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Synthesis of Matsuoka-based Neuron Oscillator Models in Locomotion Control of Robots

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***Abstract*—In this paper we present a numerical study of the Matsuoka-based neuron oscillator model. The Matsuoka-based neuron oscillator model is one of the most popular CPG (central pattern generator) models in robot motion control. In this paper, numerical simulation is conducted to analyze the influence of the parameters on the output signals. A mass-spring-damper system is used as an example to analyze the entrainment properties of the neuron oscillator. The main engineering application methods of these CPG-inspired control methods are concluded. The motivation is to present a practical guide to researchers and engineers interested in the CPG-inspired control approaches.**

Keywords-CPG; Neuron oscillator; Matsuoka model; motion control; robot

I. INTRODUCTION

In biology, the mechanism and biological CPG modeling have been studied in great detail [1]. In robotics, studying and mimicking animals' motion mechanisms for engineering applications is gaining increasing interest. It is believed that the CPG-inspired control method is an efficient way to break the bottleneck of motion control for robots: (1) it can produce periodic control signals even without sensory inputs, while sensory feedback signals can also modulate the activity of the CPG. So, with the CPG-inspired method, robots can either walk on a flat terrain with open-loop control or adaptively walk on an irregular terrain with closed-loop control; (2) it is a distributed control method. A CPG network coordinates all joints to complete a movement. By modulating the parameters of the CPG model, it can generate outputs with different phase relationships. These phase relationships can be used to acquire different gait patterns; (3) it can adapt to the environment via its entrainment property, which combines the neural system, body, and environment.

In applying CPG control in engineering applications, the first step is to mimic the CPG mechanism. Various kinds of mathematical models are commonly used in CPG-related studies. In general, there are three kinds of modeling methods: using biological neuron models to mimic the intrinsic properties of biological CPG; using half-center models to mimic the muscle control mechanism of animals; and using nonlinear oscillator models to mimic the dynamic properties of CPG.

In the first modeling method, biologists try to mimic biological CPG models by using a neuron model. However, due to the complexity involved in neuron structure and neural system characteristics, it is difficult to clearly identify the existing biological CPG models. The most famous neuron model is the Hodgkin-Huxley model [2]. While analyzing biological neuron models, detailed dynamic characteristics of small circuits usually need to be considered, such as pacemaker properties of signal neurons, and the mechanism of the rhythmogenesis of a large population of neurons.

In the third modeling method (skipping the second for the moment), models of physical dynamic systems are usually used, and relevant examples include the Kuramoto model [3], Hopf model [4], Van der Pol model [5]. The motivation for using a nonlinear oscillator as a CPG unit is that we do not have to study the detailed oscillatory mechanisms; this method only focuses on the bulk properties of the network, such as how to adjust parameters to get outputs with the desired amplitude, frequency and phase relationships. The advantage of the third class of models for engineering applications is the relative ease of implementation. However, the third type of models has less biological meaning than the other two models and it is more difficult to mimic the tonic input and sensory feedback of the biological CPG.

In engineering applications, the second class of models is used most widely. In nature, one degree of freedom (DoF) of joints is usually operated by two antagonistic groups of muscles. Inspired by this, half-center oscillator models have been proposed. Brown [6] proposed a half-center oscillator model as the basis to alternate activities of flexors and extensors. When the two neurons were reciprocally coupled, the oscillator would produce alternating rhythmic movement. The Matsuoka oscillator model [7, 8] has been widely used in rhythmic locomotion control of robots. Matsuoka analyzed mutually inhibiting neurons and found the conditions under which the neurons generate oscillation. Based on Matsuoka's model, Taga et al. proposed a similar model [9], which used a set of inhibitory-connected neuron oscillators to build a

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network. Kimura et al. [10] constructed a neural system based on the neural oscillators proposed by Matsuoka and Taga.

A major difficulty in applying CPG controllers is that the parameters and outputs are strongly coupled. So, before applying CPG models to robots, the parameters and properties of the models must be analyzed. There is no well-established parameter analysis methodology for the CPG model. A trial-and-error method is usually used in engineering applications. This method is tedious and inefficient. Sometimes, genetic algorithms (GA) have been used to evolve the parameters of the CPG model. The main disadvantage of this method is that it is difficult to design a proper fitness function, since too many aspects need to be considered. In this paper, we will focus on the Matsuoka-based half-oscillator model. The motivation of the paper is to present a useful exploration of Matsuoka-based motion controllers. We focus on a numerical analysis method to analyze the influence of the parameters to the outputs of the oscillator model. This will be the basis for the other parameter analysis methods.

The rest of the paper is organized as follows. Section II reviews the existing Matsuoka-based oscillator models. In Section III, by using numerical simulation methods, the influences of the model parameters on the outputs are investigated in detail. Coupled with a simulated mass-spring-damper system, the entrainment property of the model is studied. Section IV analyzes the application of the Matsuoka-based oscillator models in locomotion control of robots. Section V gives some concluding remarks.

II. Matsuoka-based Neuron Oscillator Models

The neural oscillator model proposed by Matsuoka is the best known CPG model in robotics engineering applications. It is composed of two identical neurons. The neuron model mimics the average of spike activity of the biological neuron. The dynamics of the two neurons are given by the following differential equations [7, 8]:

$$
\begin{aligned}
&T_r \dot{x}_i(t) = -x_i - w_{ij} y_j(t) - \beta v_i(t) + s_0 \\
&T_a \dot{v}_i(t) = -v_i(t) + y_i(t) \\
&y_i(t) = g\left(x_i(t)\right), \quad g\left(x_i(t)\right) \triangleq \max\left(x_i(t), 0\right)
\end{aligned} \tag{1}
$$

where $i, j = 1, 2$ and $i \neq j$. Variables $x_i(t)$ and $y_i(t)$ represent the membrane potential and firing rate of the neuron, respectively. In this model, the self-inhibitory term $v_i(t)$ is used to mimic the fatigue property of the neuron. Parameters T_r and T_a are the time constants which determine the reaction times of the variables $x_i(t)$ and $v_i(t)$. Parameters w_{ij} and β represent the strengths of mutual- and self-inhibition, respectively. Parameter s_0 mimics the tonic input to the neuron. Function $g\left(x\right)$ represents a threshold property of the neurons.

In the robotics field, the Matsuoka oscillator model has been widely applied to the locomotion control of robots because of its simplicity and other attractive properties. Based on Matsuoka's oscillator model, Taga proposed a similar oscillator model to generate neural rhythmic signals [9]. The Matsuoka and Taga oscillators only generate positive output signals. But for the application of joint control of robots, we need to control the motor with positive and negative angles, so Kimura et al. [10] constructed a neural system based on the oscillator models proposed by Matsuoka and Taga. This model consists of two mutually inhibiting neurons, which are represented by the following nonlinear differential equations:

$$
\begin{aligned}
&T_r \dot{u}_i^{\{e,f\}} = -u_i^{\{e,f\}} - w_{fe} y_i^{\{f,e\}} - \beta v_i^{\{e,f\}} + \sum_{j=1}^{n} w_{ij} y_j^{\{e,f\}} + Feed_i^{\{e,f\}} + s_0 \\
&T_a \dot{v}_i^{\{e,f\}} = -v_i^{\{e,f\}} + y_i^{\{e,f\}} \\
&y_i^{\{e,f\}} = \max\left(u_i^{\{e,f\}}, 0\right) \\
&y_i = -y_i^{\{e\}} + y_i^{\{f\}}
\end{aligned} \tag{3}
$$

Here the subscripts i, e and f denote the ith oscillator, an extensor neuron and a flexor neuron, respectively. u_i is the inner state, v_i is a variable representing the degree of the self-inhibition effect; T_r and T_a are the time constants; w_{fe} is the connecting weight between flexor and extensor neurons; w_{ij} is the weight of inhibitory synaptic connection between the ith and jth neurons; Parameter β is a constant representing the degree of the self-inhibition influence on the inner states u_i, and s_0 is the external input. $Feed_i$ is the feedback signal—the term that entrains the oscillator system with the environmental information. In this model, the output y_i of the ith oscillator is the linear summation of the neural outputs $y_i^{\{e,f\}}$ to generate a zero-axial symmetric oscillatory signal. The positive or negative value of y_i corresponds to the activity of a flexor or extensor neuron, respectively.

Matsuoka-based neuron models have clear biological meanings as well as simple mathematical expression. Matsuoka-based models can easily couple feedback information from the environment and the higher-level commands. In Kimura's model, sensory feedbacks can be integrated to the oscillator network through the term $Feed_i$ and the external input term s_0 simulates control signals from the higher-level nervous system control. This provides the opportunity to obtain mutual entrainment between the oscillator network and the mechanical body.

III. Analysis of the Neuron Oscillator Model

Because of the strong coupling of parameters, the performance analysis of the oscillators becomes the major difficulty for engineering application. The oscillator control network is a nonlinear dynamic system with output signals that are sensitive to parameters. We must grasp the relationships of the parameters and the important qualities, such as frequency, amplitude, and phase relationships, between the neurons and the waveform of the output signals.

A. Parameter analysis

In this paper, numerical analysis methods will be introduced to analyze the effect of the parameters on the system output. With this method, we first find the general relationships between parameters and outputs through computer simulation.

Then we adjust the parameters according to the desired patterns. For example, as shown in equation (3), there are many tunable parameters, if we use this oscillator to construct a controller to realize locomotion control of a robot. The parameters of the oscillator must be modulated according to the request of the controlled robot, like the walking cycle, walking pattern, etc. In the numerical simulation method, the effect of each parameter on the output is analyzed, focusing on the ability to change the output's waveform and the impact of the change on the period as well as the phase relationship of the generated rhythmic signal. During parameter analysis, the other parameters are fixed as Table I shows, while one parameter varied over an acceptable range (the parameters in Table I are set according to the parameter relationships used to generate stable oscillation in Matsuoka's work [7][8]).

TABLE I VALUES OF THE PARAMETERS

Parameter	Values
T_r, T_a, s_0	0.04, 0.4,1.0
w_{fe}, β	2.0, 2.5
$\left[u_0^e, v_0^e, u_0^f, v_0^f\right]$	$\left[0.0111 \quad 0.0081 \quad 0.0022 \quad 0.0057\right]$
W_{walk}, W_{trot}	$\begin{bmatrix} 0 & -1 & -1 & -1 \\ -1 & 0 & -1 & -1 \\ -1 & -1 & 0 & -1 \\ -1 & -1 & -1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & -1 & 1 & -1 \\ -1 & 0 & -1 & 1 \\ 1 & -1 & 0 & -1 \\ -1 & 1 & -1 & 0 \end{bmatrix}$

Parameter s_0: this value must be positive to oscillate the interconnected neurons. As Fig. 1 shows, the output amplitude increases linearly with s_0 and it does not affect the frequency of the output. So in engineering applications, this value can be used to adjust the amplitude of the output rhythmic signal.

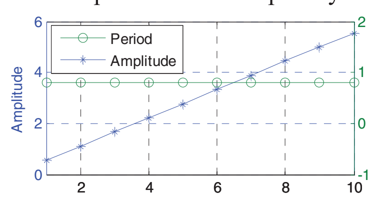


Figure 1. The influence of s_0.

Parameters β and w_{fe}: parameter β is used to mimic the strength with which the internal state v_i suppresses the firing rate of the neuron. Parameter w_{fe} is the gain of mutual inhibition between two neurons. In the acceptable values, as shown in Fig. 2, the output amplitude and oscillation period decrease with β and increase with w_{fe} in nonlinear fashions.

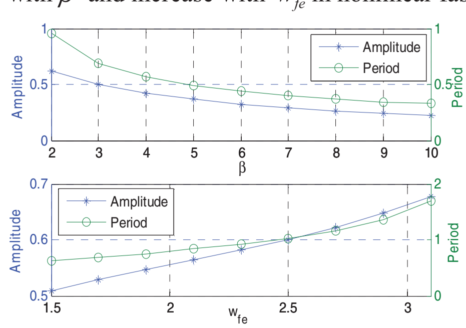
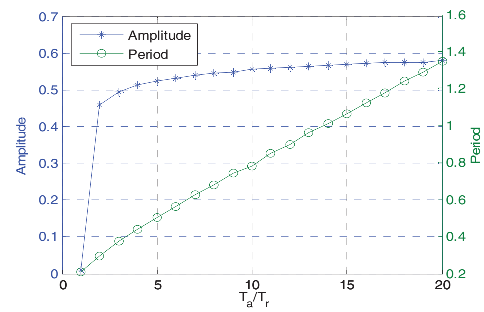
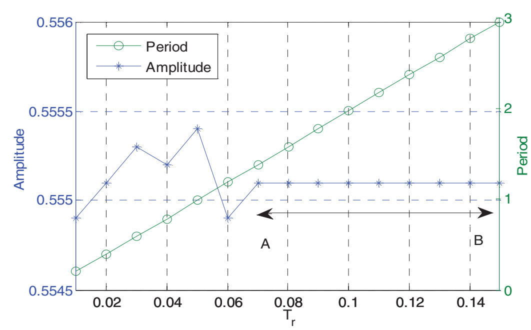


Figure 2. The influence of inhibitory parameters.

Parameters T_r and T_a: a variable $\eta = T_a / T_r$ is introduced to describe the effect of the time constants. As Fig. 3(a) shows, the time ratio η affects the amplitude of the oscillator in a nonlinear way, and the period in a more linear way. If the time ratio η keeps as a constant, take $\eta = 10$, for example, Fig. 3(b) shows the relationship between T_r and the output signals; the oscillation period increases in an almost linear fashion, while the amplitude varies nonlinearly. But in some range, the amplitude will not affected by the parameter T_r, the amplitude will keep constant like Fig. 3(b) (from (A) to (B)) shows. So, in engineering applications, if β and w_{fe} and the ratio η are kept constants, there is a linear relationship between the period and parameter T_r. When the period is adjusted, in some range, the amplitude of the signal will not be affected.



(a) The influence of $\eta = T_a / T_r$



(b) The influence of T_r (η=10)

Figure 3. The influence of time constants.

Parameter w_{ij}: adjusting this term can modify the phase relationship of the output oscillation signals. Take a four-connected-oscillator network for example (Fig. 4). If we want oscillator signals that are $\pi/2$ out of phase (like a walk sequence for a quadruped robot), we can set the connection matrix as W_{walk} (Table I). For this parameter setting method, the initial values of the four oscillators $State_0$ affect the phase relationships. For example, if we set

$$State_0 = \begin{bmatrix} -0.54 & 0.16 & 0.38 & 0.11 \\ 0.38 & 0.11 & -0.54 & 0.16 \\ 0.21 & 0.22 & -0.58 & 0.10 \\ -0.58 & 0.10 & 0.21 & 0.22 \end{bmatrix},$$

we can get the general transverse walking gait. Four units oscillate with $\pi/2$ out of phase (Fig. 5(a)). If we instead set the initial states as

$State_0 = \begin{bmatrix} 0.37 & 0.20 & 0.49 & 0.34 \\ 0.95 & 0.92 & 0.05 & 0.74 \\ 0.27 & 0.42 & 0.55 & 0.94 \\ 0.42 & 0.98 & 0.30 & 0.70 \end{bmatrix}$, the rotary walking sequence shown in Fig. 5(b) is generated. As Fig. 5(c) shows, if we set the connection matrix to W_{trot} (Table I), and the initial states as $State_0 = \begin{bmatrix} 0.37 & 0.20 & 0.49 & 0.34 \\ 0.95 & 0.92 & 0.05 & 0.74 \\ 0.27 & 0.42 & 0.55 & 0.94 \\ 0.42 & 0.98 & 0.30 & 0.70 \end{bmatrix}$, the trotting sequence will be generated.

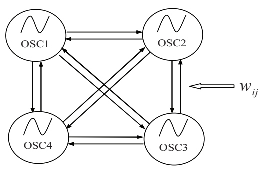
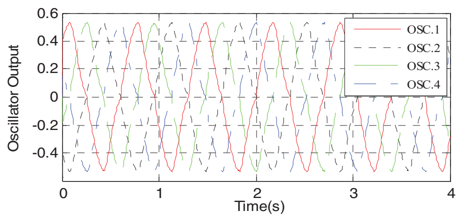
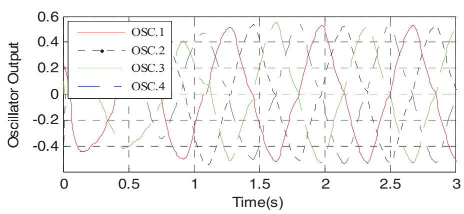


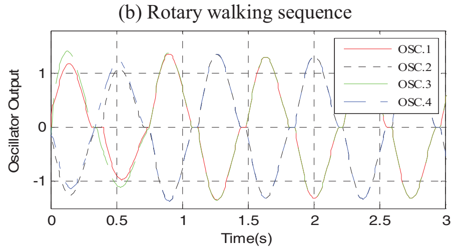
Figure 4. Oscillator network.



(a) Transverse walking sequence



(b) Rotary walking sequence

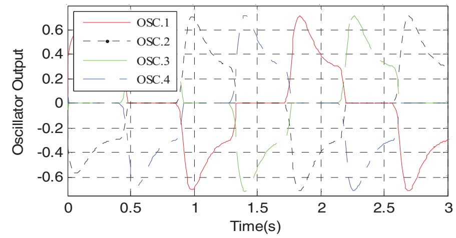


(c) Trotting sequence

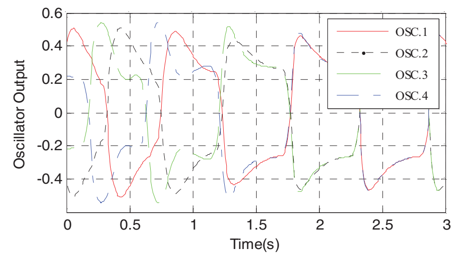
Figure 5. Oscillation sequences of the four connected oscillators.

As Fig. 6 shows, the values of w_{ij} also influence the phase relationship and waveforms of the outputs—for example, if the values of w_{ij} are too large—if we enlarge the values of w_{ij} to 4 times W_{walk} —it will affect the waveform as Fig. 6(a) shows. If we reduce w_{ij} to 0.5 times W_{walk} , it will affect the waveform and phase relationships as Fig. 6(b) shows.

In the acceptable value ranges, if we switch the connection matrix, we can get a smooth sequence transition from walking to trotting, as Fig. 7(a) shows. However, if we transform from a trotting to a walking sequence, as shown in Fig. 7(b), the phase-locked phenomenon (from (A) to (B)) will be generated. There is clearly a transitional phase between gaits. In engineering applications, it is usual to change the connection matrix to realize a gait transition for the robot.

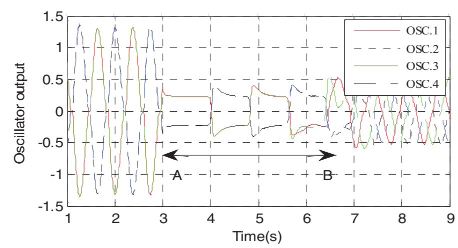


(a) $W = 4 \times W_{walk}$

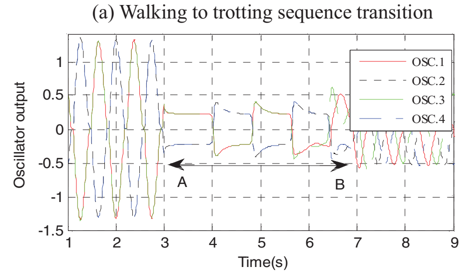


(b) $W = 0.5 \times W_{walk}$

Figure 6. The influence of the w_{ij} values on the outputs.



(a) Walking to trotting sequence transition



(b) Trotting to walking sequence transition

Figure 7. Oscillation sequence transition by changing the connection matrix

B. *Property analysis*

In this section, we will use a simulated motor to study entrainment property, which makes the CPG autonomously adapt to different working condition without changing any of its parameters. There is no need for a reference control input; the only input the CPG requires to entrain to the state variable of the system is as Fig. 8 shows.

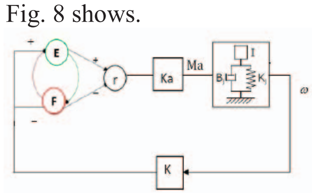


Figure 8. Entrainment setup diagram: the whole system consists of a simple mass-spring-damper system coupled to an oscillator.

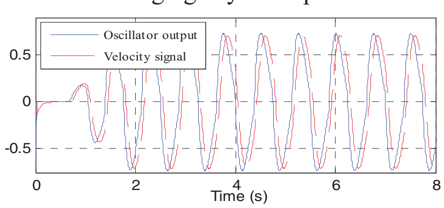
We simulate a simple mass-spring-damper (MSD) system. The oscillator can receive feedback information from the MSD system. In the simulation study, we will focus on adaption of the oscillator to entrain to the MSD system under various working conditions. The equation of the MSD and the feedback design are shown as follows:

$$\begin{aligned} m\ddot{x} + B_j\dot{x} + K_j x = 0 \\ feed^{\{e,f\}} = \pm K(r - x) \end{aligned} \quad (4)$$

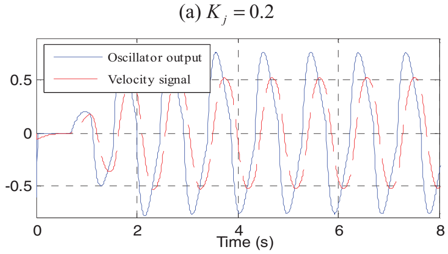
where m is the mass, B_j is the damping parameter and K_j is the coefficient of spring elasticity. K_a is the actuator gain between the oscillator output and applied moment of force M_a. The velocity signal of the MSD system is fed to the oscillator as feedback information to realize entrainment. K is the feedback gain, and the feedback is provided with positive sign to the flexor neuron and negative sign to the extensor neuron.

The oscillator parameters are set as shown in Table I. The MSD system parameters are set as: $m = 6.0$, $B_j = 1.0$, $K_j = 0.2$, $K_a = 5.0$ and $K = 10$. As shown in Fig. 9(a), with these parameters, the oscillator almost totally entrains with the velocity output signals of the MSD system. In order to test the oscillator's capability of adapting to the dynamics of the controlled system, the coefficient of spring elasticity will be changed to change the frequency of the MSD system. As shown in Fig. 9 (b), if the parameter K_j is enlarged to 0.5, the amplitude and frequency of the output and input signals are changed. As K_j increases, frequency of oscillation of the dynamic system will be reduced; the amplitude of the dynamic system's oscillation is also decreased. The oscillator and the MSD system are partly entrained, with the same phase difference. If we set $K_j = 2.0$, as Fig. 9 (c) shows, the oscillator reduces its frequency considerably, and the amplitude of the motor is much smaller than that of the oscillator.

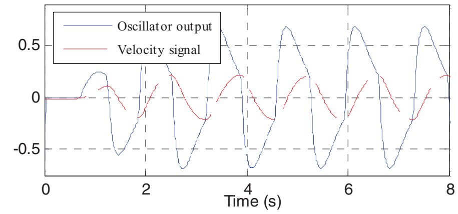
From the simulation results, we see that the oscillator uses error feedback from the controlled dynamic system to adapt its frequency and amplitude to the system response. That is, the oscillator can autonomously adapt to different working conditions without changing any of its parameters.



(a) $K_j = 0.2$



(b) $K_j = 0.5$



(c) $K_j = 2.0$

Figure 9. Simulation results: output of the oscillator and the entrained motor.

There are many ways to use this entrainment property of CPG. For example, we can adjust the frequency and amplitude of the output by using the feedback information. Fig. 10 shows the output signal entraining with a sinusoid signal. The frequency of the oscillator output is immediately entrained to the frequency of the input sinusoid and the phase difference between the input and output becomes constant. This simulation result shows that the oscillator has the dynamic property of being able to be modulated by a feedback signal. In the application, adjusting the frequency and amplitude of the control signal is a necessary condition to realize adaptive locomotion control.

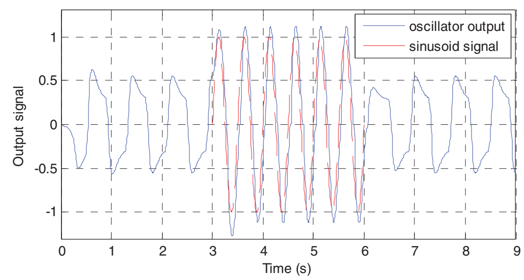


Figure10. Entrainment property of a neuron oscillator.

IV. Application Methods in the Locomotion Control of Robots

In this section, the Matsuoka-based motion control of robots will be reviewed with a focus on two general approaches. The first one is that one CPG unit is assigned to one DoF, and the distributed CPG network can generate complex coordinated multi-dimensional control signals used as force or torque control signals to realize coordinated locomotion, referred as the "CPG-joint control method" [10-13][18][19]. Another approach is to assign CPGs to the periodic variables that can reflect the characteristics of the motion [14-16]. The motivation of using CPGs is that there is no need to investigate the details of the underlying driving mechanism of locomotion. Rather, the focus should be on the properties of CPGs.

A. Joint space control methods

This type of control methods is very suitable for fish-like and snake-like robots. Many scholars have studied these robots that imitate the mechanical structures of natural fish and snakes [11] [13]. Ma et al. [18] studied the adaptive creeping locomotion of a snake-like robot to environment change. Based on Matsuoka's oscillator, they constructed a network with a feedback connection that can generate uniform outputs with the same amplitude and the specified phase difference without any additional adjustment of oscillator network output. Lu et al. [19] built a mutual cyclic inhibitory

CPG based on Matsuoka's model to control the 3D movement of a snake-like robot named Perambulator.

The Matsuoka neuron oscillator, as modified and used for quadruped locomotion control, has been widely investigated by Kimura's group. They have focused on using a reflex mechanism—that is, using the property of entrainment to modify the activity of the oscillators. They use sensory feedback that mimics the animals' reflexes and responses to modify the outputs of oscillators according to the walking terrain [10].

But for more complex legged robots, such as quadruped or humanoid robots, joint control signals are very complex for the current CPG models to generate. Moreover, using a CPG-joint control method to guarantee stability of the locomotion is very different. For this control method, the stability of a walking robot has to be realized by adjusting CPG parameters to generate coordinated joint control signals. Due to the large number of parameters involved, it is difficult to choose a set of appropriate parameters and topology of CPG control network to guarantee stability.

B. *Task space control methods*

This method has several advantages when compared with the CPG-joint space control method. Assigning CPG outputs to the periodic variables during robot locomotion simplifies the CPG unit connections and feedback pathways from the environment. Adjustment of walking patterns of robots is therefore sometimes easier to realize. This method can substantially reduce the number of CPGs used and require less tuning of the parameters than the CPG-joint space control method.

For legged robots, some periodic variables which can reflect the characteristics of gait patterns during walking in task space can be controlled or generated based on CPGs. Results in [20-22] have developed some locomotion control schemes in task space. Aoi, Tsuchiya and Tsujita et al. [20], and Endo et al. [21] have explored locomotion control methods in the task space of legged robots. Endo et al. proposed a novel CPG arrangement with respect to the position of the tip of the leg in the Cartesian coordinate system, which can be considered as workspace coordinates for walking. This method can greatly reduce the number of CPGs and require fewer tuning parameters. In our previous work [22], we used CPGs to generate toe trajectories online in workspace for a robot to realize adaptive quadruped walking on various terrains, called the "CPG workspace control method".

V. CONCLUSION

In this paper, Matsuoka-based oscillator models have been thoroughly investigated. Simulation studies described here were systematically performed to study the relations of the parameters to the outputs. Through simulation analysis, some new findings about the influence of the parameters are given. Some entrainment properties of the neural oscillator are addressed and verified through simulation study, especially with a focus on the sensory feedback of rhythmic patterns. Finally, the application methods of the oscillator model in engineering applications are discussed. The discussions of the Matsuoka-based oscillator model presented in this paper may be useful as guidelines to design CPG-inspired locomotion control of robots for real world engineering applications.

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