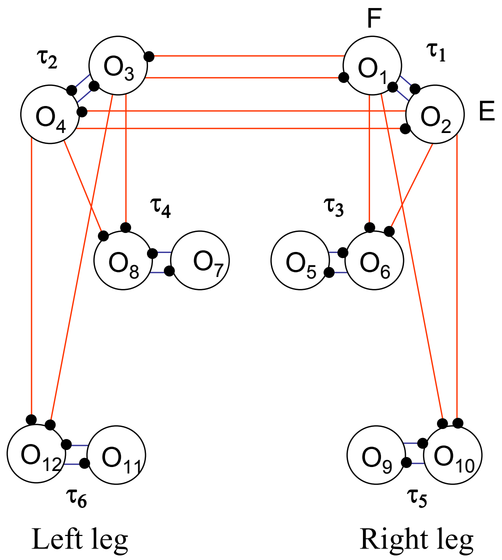

Figure 4: One-rank CPG network of biped model

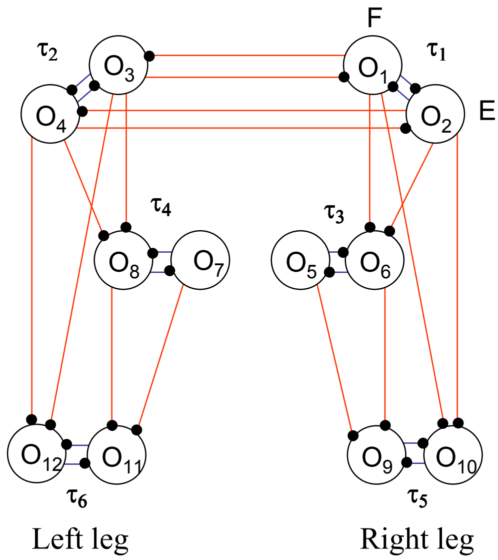

Figure 6: Two-rank CPG network for a biped locomotion

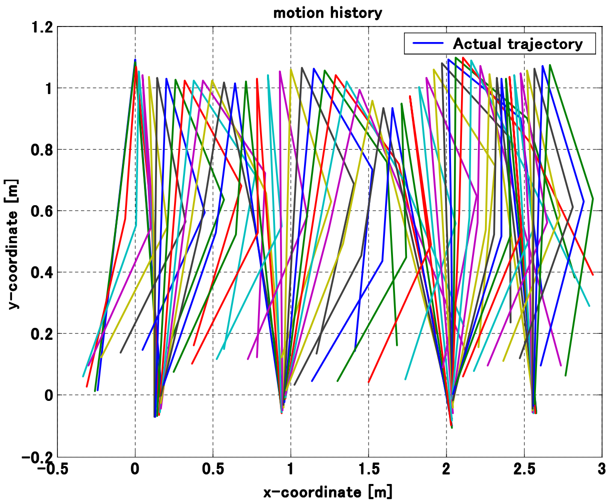

Figure 5: The simulated walking gait of bipedal using one-rank model in Fig. 4

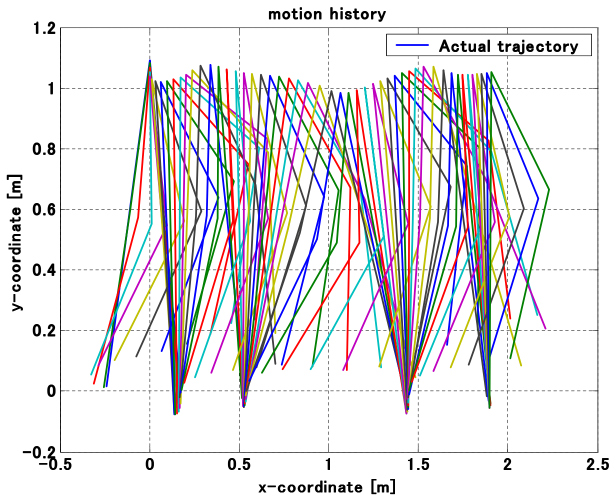

Figure 7: The simulated walking gait of bipedal using two-rank model in Fig. 6