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Special Focus

Survey of locomotion control of legged robots inspired by biological concept

WU QiDi, LIU ChengJu, ZHANG JiaQi & CHEN QiJun†

[1] School of Electronics and Information Engineering, Tongji University, Shanghai 201804, China;

[2] The Key Laboratory of Embedded System and Service Computing, Ministry of Education, Tongji University, Shanghai 201804, China

Compared with wheeled mobile robots, legged robots can easily step over obstacles and walk through rugged ground. They have more flexible bodies and therefore, can deal with complex environment. Nevertheless, some other issues make the locomotion control of legged robots a much complicated task, such as the redundant degree of freedoms and balance keeping. From literatures, locomotion control has been solved mainly based on programming mechanism. To use this method, walking trajectories for each leg and the gaits have to be designed, and the adaptability to an unknown environment cannot be guaranteed. From another aspect, studying and simulating animals' walking mechanism for engineering application is an efficient way to break the bottleneck of locomotion control for legged robots. This has attracted more and more attentions. Inspired by central pattern generator (CPG), a control method has been proved to be a successful attempt within this scope. In this paper, we will review the biological mechanism, the existence evidences, and the network properties of CPG. From the engineering perspective, we will introduce the engineering simulation of CPG, the property analysis, and the research progress of CPG inspired control method in locomotion control of legged robots. Then, in our research, we will further discuss on existing problems, hot issues, and future research directions in this field.

biological inspired control, central pattern generator (CPG), locomotion control

1 Introduction

Creating effective locomotion for legged robots is a very challenging task especially in an unknown environment, where ground conditions affect the robots much. Currently, most research works on locomotion control are focused on the trajectory-based method. With pre-designed foot trajectories and the relative gait, the trajectory for every joint can be calculated via the inverse kinematics theory such that robots can walk and keep balance at the same time[1]. In the walking process, robots walk exactly according to the pre-designed trajectories. The trajectories can be acquired by experience or some offline optimization methods. However, the pre-designed trajectories are unchangeable and therefore, have many limitations: 1) It is

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†Corresponding author (email: qjchen@tongji.edu.cn)

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difficult to get proper walking trajectories. 2) The trajectories are sensitive to ground conditions. If ground conditions change the trajectory may not fit the ground conditions any more. Although we can design many trajectories for different terrains and switch among them while walking[2], it cannot cover all the situations the robot encounters. In short, this method cannot solve the problem of robots' walking in an unknown environment.

Nature has always been a major inspiration source for engineers and scientists to solve technical problems. Animals walk smoothly and freely. It is expected to have better performances for locomotion of legged robots if we could design a system that has a similar structure and function as animals'.

Animals' or human's locomotion usually has high stability and adaptability. For instance, when we are walking, we do not need to consider how high we should lift up our feet and where to step. We just do it subconsciously. While walking on a slippery ground, we step in a shorter distance and with slower speed. On the other hand, when going up a hill, we bend down a little bit. What an easy thing for us.

Why does human has such a good rhythmic movement? Biologists believe that central pattern generator (CPG) is the answer to this question. CPG is a kind of neural network that can endogenously produce rhythmic patterned outputs[3−5]. It is distributed throughout the lower thoracic and lumbar regions of the spinal cord and responsible for different walking patterns[6,7].

Based on biology discoveries, Shik[8], Cruse[9] and Brewer et al.[10] initially introduced the CPG mechanism into robot locomotion control. Thereafter, various CPG models have been built and have been used to control rhythmic motions for robots. Acting as a locomotion control mechanism, CPG has many features:

(1) It can produce periodic control signals even without any sensory inputs and higher orders. However, the sensory inputs and higher orders can modulate the activity of CPG. So, with the CPG inspired method, robots can either walk on flat terrain with an open loop control or adaptively walk on irregular terrain with a closed loop control.

(2) It is a distributed control method. Normally one CPG unit controls one joint of a robot, and a CPG network coordinates all joints to complete a movement. By modulating the parameters of a CPG network, it can generate output signals with different phase relationships. These phase relationships can be used to acquire different gaits.

(3) It can adapt to the environment. The motion planning process is separated with the control loop in the traditional programming method. But CPG network is a dynamic system. It combines neural system, body, and environment. The neural system produces signals to control the body to move in an environment. The reaction from the environment to the body modifies the parameters of the neural system to change control signals.

With these features, CPG brings a new way to deal with locomotion control of robots with multi degrees of freedom in a real environment. In this paper, we will begin with the biological research and the development of CPG. Then we will review the applications in engineering fields, and introduce our own research and experiments. At last, we will discuss the existing problems and the future study directions.

2 Biological development of CPG

2.1 Neurobiology research on CPG

Since the original research on animals' locomotion, there exist two hypotheses. One is Reflex theory, and the other is CPG theory. The Reflex theory is based on feedbacks from the peripheral stimulus. According to this theory, the activation of effector organs during locomotion might be triggered by feedbacks from sensor organs in the skin and the moving parts of the body. So, if the neural feedback loop is cut off, the body would not produce next movement[11]. But this theory is proved to be unreasonable. In his famous experiment, Brown in 1911[12,13] tested a decerebrated cat on a treadmill. When the treadmill was set to run, not only could locomotion patterns be observed which were very close to the normal ones, but also the cat changed gaits according to the treadmill's running speed. From this experiment, we can know that there might exist a locomotion pattern generator that produces movement even without brain. Besides, Brown proposed a half-centre oscillator model as the basis to alternate activities of flexors and extensors during walking. The half-centre oscillator model consisted of two neurons that did not have rhythmogenic ability individually. But, when the two neurons were reciprocally coupled, the oscillator would produce alternating rhythmic movement[14]. A research on the walking learning infant indicated that lower level central nervous system, especially the spinal cord, played an important role in walking control[15]. All these experiments above demonstrate that central nervous system does not necessarily need sensory feedbacks to generate rhythmic movement.

After Brown's experiment, more scholars have focused on CPG and tried to find out its configuration. In 1966, Skin et al.[16] explicitly argued that CPG controlled animals' rhythmic movements. Grillner and other scholars[17,18] gave further demonstration and found that CPG could be a small neural network to produce periodic oscillation under certain physical conditions. This conclusion emerged from experiments on a variety of invertebrate and vertebrate species, such as the heart beating CPG of leech[19], the swallowing CPG of lobster[20], and the swimming CPG of lamprey[21,22].

Because the central nervous system does not change too much during evolution, bipedal, similar to quadruped, may possess CPG as well to control locomotion[23]. Duysens and Henry forecasted the possibility of the CPG's existence in primates and humankind[24]. For example, infants could produce certain quasi walking movement with a peripheral stimulus[25]. The anencephalus still had stepping movement on stimulation[26]. Whether CPG works on human is still controversial[27,28].

2.2 The properties of CPG

CPG can produce basic rhythmic signals all by itself. Sensory information may modify the outputs of the pattern generator. Also, CPG accepts orders from higher level nervous system, such as brain, to adjust the initiation of a rhythmic movement, control walking speed, and perform gait transitions[29−31]. A decerebrate adult salamander was tested by Cabelguen[32]. He found that when the salamander was stimulated by electrical microstimulation, it generated two locomotor modes, stepping and swimming. Grillner[33−37] gained the same result from his research. At the same time, experiments proved the peripheral stimulus's effect on CPG. In ref. [38], Masakazu proposed that CPG could be coupled with an input signal, and the output signal would be affected by the input signal's amplitude, frequency and phase information. Selverston[39] studied neuron chain and neuron matrix. He proposed that the behavior of a CPG network was a collective behavior of neuron circuits. In other words, the neuron circuits in a CPG network with different frequencies will become entrained at intermediate frequencies.

Drew[40] did a survey on CPG from the view of neurophysiology. He drew the following conclusions: (1) CPG existed in animal bodies. (2) CPG was made of many coupled units, and we could use one CPG or several CPGs to control one degree of freedom. (3) CPG produced rhythmic signals by itself, while the higher order and feedbacks from environment would modulate the outputs of CPG.

2.3 Walking control network of vertebrates

The walking control network of vertebrate can be illuminated by Figure 1.

Animals' walking control can be considered hierarchical and modular[41]. In Figure 1, the control structure is mainly divided into three parts: higher-level central nervous system, lower-level central nervous system (CPG), and feedbacks. The higher-level central nervous system determines the initiation of locomotion, walking direction, and walking speed. CPG controls extensors and flexors, and coordinates all joints. Higher orders and feedbacks are necessary to modulate the whole network working properly.

Musculo-skeletal system is a key point in walking control and is used as an actuator. It is connected with motoneurons and therefore, gets control sig-

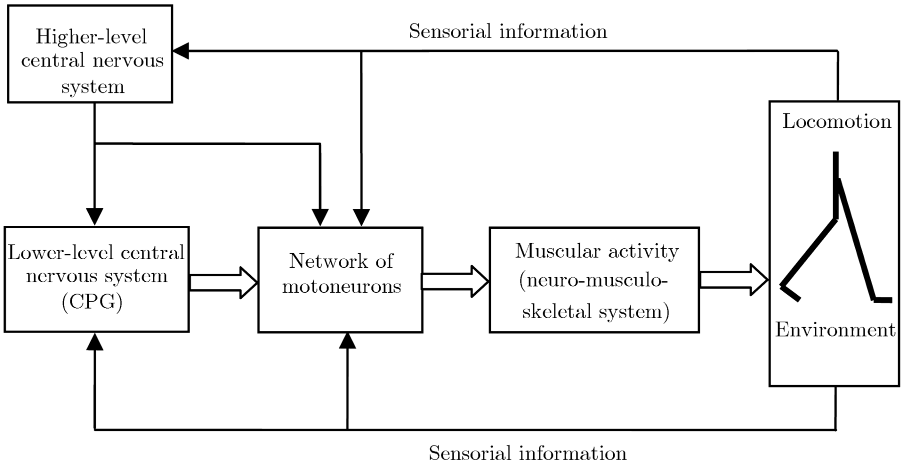

Figure 1 The basic control system of the animal locomotion (modified from ref. [42]).

nals from CPG. Sensory information about an environment is used as feedbacks. Central nervous system processes the feedback information quickly to adapt the gait to the new environment. The main reflexes in adaptive walking control are spinal reflexes and vestibular reflexes. Spinal reflexes, such as stretch reflex, flexor reflex, and posture reflex, refer to the reflexes confined on the spinal cord. They play an important role in walking control. Stretch reflex controls muscles' contraction degree, enhances muscles' strength, and maintains limbs and spinal column in their correct positions. Flexor reflex is activated to contract limbs when receiving stimulation from skin or muscles. It helps animals to avoid obstacles. Posture reflex can coordinate different muscles to maintain a proper posture[43]. Vestibular reflexes are responsible for the body's balance[44].

So, the final walking control signals are the result of the mutual interaction of central nervous system and reflexes system. Higher-level central nervous system sends orders. Then, CPG produces rhythmic signals and these signals are passed to musculo-skeletal system by motoneurons to generate a movement. Last, body receives feedback information and reflexes to produce further movement commands. A new loop begins.

3 Engineering simulation and property analysis of CPG

From the control perspective, animals' locomotion control network can be treated as a feedforward plus feedback control system. Higher-level central nervous system, like cerebrum, cerebellum, brainstem, etc. performs as a feedforward controller to send out initial values of the locomotion. Sensory information about an environment is used as feedbacks to maintain the stability of the locomotion. From the engineering perspective, CPG neural circuits are distributed systems composed of nonlinear coupled oscillators. Rhythmic signals are generated through the phase coupling of oscillators, and different phase relationships can be produced by changing the coupling methods among oscillators. For robots, different phase relationships correspond to different gait patterns.

This biologically inspired control technique is well suited to control robots with multiple degrees of freedom as it can generate coupled control signals for all joints. Therefore, from the perspective of engineering applications, the study of CPG inspired control method has become a hot topic. In this section, we will review different kinds of mathematical models that are commonly used in the CPG related studies.

3.1 Typical engineering CPG models

3.1.1 Neuron CPG models.

(1) H-H type models. One of the most famous neuron models is the Hodgkin-Huxley (H-H) model[45−48]. It uses a squid giant axon preparation to measure membrane potentials and ionic currents, and models these currents with a four-

variable nonlinear system. However, the proposed H-H neuron model is complicated and has many parameters. Since then, many scholars had been working on it to get a better understanding of the basic behavior of the neuron and to build more concise models. The well-known FitzHugh-Nagumo model is a simplified H-H type model defined by[49,50]

$$\begin{aligned}\dot{x}_i &= c\left(y_i + x_i + \frac{x_i^3}{3} + f_{ci}\right),\\ \dot{y}_i &= -(x_i - a + by_i)/c,\end{aligned} \tag{1}$$

where x_i is the membrane potential of the ith neuron; f_{ci} is the driving signal for neuron i; a, b and c are constants that do not correspond to any particular physiological parameters.

Morris and Lecar[51] also developed an H-H type model called Morris-Lecar (M-L) model. Lakshmanan and Murali used a two-variable first order autonomous system to build an H-H type neuron model[52,53]. The difference between these various H-H type models lies in the way they simulate a neuron's behaviors.

While analyzing biological neuron models, detailed dynamics characters of small circuits usually need be concerned with, such as pacemaker properties of signal neurons, the mechanism of the rhythmogenesis of a large population of neurons, etc. However, for engineering applications, we mainly focus on the rhythmic activities.

(2) Stein's model. Stein's model, which is capable of producing oscillatory output, is defined by the following differential equations[54,55]:

$$\begin{aligned}\dot{x}_i &= a\left[-x_i + \tfrac{1}{1+\exp(-f_{ci}-by_i+bz_i)}\right],\\ \dot{y}_i &= x_i - py_i,\\ \dot{z}_i &= x_i - qz_i,\end{aligned} \tag{2}$$

where x_i represents the membrane potential of the ith neuronal oscillator; parameter a is a constant affecting the frequency of the oscillations; f_{ci} is the driving signal for oscillator i; b allows the model to adapt a change in stimulus; q and p control the rate of this adaption.

Collins and Richmond[56] had used Stein's model to study gaits. Constructed by four coupled Stein oscillators, their CPG control network produced multiple phase-locked oscillation patterns. For quadrupedal robots, these patterns corresponded to several common gaits–the walk, trot and bound.

(3) Leaky-integrator models. Leaky-integrator models describe basic behaviors of neurons, but they cannot simulate the degree of fatigue or adaptation of neurons. Therefore, they have been improved to better fit for the properties of neurons.

The most famous neuron oscillator model with an adaptation item was proposed by Matsuoka[57]. A mutual inhibition network consisting of n neurons is represented by

$$\begin{aligned}&T_r\dot{u}_i + u_i = -\sum_{j=1}^{n}\omega_{ij}y_j - \beta v_i + s_i,\\ &T_a\dot{v}_i + v_i = y_i,\\ &y_i = g(u_i) \quad (g(u_i) = \max(u_i, 0)),\end{aligned} \tag{3}$$

where u_i is the membrane potential of the ith neuron; v_i is a variable representing the degree of the adaptation in the ith neuron; T_r and T_a are the constants of rising time and adaptation time; ω_{ij} is the weight of inhibitory synaptic connection from neuron j to the i; β is the parameter that determines the steady-state firing rate for a constant input; s_i is an external input, and y_i is the output of the neuron.

Matsuoka[57,58] analyzed mutually inhibiting neurons and found the conditions under which neurons generate oscillation. Because it simulates neuron properties more precisely, Matsuoka's model has been widely applied to locomotion control of legged robots. Based on Matsuoka's model, Taga et al.[59−61] proposed a similar model, which used a set of inhibitory connected neuron oscillators to build a network. Kimura et al.[62−64] constructed a neural system based on the neural oscillator proposed by Matsuoka and Taga. This CPG model consists of two mutually inhibiting neurons as shown in Figure 2. Each neuron is represented by the following nonlinear differential equations:

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

$$y_i = -y_i^{\{e\}} + y_i^{\{f\}}, \tag{4}$$

where the suffix e, f and i denote an extensor neuron, a flexor neuron, and the ith neuron, respectively; $Feed_i$ represent the feedback signals from the robot, i.e. a joint angle, angular velocity, etc. $y_i^{\{e\}}$ and $y_i^{\{f\}}$ are the output of extensor and flexor neurons; w_{fe} is the connection weight; y_i is the output signal of a CPG, and the sign of y_i corresponds to the activity of a flexor or extensor neuron.

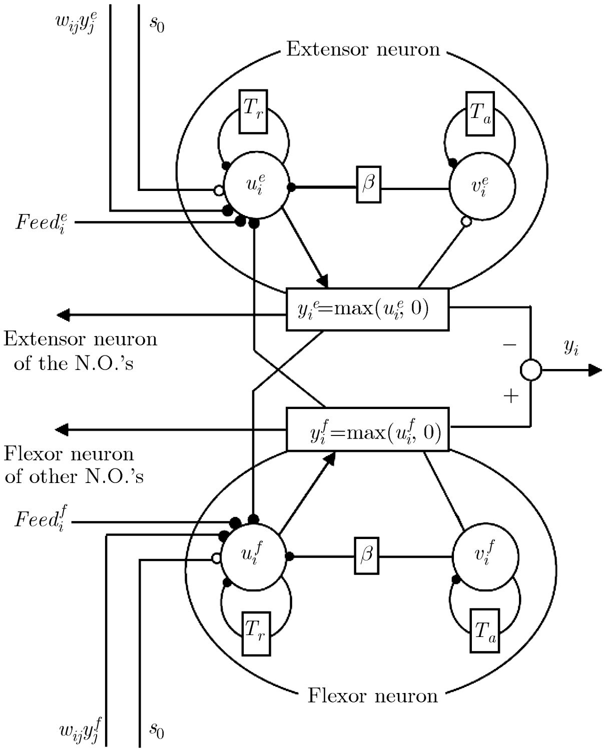

Figure 2 Neural oscillator as a model of CPG.

In Kimura's model, the linear summation of the outputs of the two neurons is used as system's output. Since the output of each neuron has been through a threshold function and therefore, is always positive, the sum of the outputs will have a zero crossing dead zone. Zhang et al.[44] improved Kimura's CPG model by building the output of an oscillator with two neural states, $u_i^{\{e\}}$ and $u_i^{\{f\}}$, in order to eliminate the zero crossing dead zone.

Neuronal oscillator models have clear biological meanings, especially Matsuoka's model. This kind of models can easily couple the feedback information of environment and the higher level orders. In Matsuoka's model, sensory feedbacks can be integrated to the CPG network through the term $Feed_i$ and the external input term s_0 simulates control signals from the higher level control nervous system. This provides the opportunity to obtain mutual entrainment between the CPG network and the mechanical body. Since so many parameters are involved in these models, selecting proper parameter is essential to the CPG inspired control method.

3.1.2 Nonlinear oscillator models. In engineering applications, the main task of CPG is to produce periodic oscillatory signals instead of simulating neuron behaviors. So, the nonlinear oscillators have been widely used to simulate CPG, such as phase oscillators, harmonic oscillators and relaxation oscillators. In this section, we will introduce several kinds of typical oscillators that are usually used in engineering applications.

(1) Kuramoto's model. Phase oscillator is a simple oscillator, whose radius is completely neglected while phase remains. Kuramoto's model is a typical example of this oscillator[65]. It consists of a population of N coupled phase oscillators, and the phase oscillators are coupled through the sine function of their phase differences. In Kuramoto's model, each oscillator runs independently at its own frequency, while the coupling tends to synchronize them together. The mathematical model is as follows:

$$\dot{\theta}_i = \omega_i + \sum_{j=1}^{N} K_{ij} \sin(\theta_j - \theta_i), i = 1, 2, \ldots, N, \tag{5}$$

where θ_i is the phase of the ith oscillator; ω_i is the natural frequency of the ith oscillator; $K_{ij} > 0$ is the coupling strength from the jth to ith oscillator.

Since it displays a lot of synchronization patterns, Kuramoto's model has been well studied. A variety of more complex realistic models have been proposed from original Kuramoto's model[66−68]. When coupling is sufficiently weak, oscillators run incoherently. But, after it goes beyond a certain threshold, collective synchronization emerges spontaneously. This synchronization property of the Kuramoto model is the main reason why we use it as a CPG unit.

Inspired by a lamprey's swimming CPG, Ijspeert et al.[69−71] constructed a novel coupled amplitude-controlled phase oscillators (ACPO) model based on Kuramoto's model. The ACPO network has been successfully implemented on bionic robots, like a salamander robot, a snake robot, and a fish robot. Based on Kuramoto's model, Conradt[72] built a distributed CPG network to control the motion of a serpentine robot, and it showed various motion patterns under different environments.

(2) Hopf model. Hopf oscillator can be described by

$$\begin{aligned} \dot{x} &= (\mu - r^2)x + \omega y, \\ \dot{y} &= (\mu - r^2)y + \omega x, \end{aligned} \tag{6}$$

where $r = \sqrt{x^2 + y^2}$; $\mu > 0$ determines the amplitude of the output signals; the parameter ω controls the frequency of the oscillator. The oscillator has a stable limit cycle with radius $\sqrt{\mu}$ and angular velocity ω rad/s.

Ijspeert et al.[73,74] demonstrated a programmable CPG model based on Hopf oscillators and applied it to the locomotion control of humanoid and quadruped robots. This CPG network could learn arbitrary rhythmic teaching signals. Because of the dynamic characteristics of the programmable CPG network, the learning process was completely embedded in the system. Ijspeert[75] validated his CPG control network with a humanoid robot HOAP-2 in simulations. Nicolas[76] studied the coupling methods of Hopf oscillators and used two oscillators to control each degree of freedom to get various phase differences. Righetti et al.[77] constructed a locomotion controller with modified Hopf oscillators which could independently control the swing and stance phases of an oscillation. We can control the locomotion speed of robots by using the ascending phase of the oscillation to control the swing stage and the descending phases to control the stance stage of legs.

(3) Van der Pol's model and Rayleigh's model. Van der Pol's model (VDP) and Rayleigh's model are all relaxation oscillators that can produce various waveform signals. By adjusting the parameters of the nonlinear oscillators, self-sustained limit cycles can be generated.

Van der Pol's analysis of electronics and heartbeat is generally credited as the original significant work for modeling biological phenomena with nonlinear oscillators[78]. The basic equation of the VDP oscillator is

$$\ddot{x} + a(x^2 - p^2)\dot{x} + \omega^2 x = 0, \tag{7}$$

where x and $\dot{x}$ describe the states of the system, and $a > 0$ is the coefficient of the resistance. This resistance is negative for a small amplitude of x, as given by $x^2 - p^2$, and is responsible for the generation of self-sustained oscillation.

Rayleigh investigated the sound generating principles of the musical instruments and created Rayleigh's model[79], which was very similar to VDP oscillator. The basic equation of Rayleigh's model is

$$\ddot{x} + a(\dot{x}^2 - p^2)\dot{x} + \omega^2 x = 0. \tag{8}$$

The parameters of Rayleigh oscillator are almost the same as the VDP oscillator's, except that the resistance is negative when the amplitude of $\dot{x}$ is small.

As early as 1987, Bay and Hemami[80] made a CPG model with coupled VDP oscillators. By numerical simulations, they analyzed the property of the system, and studied the ring and chain connection methods. Bay's early work verified that the VDP oscillator is a good model to simulate CPG. Zielinska[81] used coupled VDP to generate rhythm locomotion control signals for a two-legged walking machine. Filho et al.[82,83] studied the behavior of hips and knees in locomotion, and used mutually coupled Rayleigh oscillators and VDP oscillators to generate control signals that were similar to human locomotion.

Based on these studies, we conclude that the use of mutually coupled nonlinear oscillators is a good method to construct CPG network for locomotion control of legged robots. The motivation of using nonlinear oscillator as a CPG unit is that we do not have to study the oscillatory mechanisms because they have been well investigated in dynamic system theory. We can just focus on the study of inter oscillators' coupling methods and the overall properties of CPG networks. The advantages of these models are that various output patterns can easily be realized by changing the topology of CPG network and the engineering applications are relatively easy to implement. However, these models have less biological meaning than neuron CPG models.

3.2 Analysis of engineering CPG models

Before applying CPG models to robots, the properties of the models must be analyzed first. There is no well-established design methodology for CPG networks. Generally, when constructing a CPG network, the following issues must be considered:

(1) The choice of CPG models. We have reviewed some well-known CPG models that are widely used in neurobiology and robots. Before constructing a CPG network, we must choose an appropriate CPG model according to the particular type of locomotion.

(2) The configuration of CPG networks. Many factors must be considered including the number of CPG unit, the topology of couplings, etc. There are normally two configurations of CPG networks: chain and ring. And, neurons are usually coupled by unidirectional or bidirectional connections.

(3) Modulating parameters. The CPG network is a nonlinear dynamic system, whose output signals are sensitive to parameters. We must grasp the relationship of the parameters and the important qualities, such as frequency, amplitude, phase relations between the neurons, and the waveform of the output signals.

(4) The feedback information. The feedback information is essential for animals to realize adaptive locomotion in a complex environment. However, we face such problems as how to add the feedback information to the CPG network and how feedback affects CPG.

A major difficulty in designing CPG networks is that parameters and outputs are strongly coupled. In engineering applications, three parameter modulation methods are usually used.

(1) Trial-and-error method. With this method, we modify the parameters from time to time according to our experience or experiment results. The drawbacks are obvious. This method is tedious, inefficient and the final parameters are only applicable to the specially studied robot, and cannot be used as a reference.

(2) Evolutionary algorithms. In particularly, genetic algorithm (GA) has been used extensively. With GA, we only need to design a fitness function according to the desired performances[84], such as the speed of the locomotion, the stability of the body, and the phase relations of the legs. 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.

(3) Numerical analysis method. First, we find out the general relationships between parameters and outputs through computer simulation. Then, we adjust the parameters according to the desired patterns. Because of the strong coupling between the parameters and the outputs, it is still difficult to use.

In engineering applications, the methods mentioned above can be combined when necessary. For instance, when applying CPG methods to control locomotion of quadruped robots, we first get the approximate range of parameters through computer simulation and then, use GA to take further optimization. Finally, during the practical application, we adjust the parameters carefully according to the actual control results. Because parameter modulation of the CPG network plays an essential role in determing the efficiency of the CPG-based control method, the design method will be a direction for future research.

4 The application of CPG in robot locomotion

CPG methods have been used to control various kinds of robots and modes of locomotion. They are totally different from the traditional ones. It produces motor commands in real time, and reduces the dimensions of the locomotion control. In addition, this is a multi-subject research topic, involving biology, neurophysiology, computational neuroscience, bionics, robotics, etc. on the one hand, the development of CPG inspired methods provides a new way to control robots' locomotion; on the other hand, robots can be used as tools to verify the mechanism of animals' locomotion and promote the development of other subjects.

Engineering applications of CPG-inspired methods emerged mostly in the 1990s. The main research was focused on basic gait control, gait transitions control, dynamic adaptive locomotion control, etc. There are usually two methods to use

CPG: the first one, inspired by biology, uses one CPG unit for each degree of freedom; the second one is to use the properties of CPG networks, like synchronization, entrainment, etc.

4.1 Crawling robots

Lampreys and salamanders are known as the "Living Fossil". Although they have gone through millions of years, they still keep the same characteristics as their ancestors. This is the reason why biologists choose them to study the mechanism of CPG. Ijspeert's team[85−88] from EPFL has made great contributions to the research of the motion of crawl type robots. Inspired from a lamprey's swimming CPG, they constructed a CPG network which could produce control signals for a salamander robot, a fish robot, and a snake robot to realize the swimming and serpentine locomotion. The control signals were modulated online easily through adjusting several parameters.

Many scholars and education institutions studied snake-like robots that imitate the mechanical structure of nature snakes. For examples, University of Zurich developed a snake-like robot named WormBot. Conradt et al.[72] constructed a CPG network to control the serpentine locomotion of WormBot. Ma et al.[89−91] built a mutual cyclic inhibitory CPG based on Matsuoka's model to control the 3D movement of a snake-like robot named Perambulator. The successful applications of CPG inspired methods in salamander robots and snake-like robots set the foundation for the biological mechanism to control the locomotion of legged robots.

4.2 Legged robots

The investigation on insects' locomotion greatly helps the development of multi-legged robots, especially hexapod and octopod robots[92−95]. Inagaki et al.[96] proposed a wave CPG model which could change the oscillators' number automatically. Furthermore, the gait generation and transition could be realized by controlling the virtual energy of the oscillators. This wave CPG model was used to control the leg movements of an autonomous decentralized multi-legged robot NEXUS. Barnes[97] designed a gait generation system to control the locomotion of a hexapod robot MAX. UC Berkeley developed a hexapod robot which looked like a cockroach and could vertically climb[98,99]. UC San Diego developed a lobster robot and studied the control method of this underwater walking machine[100,101]. But, the main purpose of these robots is to use bionics functions of cockroaches and lobsters to accomplish specific tasks. So, their locomotion control signals are only the basic rhythmical signals.

Quadruped locomotion control with CPG had been studied by Kimura's group[63,64]. The study was mainly focused on the autonomously adaptive dynamic walking on irregular terrains, and sensory feedbacks was found to lead to the most stable locomotion on a complex terrain. They also developed a 12 DOF quadruped robot Patrush and a 16 DOF robot Tekken. With feedbacks, these quadruped robots could walk on ground containing scattered pebbles and grasses, hollows, and slippery surfaces[102,103]. To a large degree, the success of Kimura's experiments relied on a good mechanical design. Tekken, for example, has relatively simple mechanical structure, large motor torque, small moment of inertia, low friction, and high back-drivability. Also, this robot is equipped with passive-ankles, which help to cushion the landing effect from the ground. Ilg et al.[104] presented a three-level adaptive architecture to control a quadruped robot BISAM. Tsujita et al.[105,106] proposed a control system for a quadruped robot with nonlinear oscillators. This robot was equipped with a leg motion controller which drove the actuator by a local feedback control, and a gait pattern controller consisting of a set of nonlinear oscillators. The adaptability of the proposed control system was verified through hardware experiments. Billard et al.[107] studied the locomotion of the quadruped robot AIBO with a set of leaky-integrator neurons. Combined with sensory feedbacks, the AIBO could accomplish many gaits. The CPG inspired methods have not been well studied in China by now. Zhang et al.[44] constructed a CPG network modified from Matsuoka's and Kimura's CPG models to control the quadruped robot Biosbot. The Biosbot can walk with a velocity of 0.13–0.24 m/s.

The Laboratory of Robotics and Intelligent Systems of Tongji University has been seeking biological control methods for the dynamic adaptive locomotion of legged robots in unknown environments[108−111]. The main researches we have conducted are: (1) We studied the architecture of the CPG. Basic gaits and gait transitions of quadruped have been realized. (2) In order to eliminate the drawbacks of using CPG outputs directly as joints' control signals, we proposed a novel control strategy which integrated CPG and the mechanism of muscle memories. CPG outputs were used only as synchronization signals. The actual control signals were generated with the other set of oscillators through online learning. These actual control signals could be taken as muscle memories acquired after practicing. This method improved the control precision and facilitated the introduction of feedback information. (3) We developed a control strategy based on kinematics and CPG. This method was composed of a gait pattern modulator and a leg motion controller. The modulator controlled the gait patterns, and modulated the duties of swing phase and stance phase of the leg. So, we could use real-time environment feedback information to adjust output control signals to realize adaptive locomotion. (4) We have been designing a hybrid control method based on CPG and ZMP (zero movement point). Since the gravity center cannot be controlled with pure CPG method, we will combine the advantages of CPG and ZMP to achieve more stable locomotion. (5) We have been constructing a completely adaptive control network, including the higher level control modules, CPG and feedback/reflex module, to achieve real adaption to environments. All of these research results will be tested on a quadruped robot AIBO and a bipedal robot NAO.

CPG inspired methods have been increasingly used for locomotion control of bipedal robots after Taga's seminal work on neuromechanical simulations[59−61]. Tenore et al.[112,113] used the bipedal robot RedBot to validate the efficiency of his CPG control network constructed by VLSI circuits. The patterns generated by these circuits were shown to be sufficient to control a biped robot with different locomotory gaits. Komatsu et al.[114] proposed a hybrid central pattern generator (H-CPG) to realize the adaptive dynamic walking and running of a bipedal robot KAAL. This H-CPG method consisted of not only basic CPG models but also an extra force control system that controlled the acting force from legs to the ground in the vertical and the horizontal direction. Nagashima et al.[115] constructed a CPG network using a group of neural circuits which were modeled by recurrent neural networks (RNN). This network enabled humanoid robot HOAP-1 to walk successfully with different step distances. Integrating the sensory feedback, HOAP-1 robot could walk up and down stairs with a locomotion frequency of 2.2 rad/s. Endo et al.[116,117] used simple sine signals produced by CPG to control joints. Then, two humanoid robots CB and QRIO were used to validate the proposed strategy.

5 The existing problems and research directions of CPG inspired method

5.1 The existing problems

(1) The biological mechanism of locomotion control. Biologically inspired locomotion control is a hot topic among biology, neurophysiology, bionics and robotics. As indicated by ref. [118], the biologically inspired robots locomotion control has to be based on the neurobiological research. Meanwhile, the applications of biological inspired method in robotics can in turn promote the development of other aspects, that is, robots can be used as scientific tools to test corresponding problems in other subjects. Besides, most of the present researches focus only on the CPG models. Actually, the higher level control signals and the peripheral feedback loops are also essential in applications.

(2) The limitation from mechanical configuration. The mechanical configuration of a robot ensures its good performance. However, we cannot build a robot exactly according to an animal. For example, on a robot, every joint is controlled by a motor. On the other hand, animals' joints are controlled by muscles. Motors and muscles have different motion properties. So we cannot control a robot completely according to the biological mech-

anism. Designing better body structures and hardwares is difficult too.

(3) How to produce a special control signal. CPG outputs are usually used to control angles or force torques. For some applications, such as robot snakes, the serpentine locomotion can be easily acquired by a sine signal. But, obviously this is not an accurate design in robot walking control especially when sine or quasi-sine waves are not the best signals to set walking patterns because of the complexity of tasks. So, producing a special control signal is necessary to fulfill skillful walking.

(4) Analysis of the whole system. Since the whole system includes the neural system, robot body, and environment, it is a big and complicated nonlinear system, and it is difficult to analyze the stability condition and find proper parameters for the system. There is not any uniform engineering method to do it yet.

5.2 Research directions

Based on the CPG walking method, the following points call for more attentions.

(1) Parameters modulation. One problem of CPG methods is how to produce special control signal by modulating parameters. Since CPG is a nonlinear coupled system, it is difficult to find a simple mapping from the parameters to outputs. Additionally, if we consider the problem in the neural system, body and environment loop, it is even more difficult to find good parameters.

(2) Gait transition. Animals can easily change gaits to get used to different environments. But, this is actually a complex process because it has to coordinate the higher orders, CPG, and reflex. For legged robots, it is even more difficult to make a stable and continuous gait transition. The normal method to change gaits is to switch among several pre-designed modes. The transition is sharp and can easily cause instability. So, we need to put emphasis on getting smooth and quick gait transition. The bifurcation theory may be helpful in analyzing the system's stability[119,120].

(3) Environment adaptability. Since it is a nonlinear system, CPG can produce coupled periodic control signals even without feedbacks. But it is only one of the biologically inspired locomotion designs. To adapt to an environment, we need to add feedbacks and consider the reaction from the environment to the robot body. It is hard to organize the feedbacks to represent the dynamics of body and design feedback loops.

6 Conclusions

In this paper, we have studied the biologically inspired robots locomotion control and especially emphasized on CPG methods, the biological mechanism, and their applications on robots. Considering the nonlinear characteristics of CPG, we have also discussed the related hot issues and interesting research directions.

CPG methods establish a new way to design better robots' locomotion and improve robots' adaptability to environments. It is a crossing of many subjects like biology, neurophysiology, bionics and robotics. Therefore, the development of this research also brings benefits to other related subjects.

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