A Survey on CPG-Inspired Control Models and System Implementation

Junzhi Yu, Min Tan, Jian Chen, and Jianwei Zhang

***Abstract*—This paper surveys the developments of the last 20 years in the field of central pattern generator (CPG) inspired locomotion control, with particular emphasis on the fast emerging robotics-related applications. Functioning as a biological neural network, CPGs can be considered as a group of coupled neurons that generate rhythmic signals without sensory feedback; however, sensory feedback is needed to shape the CPG signals. The basic idea in engineering endeavors is to replicate this intrinsic, computationally efficient, distributed control mechanism for multiple articulated joints, or multi-DOF control cases. In terms of various abstraction levels, existing CPG control models and their extensions are reviewed with a focus on the relative advantages and disadvantages of the models, including ease of design and implementation. The main issues arising from design, optimization, and implementation of the CPG-based control as well as possible alternatives are further discussed, with an attempt to shed more light on locomotion control-oriented theories and applications. The design challenges and trends associated with the further advancement of this area are also summarized.**

***Index Terms*—Bioinspired control, central pattern generator (CPG), neural network, parameter tuning, robotic applications.**

I. INTRODUCTION

THERE has been growing interest in bioinspired robotics over the last decades, where robots have either been used to address specific biological questions or have been directly inspired by biological systems in the natural environments [1], [2]. After 3.8 billion years of development, failures are fossils, and what surrounds us is the secret to survival [3]. For animals, the ability to efficiently move in complex and changing environments is a critical requirement. Similarly, offering good locomotor skills to robots is of paramount importance in creating robots that can perform real-world tasks in different environments [4]. Traditional model-based control via numerical techniques, kinematic approaches, and geometric approaches [5], however, is not always well suited to dynamic and changing conditions yet requiring high stability and adaptability. The locomotion control problem, in this sense, is an area in which biology and robotics should closely interact [6].

As suggested by biologists, there exist many movement patterns in animals and most of them generally fall into two categories depending on what kind of time sequence is exhibited: rhythmical and discrete [7]. Previous neurobiological studies have pointed out that rhythmic and discrete movements employ at least partially separate control mechanisms in the motor system [8]. Studies have also shown that locomotion of animals is hierarchically controlled by the central nervous system, from the cerebral cortex level, the brainstem level, to the spinal cord level. Central to the producing of rhythmic patterns is the presence of a functional unit called central pattern generator (CPG) [9], [10]. Despite the lack of a unified definition, according to Wikipedia, CPGs are usually viewed as neural networks that produce rhythmic patterned outputs without sensory feedback [11]. In the authors' opinion, CPGs can be considered as a dedicated neural mechanism involving a group of neurons that coordinately generate rhythmic signals without sensory feedback, while sensory feedback is needed to shape the CPG signals. Undoubtedly, this fundamental mechanism underlying rhythmic movements of animals not only provides a paradigm for controlled oscillations of engineering systems, but also has been attracting constantly growing attention in neuroscience and robotics [12].

Today, it has been widely proven that CPGs are mainly located in the central nervous system of vertebrates (e.g., cat, lamprey, and human) or in relevant ganglia in invertebrates (e.g., leech, worm, and mollusc *Tritonia diomedia*) [13]–[15]. The fundamental function of CPGs is identified as producing primary rhythmic behaviors such as locomotion, respiration, sucking, licking, and mastication. Some comprehensive review papers that are related to biological mechanisms and evidence can be found in [4] and [16]–[19]. Compared with these existing reviews, this paper brings its own contribution by surveying more recent literatures and by going more deeply into the technical aspects of implementing CPG models in robotics and simulations that employ CPGs. Specifically, oscillator models, organization of the networks, and system implementation will be examined.

As a fundamental neural component, CPGs are primarily responsible for generating coordinated, rhythmic movements for locomotion of animals in real time, such as crawling, flying, swimming, hopping, walking, and running. Inspired by the prominent traits of stability and self-adaption of biological CPGs in the face of unexpected and varying perturbations,

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researchers in the engineering domain have made continuous and repeated attempts to import artificial CPGs for enhanced steady-state locomotion performance. Another longstanding and yet unsolved issue in robotics, particularly in implementing effective legged robots, is to produce nonlinear properties in actuators that are observed in muscles. Fortunately, a CPG is able to generate different output signals such as kinematics, force, torques, and muscle lengths. Thus, the CPG-based control methods can be used in conjunction with other control methods including model-based control, particularly for nonsteady locomotion in dynamic environments. We will give a comprehensive introduction to current state-of-the-art CPG modeling, design, and implementation issues, which will shed light on stable, adaptive, multimodal locomotion generation for a variety of robotic applications.

The rest of this paper is organized as follows. Section II presents the primary motivation and research framework for CPG-based control. Section III reviews the CPG modeling methods. The CPG modulation and implementation are detailed in Sections IV and V, respectively. Some critical issues and future developments of the CPG-based methodology are discussed in Section VI. Finally, conclusion is summarized in Section VII.

II. Primary Motivation and Framework

Before discussing the specific design and implementation of the CPG-based locomotion control, we first review the impetus and research framework in a general way.

A. Primary Motivation

A question is frequently raised regarding the reason to investigate the CPG-based locomotion control. The answer may be twofold. On the one hand, an early impetus for this paper of CPG circuits is largely to test (or verify) the hypotheses about neural circuits and biomechanical principles in invertebrates and vertebrates [20]. Considering the notion of CPGs originating from the experimental investigations of living organism locomotion control systems, there is no doubt that the results of computational and hardware experiments on the artificial CPGs will feedback into animal motor control. On the other hand, more importantly, as a class of bioinspired neural networks, CPGs that are capable of autonomous, self-modulatory control offer an ideal candidate for practical engineering solutions to rhythmic movements. In [4], Ijspeert summarized five properties that make CPG models useful for the control of locomotion in robots: 1) intrinsic limit cycle property; 2) distributed nature; 3) a few control parameters that allow for flexible modulation of the locomotion; 4) easy feedback integration; and 5) offering a good substrate for learning and optimization algorithms. Notice that there are certain overlaps between these aforementioned features. For simplicity, the fascinating features of the CPG models, which apply well to robotic controllers can be summed up in four keywords.

1) *Rhythmicity:* First and foremost, rhythmicity is one of the most common and basic features of locomotion behaviors. For rhythmic movements, it is critical to ensure a uniform and steady rhythm over the course of the whole locomotion. Essentially, the rhythmic neural activities are governed by the CPGs, which are further transferred into muscle activities, finally, resulting in rhythmic behaviors [21]. It should, however, be pointed out that the CPG models for the generation of both rhythmic and discrete movements are possible with the aid of sensory integration [7], [22], [23].
2) *Stability:* Another advantage of the CPG models is their stability, mathematically corresponding to stable limit cycles (i.e., an isolated closed trajectory that exhibits self-sustained oscillation) that occur in locomotion followed by robustness against small perturbations. One popular view holds that movements emerge as a stable limit cycle, which is generated through the global entrainment among the CPGs, the musculoskeletal system, and the environment.
3) *Adaptability:* The behavioral adaptability is considered as a result of the locomotion pattern modified by the sensory feedback signals. As the intrinsic stability properties allow for feedback integration, sensory feedback that modulates CPG activity tends to result in an environment-adaptable locomotion. In addition, feedback loops coupled with learning algorithms and optimization techniques allow the CPGs to find the most effective or efficient output through continuously interacting with the environment.
4) *Variety:* It is established that different motor behaviors (or gaits) can be generated by the same network, and that switching between behaviors arises from changes in parameters. In neuroscience, neurons talk to each other using chemicals called neurotransmitters, and the process of regulating this communication between neurons is called neuromodulation. As specific neurotransmitters, neuromodulators set the parameters of CPG neurons and synapses to render the networks functional in the face of different locomotor demands [24], [25]. In view of smooth and online modulation, CPGs provide a paradigm to generate multichannel coupled control signals.

These fascinating properties make CPGs suitable for locomotion control of robots with multiple joints or DOFs and even of hyperredundant robots. In particular, CPGs eliminate the need for trajectory planning and precise knowledge of mechanical system properties. However, there is an implicit assumption that CPGs magically deal with the dynamics of the control system. The CPG controllers will become powerless against more complex control systems where dynamics is crucial. An example is the locomotion control of humanoid robots over rough terrain, where foothold selection and balancing control are very critical. In such a case, creating desired kinematic trajectories and then employing model-based control to realize these trajectories is much easier than achieving a robust CPG controller. See a related discussion in [26].

The bioinspired CPG control has proven to be successful in diverse robotic applications, including legged robots (e.g., biped/humanoid, quadruped, hexapod, octopod, and reconfigurable), crawling robots (e.g., snake-like and salamander-like),

TABLE I
SUMMARY OF REPRESENTATIVE CPG-CONTROLLED ROBOTS

Locomotion	Robot Type	Methodology	Year	Reference
Legged	Biped	Using dynamic interactions among the coupled neural oscillators, the musculoskeletal system, and the environment	1991,1995	[27], [28]
	Humanoid	Using a CPG circuit modeled by recurrent neural networks	2002	[29]
	One-leg hopping	Using a Matsuoka oscillator to control resonant hopping	2008	[30]
	Biped hopping	Using a two-level CPG control mechanism coupled with feedback information	2012	[31]
	Quadruped (Patrush-I)	Using an artificial nervous system consisting of a neural oscillator network reflex mechanisms, and spring mechanisms	1999	[32]
	Quadruped (Tekken)	Using an artificial neural system model consisting of a CPG and reflexes	2003,2007	[33], [34]
	Quadruped (AIBO)	Using a CPG-based 3-D workspace trajectory generator and a motion engine	2011	[35]
	Hexapod	Implementing a CNN-based CPG structure on a VLSI chip	2006	[36]
		Exploiting superposition of discrete and rhythmic primitives	2012	[37]
	Octopod (scorpion-like)	Using a combination of CPG and reflex for producing basic motion patterns	2002	[38]
	Octopod (lobster-like)	Using a lobster circuitry inspired CPG model	2004	[39]
	Octopod (crab-like)	Using a simplified H-H surging nerve cell model evolved with genetic algorithm	2006	[40]
	Reconfigurable	Using CPG as a distributed motion controller connected with certain optimization algorithms	2005,2010	[41], [42]
Crawling	Snake robot	Using a neural oscillator network	2004	[43]
		Constructing a cyclic inhibitory CPG model for 3-D movements	2006	[44]
		Using a CPG network with feedback connection	2010	[45]
		Using a frequency-adaptive oscillator for undulatory snake-like locomotion	2010	[46]
	Salamander robot	Using a spinal cord model involving a phase oscillator coupled CPG network	2007	[47]
Swimming	Anguilliform	Using a CPG model inspired by the lamprey locomotor network	2001,2002	[48], [49]
	Carangiform	Using a Hopf oscillator coupled CPG network for multimodal swimming	2006,2012	[50], [51]
	Ostraciiform/crawling	Using a nonlinear oscillators coupled CPG network	2008	[52]
	Undulatory fin	Using coupled nonlinear oscillators for multi-DOF undulatory fin prototype	2010	[53]
	Dolphin-like	Using CPG-based approach with explicit frequency and amplitude modulation	2011	[54]
	Flapping	Using CPG-based control for a turtle-like flapping fin robot	2009,2010	[55], [56]
	Amphibious	Using a CPG inspired underwater locomotion control model	2012	[57]
Flying	Flapping	Using Hopf oscillator based CPGs for generating stable flapping-flight patterns	2010	[58]
Climbing	Caterpillar robot	Integrating the intrinsic half-wave of caterpillar locomotion into CPGs	2011	[59]
Other rhythmic	Robot arm	Exploiting the dynamical properties of a simple neural network oscillator circuit coupled to the joints of a robot arm	1998	[60]
		Employing CPG-based control to generate self-adapting movements for a 7-DOF robot arm	2010	[61]
	Neuroprosthesis	Using an adaptive CPG based controller for a lower limb prosthesis	2009	[62]
	Robotic marionette	Using an alternation-based CPG for multidimensional trajectory generation	2012	[63]
	Industrial robots	By generating online rhythmic point-to-point motions for industrial robots	2012	[64]

swimming robots (anguilliform, carangiform, ostraciiform, undulatory dorsal or pelvic fins, dolphin-like, flapping fins, and amphibious), flying robots (i.e., flapping flight), climbing robots (e.g., caterpillar), and other rhythmic motions (e.g., robot arm, neuroprosthesis, robotic marionette, and industrial robots). Note that the rhythmic movements are not applicable to wheeled and tracked locomotion. Table I lists typical CPG-related robotic applications. See also [65] for an overview of CPG-controlled legged robots.

B. Main Focus

As mentioned, the CPG-based control has progressed from concept to reality over the last decades. Particularly, there have been a growing number of research groups actively involved in all aspects of the process. Numerous studies have demonstrated the efficacy and advantages of the CPG-based control for producing stable and adaptive locomotion, which can reduce the complexity associated with engineered locomotion mimicry to a great extent. A general design framework for the CPG-based control is shown in Fig. 1. The vast majority of research on the CPG-based control has focused on three aspects: CPG modeling and analysis, CPG modulation (i.e., parameter tuning and gait transition), as well as CPG implementation, which will sequentially be elaborated in the following sections. It should be remarked that, as the CPG-based control is a topic, which is often interwoven with neurobiology, robotics, and simulations, freely given examples below are assumed to be robotics- or simulation related unless otherwise stated.

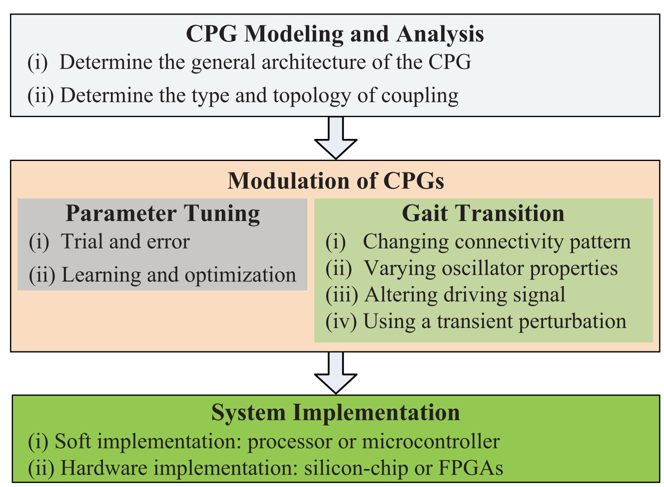

Fig. 1. General design framework for the CPG-based control.

III. CPG Modeling and Analysis

As the first step toward constructing an artificial CPG controller, an appropriate CPG control model should be decided on. The basic task is to determine the general architecture of the CPG as well as the type and topology of coupling. In practice, it is usual to model CPGs as networks of nominally identical systems of differential equations, variously described as oscillators, units, or cells [66]. As will be reviewed later, many alternatives are available for choosing the type of oscillators/neurons. Once the type and number of the oscillators/neurons along with the control output type (e.g., position control or torque control) are determined, the topology of coupling can be sought.

In general, oscillators/neurons are coupled by unidirectional or bidirectional connections. In terms of the possible structures for the connection between the oscillators/neurons, most of the existing topological structures can be loosely divided into two main categories: 1) chain and 2) network. Biologically, the chain structure is often found in low-level invertebrates, whereas the network structure is found in higher level vertebrates (e.g., cats and humans). Besides the simple chain structure, more diverse and complex network structures such as star, tree, partial connection, and full connection can be employed when implementing CPGs. For the convenience of readers, a short list of commonly used topological structures is given as follows.

1) Chain [43], [47], [67], [68], which is predominantly applied to multilink robots such as snake and fish robots.
2) Star [69]–[72], which presents a pacemaker/clock oscillator configuration offering a synchronization signal to other oscillators.
3) Tree [73]–[75], in which the oscillators are connected as a tree network from proximal to distal joints.
4) Partial connection [76]–[79], in which only homologous joints with a similar function are connected.
5) Full connection [80]–[82], in which all oscillators are mutually connected.

In practice, the symmetry principle is often applied to reduce the topological complexity when analyzing and building a CPG network. However, such a measure might limit the resulting patterns, as the possible variety of CPG parameters is restricted in advance. It should be remarked that there are no standard principles, which determine the structure to be used. This choice, to a large extent, depends on the intrinsic features of the robot application scenario.

As our main interest is the applicable CPG control models in robotics, an accompanying question arising from engineering practice is to classify the existing CPG control models within a reasonable framework. According to the applied neuron type and exhibited topology, CPG-related models can be classified into four categories: 1) neuron; 2) oscillator; 3) network; and 4) hybrid models.

A. Neuron Models

The neuron is viewed as the fundamental unit of a nervous system. To accurately describe and predict the biological processes in neurons, many neuron models have been proposed. The most basic model of an artificial neuron comprises an input with some synaptic weight vector and an activation function or transfer function inside the neuron determining output, which is commonly described by

$$Y_j = \phi\left(\sum_i w_{ij} X_i\right) \tag{1}$$

where Y_j is the output of the jth neuron, X_i is the ith input neuron signal, w_{ij} is the synaptic weight between the neurons i and j, and ϕ is the activation function. It should be emphasized that the output in (1) is not usually an instantaneous function of the input.

To model a biological neuron, physical analogues are used in place of abstractions such as weight and transfer function. The input to a neuron is often described by an ion current through the cell membrane that occurs when neurotransmitters cause an activation of ion channels in the cell. One of the earliest models of an abstracted neuron is the integrate-and-fire model [83]. The disadvantage of this model is that it implements no time-dependent memory. Namely, if the model receives a below-threshold signal at some time, it will retain that voltage boost forever until it fires again. This characteristic is inconsistent with the observed neuronal behavior. A leak term is thus added to the membrane potential so that the memory problem is fixed, accompanying the emergence of a leaky-integrator neuron model [83]. The leaky-integrator models are able to describe basic behaviors of neurons, but fail to simulate the degree of fatigue or adaptation of neurons.

Among the existing biological neuron models, the most successful and widely used model is the Hodgkin–Huxley model (also termed H–H model) developed in the early 1950s. It is a model of a squid giant axon that describes the generation of an action potential quantitatively. Mathematically, the original Hodgkin–Huxley model is a set of nonlinear ordinary differential equations possessing four variables (i.e., membrane voltage, activation and inactivation variables of the Na^+ current, and an activation variable of the K^+ current) [84]. However, it is very complicated and computationally expensive for computer simulations involving large populations of neurons. Since then, several simplified neuronal models such as the FitzHugh–Nagumo, the Morris–Lecar, and the Hindmarsh–Rose models have also been developed [85], facilitating large-scale simulation of interconnected neurons that form a neural network, as well as providing mathematical insights into dynamics of action potential generation.

Even so, the biophysical neuron models should be extensively modified for practical rhythmic locomotion control from the engineering viewpoint. Among them, the sustained-type analog neuron model (e.g., leaky-integrator model) and the transient-type analog neuron model are widely chosen to specify the dynamics of mutual inhibitory CPG, cyclic inhibitory CPG, and so on.

B. Oscillator Models

A widespread approach to model CPGs is to use dynamical systems, which are mathematically composed of coupled, nonlinear oscillators. Unlike neural oscillators (NOs) usually having clear biological meanings, nonlinear oscillators are created for the description of nonlinear dynamics, which are not necessarily bioinspired or biologically meaningful. Nonlinear oscillators share many characteristics, e.g., self-sustained limit cycle generation and selective entrainment. In biophysics, a key to understand the rhythm generation is the concept of the half-center (or bipartite) model proposed in [86] and refined in [87]. According to this concept, the rhythmic pattern of alternating bursts of flexor and extensor activities is produced by two symmetrically organized excitatory neural populations that drive alternating activity of flexor and extensor motoneurons and reciprocally inhibit each other via inhibitory interneurons. To explore the coupling between NOs, three mathematical methods are chiefly employed: 1) weak coupling; 2) firing time maps; and 3) leaky integrate-and-fire methods [88]. As for engineered CPGs applied to various robots, most coupled oscillators used as input–output elements of a feedback system take the form of weak coupling for simplicity. It is noteworthy that although phase models of coupled oscillators are known to approximate weakly coupled limit-cycle oscillators, coupling strengths are not necessarily weak when phase models are used to model CPGs. In contrast, strong coupling can create instabilities (that can induce transitions to nonphase locked states) more easily and is harder to analyze. For the sake of convenience, some typical oscillator models used in the engineering applications will be reviewed as follows.

1) Matsuoka NO: The most popular NO model used is the Matsuoka oscillator, named for its developer. The Matsuoka oscillator is consistent with the conceptual model of half-center oscillators that constitute a CPG, consisting of two mutually inhibiting neurons with adaption. Matsuoka analyzed the rhythm generation mechanism of the frequency and pattern of the mutually inhibiting neurons and proved that the model can fully simulate the biological characteristics of CPGs [89], [90]. However, he did not consider the effect of the sensory feedback on the NO performance. Employing the Matsuoka NO model, Taga *et al.* [27], [28] and Kimura *et al.* [32]–[34] included the sensory feedback signals into the CPGs, showing that NOs made the robot to the perturbation through mutual entrainment between the CPGs and the musculoskeletal system. Later, this approach was applied to various locomotion systems [35], [41], [43], [45], [46], [60]. Fig. 2 shows a schematic diagram of the Matsuoka oscillator as a unit of a CPG controller. A single NO comprises two mutually inhibiting neurons (i.e., extensor and flexor neurons). Each neuron is represented by the following nonlinear differential equations:

$$\begin{cases} T_r \dot{u}_i^{\{e,f\}} = -u_i^{\{e,f\}} + w_{fe} y_i^{\{f,e\}} - \beta v_i^{\{e,f\}} \\ \qquad + s_0 + \mathrm{Feed}_i^{\{e,f\}} + \sum_{j=1}^{n} w_{ij} y_j^{\{e,f\}} \\ T_a \dot{v}_i^{\{e,f\}} = -v_i^{\{e,f\}} + y_i^{\{e,f\}} \\ y_i^{\{e,f\}} = \max(u_i^{\{e,f\}}, 0) \\ y_i = -y_i^{\{e\}} + y_i^{\{f\}} \end{cases} \tag{2}$$

where the superscripts e and f and the subscript i are the extensor neuron, the flexor neuron, and the ith NO, respectively. $u_i^{\{e,f\}}$ is u_i^e or u_i^f, that is, the inner state of an extensor neuron or a flexor neuron of the ith NO, $v_i^{\{e,f\}}$ is a variable representing the degree of the self-inhibition effect of the neuron, $y_i^{\{e\}}$ and $y_i^{\{f\}}$ are the outputs of extensor and flexor neurons, s_0 is an external input with a constant rate, $\mathrm{Feed}_i^{\{e,f\}}$ is a feedback signal from the robot, that is, a joint angle, angular velocity, and so on, and β is a constant representing the degree of the self-inhibition influence on the inner state. The quantities T_r and T_a are the constants of rising time and adaption time associated with $u_i^{\{e,f\}}$ and $v_i^{\{e,f\}}$; w_{fe} is the connecting weight between flexor and extensor neurons, w_{ij} is the connecting weight between neurons of the ith and the jth NOs, and the phase signal y_i acts as the output of a CPG. More specifically, the positive or negative value of y_i corresponds to the activity of a flexor or extensor neuron, respectively.

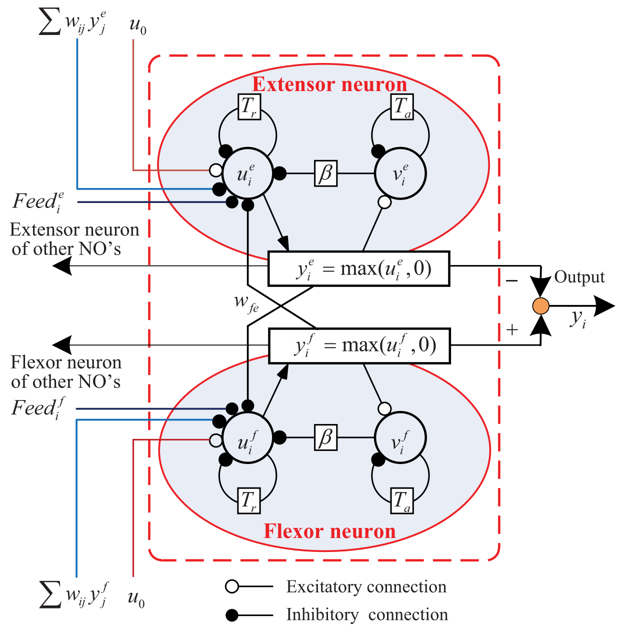

Fig. 2. Matsuoka oscillator as a model of a CPG. Adapted from [33].

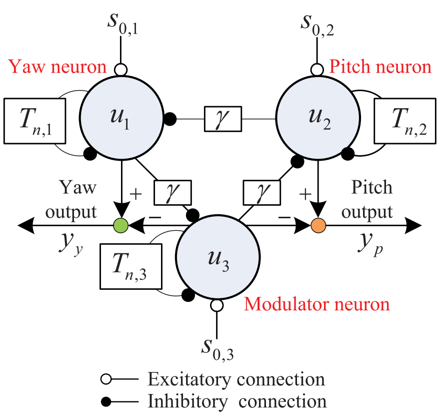

Fig. 3. Schematic diagram of a cyclic inhibitory oscillator. Adapted from [44].

2) Cyclic Inhibitory NO: To control the 3-D locomotion of a snake robot with yaw and pitch joints, Lu *et al.* proposed a cyclic inhibitory CPG model based on the sustained-type analog neurons [44]. As shown in Fig. 3, a cyclic inhibitory oscillator is composed of a yaw neuron (n_y), a pitch

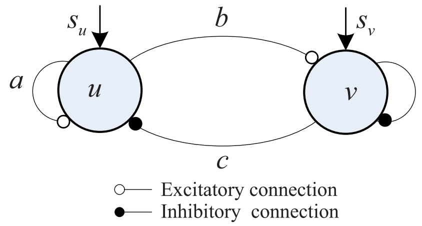

Fig. 4. Schematic diagram of a Wilson–Cowan oscillator. Adapted from [92].

neuron (n_p), and a modulator neuron (n_m). The dynamics of the cyclic inhibitory oscillator is described as follows:

$$\begin{cases} T_{n,1}\dot{u}_1 + u_1 = s_{0,1} - \gamma\, g(u_2) \\ T_{n,2}\dot{u}_2 + u_2 = s_{0,2} - \gamma\, g(u_3) \\ T_{n,3}\dot{u}_3 + u_3 = s_{0,3} - \gamma\, g(u_1) \\ y_i = g(u_i),\ g(u_i) = \max(0, u_i) \quad i = 1, 2, 3 \\ y_y = y_1 - y_3 \\ y_p = y_2 - y_3 \end{cases} \tag{3}$$

where γ is the weight of the cyclic inhibitory connection; $s_{0,1}$, $s_{0,2}$, and $s_{0,3}$ is constant and positive inputs, each of which is the summation of all inputs to n_y, n_p, and n_m by the weight of synaptic conjunction, excepting the output of the neurons in the CPG; u_1, u_2, and u_3 are the corresponding membrane potential of n_y, n_p, and n_m; $T_{n,1}$, $T_{n,2}$, and $T_{n,3}$ are the corresponding time constants of n_y, n_p, and n_m; y_1, y_2, and y_3 are the corresponding output of n_y, n_p, and n_m; y_y and y_p are the corresponding output of a CPG to control the yaw and pitch rotations, respectively.

It is worth noting that, although the Matsuoka oscillator and the cyclic inhibitory oscillator belong to sustained-type models, they have distinct mechanisms of rhythm generation. The Matsuoka oscillator primarily depends on the neuron's adjusting function to modulate periodic outputs, whereas the cyclic inhibitory oscillator does not necessitate adaptation but only uses strong cyclic inhibition among the neurons for rhythm generation. As the cyclic inhibitory CPG model can simultaneously output two different rhythmic signals, it also provides an alternative to single-oscillator-dual-output cases.

3) Wilson–Cowan NO: In the early 1970s, Wilson and Cowan studied the properties of a nervous tissue modeled by populations of oscillating cells composed of two types of interacting neurons: excitatory and inhibitory ones [91]. A simplified Wilson–Cowan NO model (also termed Amari–Hopfield neuron model), comprising an interconnected excitatory neuron u and an inhibitory neuron v (see Fig. 4), is given by

$$\begin{cases} \tau_u \dot{u} = -u + f_\mu(au - bv + s_u) \\ \tau_v \dot{v} = -v + f_\mu(cu - dv + s_v) \end{cases} \tag{4}$$

where the parameters a to d is the synaptic strength between the populations of neurons, s_u and s_v are the external inputs such as the bias current and the sensory inputs, and τ_u and τ_v are the time constants. The transfer function $f_\mu(x) = \tanh(\mu x)$ and μ is its gain parameter. Through adjusting all the parameters, the Wilson–Cowan NO shows various oscillatory behaviors such as a limit-cycle oscillation [92]. The Wilson–Cowan oscillator model has been widely used to demonstrate synchronous activity in locally coupled networks of oscillators [93] and to construct artificial CPGs [92], [94].

4) Kuramoto Oscillator: Apart from NOs, the other kind of artificial oscillators, nonlinear oscillators, are widely adopted to create CPGs. Being one of the fundamental phenomena in nonlinear science, synchronization of oscillations has received considerable interest across biophysics. An attractive oscillator to explore synchronization in complex networks is the phase oscillator, where we view the state of the system as going around the simplest loop, a unit circle. The Kuramoto model is a famous phase oscillator model, which is developed for studying the behavior of a large set of coupled oscillators [95]. The model makes several assumptions, including that there is weak coupling, that the oscillators are identical or nearly identical, and that interactions depend sinusoidally on the phase difference between each pair of objects. Mathematically, the Kuramoto model is composed of N coupled phase oscillators (often termed Kuramoto oscillators), $\theta_i(t)$, having natural frequencies ω_i distributed with a given probability density, and whose dynamics is governed by

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

where K_{ij} is a positive coupling strength from the jth to ith oscillator. Each Kuramoto oscillator tries to run independently at its own frequency, while the coupling tends to synchronize it to all the others. When the coupling is sufficiently weak, the oscillators run incoherently whereas beyond a certain threshold collective synchronization emerges spontaneously. Because of this prominent synchronization feature, the Kuramoto model is widely used to study neural oscillations and several extensions have been proposed that increase its neurobiological plausibility [96]. In addition, the Kuramoto oscillator is used to construct CPG models for robotic locomotion, e.g., reconfiguration through variable locomotion of the Roombots [42], swimming and walking of a salamander robot [47], multimodal swimming of an amphibious robot [57], and serpentine motion of a worm robot [97].

5) Hopf Oscillator: Another nonlinear oscillator that is commonly used as the dynamic model of engineered CPGs is the Hopf oscillator. The dynamics of the Hopf oscillator can be described by the following ordinary differential equations [98]:

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

where $\mu^2 > 0$; $x, y \in R$ are the states of the oscillator, ω is the intrinsic oscillation frequency, and μ determines the steady-state amplitude of oscillation (i.e., $x_\infty^2 + y_\infty^2 = \mu^2$). An attraction of the Hopf oscillator is its circular limit cycle with a radius of μ and a frequency of ω, along with the intrinsic synchronization property, making it an ideal building block to establish CPGs for robotic locomotion like swimming, flying, and walking [53], [54], [56], [58], [99].

To endow the Hopf oscillators with the capability to tune their intrinsic frequency to one of the frequency components of an input signal, Righetti *et al.* proposed an adaptive frequency Hopf oscillator [100]. The modified oscillator receives an input $I(t)$, which is an additive perturbation to $\dot{x}$ and which also affects the evolution of the frequency ω, as shown in (7)

$$\begin{cases} \dot{x} = (\mu^2 - (x^2 + y^2))x + \omega y + KI(t) \\ \dot{y} = (\mu^2 - (x^2 + y^2))y - \omega x \\ \dot{\omega} = KI(t)\frac{y}{\sqrt{x^2+y^2}} \end{cases} \tag{7}$$

where $K > 0$ is a coupling constant. By perturbation series analysis it can be proved that the adaptive frequency Hopf oscillator exhibits a limit cycle oscillation, which synchronizes with the frequency of the input perturbation, $I(t)$. The oscillator will have a tendency to accelerate or decelerate, according to the tangential component of $I(t)$ in the phase plane, which on average results in an oscillation at a frequency of $I(t)$. By employing the adaptive Hopf oscillators as the controller, agile legged robotic locomotion has been successfully demonstrated on a compliant quadruped robot [101].

6) Other Limit-Cycle Oscillators: As mentioned, there exist nonlinear systems, which are known to have a globally attractive limit cycle. Two well-studied examples are the van der Pol oscillator and the Rayleigh oscillator, whose second-order differential equations are described by (8) and (9), respectively

$$\ddot{x} + a(x^2 - p^2)\dot{x} + \omega^2 x = 0 \tag{8}$$
$$\ddot{x} + a(\dot{x}^2 - p^2)\dot{x} + \omega^2 x = 0 \tag{9}$$

where x and $\dot{x}$ are the states of the system, ω is the natural frequency, and $a > 0$ is the coefficient of the resistance. As given by $x^2 - p^2$, for a small amplitude of x, the resistance is negative, which is responsible for the generation of self-sustained oscillation. Notice that, unlike the van der Pol oscillator, $\dot{x}$ is inserted in the $(x^2 - p^2)$ in the Rayleigh oscillator. This difference alters the response of the two oscillators to changes in their natural frequency. For the van der Pol oscillator, increasing ω increases the oscillator's output frequency, whereas for the Rayleigh oscillator it has the effect of increasing output amplitude. An experimental comparison of these two oscillators for the same robotic task can be found in [79]. Besides extensive electronic applications, coupled van der Pol oscillators [102], [103], Rayleigh oscillators [104], as well as hybrid van der Pol/Rayleigh oscillators [105] have been used for the applications in the field of robotics.

C. Network Model

As a specific network of neurons dedicated to producing rhythmic outputs, CPGs can certainly be implemented as an artificial neural network.

For example, to overcome some of the disadvantages of the classical half-center models of the CPG, Rybak *et al.* proposed a two-level CPG architecture containing a half-center rhythm generator (RG) and a pattern formation (PF) network [106], [107]. The RG controls the activity of the PF network that in turn defines the rhythmic pattern of motoneuron activity. It is verified that a number of features of the real-CPG operation can be reproduced with separate RG and PF networks, which would be difficult to demonstrate with a classical single-level CPG. Now this CPG-based hierarchical network model is successfully modified to achieve dynamic gait transition of a biped robot from quadrupedal to bipedal locomotion [108].

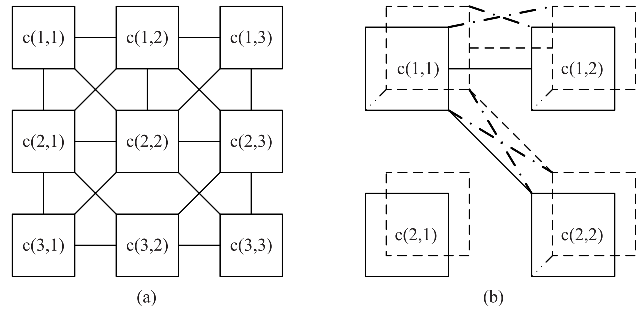

Fig. 5. Schematic diagram of a two-layer CNN model. (a) 2-D CNN model. The circuit size is 3×3. The squares are the circuit units called cells. The links denote the interactions between the cells, and the interactions may be different. (b) Two-layer CNN model. The circuit size is 2×2. Solid and dashed squares: cells. Solid, dashed, and dash-dot lines: interactions between the first, the second, the first and second layers, respectively. For simplicity, only interactions between c(1, 1) and c(1, 2), and those between c(1, 1) and c(2, 2) are drawn.

For the purpose of controlling a multi-DOF humanoid robot named HOAP-1, Shan and Nagashima used a CPG constructed by combination of groups of neural circuits that are modeled by recurrent neural networks (RNN) [29]. Test results show that RNN is appropriate for CPG modeling due to its flexibility in capturing complex nonlinear phenomena. Similarly, Ponulak *et al.* demonstrated the use of spiking neural networks for constructing a CPG model with the ability to learn the desired rhythmic patterns [109].

To facilitate the physical circuit design and implementation, Arena *et al.* extensively investigated the implementation of CPGs for robot control using cellular neural networks (CNNs) [110], [111]. CNNs are a parallel computing paradigm similar to neural networks, with the only difference that communication is allowed between neighboring units in CNNs. According to the classic Chua-Yang CNN model [112], the state of a cell is a weighted sum of the inputs and the output is a piecewise linear function. A two-layer CNN CPG is structurally shown in Fig. 5. In the model, each cell has two state variables and two outputs. So, the interactions are not simple as those in Fig. 5(a) and are substantially expanded. A cell of the CNN can be described by the following differential equation:

$$\begin{cases} \dot{x}_1 &= k\left(-x_1 + (1+\mu)\, y_1 - s y_2 + i_1 + \sum I_{1,s}\right) \\ \dot{x}_2 &= k\left(-x_2 + s y_1 + (1+\mu)\, y_2 + i_2 + \sum I_{2,s}\right) \end{cases} \tag{10}$$

where $y_i = 0.5\,(|x_i + 1| - |x_i - 1|)$ with $i = \{1, 2\}$, and x is the state variable. The terms $\sum I_{1,s}$ and $\sum I_{2,s}$ are the sum of all the synaptic inputs coming from the other neurons. Distinct locomotion gaits are then implemented using distinct connections among cells, corresponding to distinct sets of CNN templates. Further, the direct implementation of the CNN CPG controller including sensory feedback on a VLSI chip makes it particularly well suited to autonomous locomotion generation with on-board intelligence [111].

D. Hybrid Model

Each of the proposed CPG models has advantages and drawbacks. By combining multiple CPG models into a single hybrid system, however, it is possible to create a better CPG that benefits from multiple approaches while overcoming many of the drawbacks. For instance, Filho and Dutra used a coupled hybrid van der Pol–Rayleigh oscillator system for controlling a bipedal robot [104]. This hybrid oscillator system showed an improved performance when compared with the system that uses only a van der Pol or Rayleigh oscillator. To enhance the locomotion flexibility of an eight-legged walking robot named CORPION, Spenneberg proposed a hybrid locomotion control concept based on a CPG model implemented with Bezier-splines, a reflex model inspired by artificial neurons, and a posture control model [113]. Or proposed a hybrid CPG–zero moment point (ZMP) controller for the real-time balance of a simulated flexible spine humanoid robot, where the CPG component generates rhythmic motions while the ZMP component allows the robot to adjust its own postures to maintain balance in real time [114]. To achieve a better interaction with the environment, Moreno and Gomez [115] adopted a hybrid strategy combining CPGs and hormone messages for controlling a chain-type modular robot. Particularly, hormone messages are served to propagate sensory feedback information to the CPG thus providing a way to define a specific motor primitive. As the robotic behavior mostly emerges from dynamic interactions between the CPGs, the robot, and the environments, most hybrid CPG systems are dedicated to better dynamic interactions. However, getting multiple approaches to coexist in a single hybrid system is not an easy task because more parameters are involved and should be properly modulated.

IV. Modulation of CPGs

Rhythm generation and modulation are two tightly coupled issues in robotics and animal motor control. In this section, we first give a brief overview of the role of neuromodulation and sensory feedback in CPGs, and then survey two major components of CPG modulation in engineering practice, i.e., parameter tuning and gait transition.

A. Role of Neuromodulation and Sensory Feedback in CPGs

From a neuroscience point of view, three roles of modulation in CPGs have been identified [17]: 1) modulation in CPGs is a part of normal activity; 2) modulation changes the functional configuration of CPGs to produce different motor outputs; and 3) modulation alters the CPG neuron complement by switching neurons between networks and fusing formerly separate networks into larger entities. According to a recent opinion from [25], the idea that neurobiological modulatory inputs are optional modifiers that fine-tune ongoing CPG function should be discarded. Instead, modulatory inputs are essential components of the CPG function. That is, neuromodulators alter both synaptic strength and intrinsic membrane properties, and by doing so, can modulate the motor patterns produced by a given CPG circuit in terms of frequency and phasing of the units.

It is noteworthy that the role of sensory signals in shaping motoneuronal activities. Strikingly, sensory feedback is widely

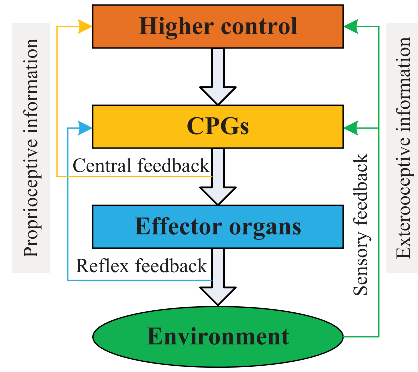

Fig. 6. Main functional features of a typical animal motor system. Adapted from [116].

employed to alter motor patterns to deal with environmental perturbations. Fig. 6 shows the key features of the motor system of many animals ranging from the *Clione* to the cat, emphasizing the presence of different types of feedback [116]. Note also that in many biological cases the functional subdivision shown in Fig. 6 does not correspond to different neural networks: the same networks may act at different levels of the structure. From Fig. 6, the feedback paths involve central feedback directed to the higher control neurons, reflex feedback from the motor output to the CPG, and sensory feedback from the environment to either the CPG or the higher level control. In particular, the feedback paths on the left of Fig. 6 show the flow of proprioceptive information, whereas those on the right correspond to the flow of exteroceptive information. With both proprioceptive and exteroceptive information, a closed-loop CPG-based control system is formed. This suggests a combined feedforward-feedback control strategy, in which feedforward pathways from centrally connected CPGs, in conjunction with nonlinear properties of effector organs, suffice to produce basic locomotion, whereas proprioception enhances flexibility in response to unexpected perturbations [117]. Thus, the closed-loop coupling between the CPG and the mechanical system permits study of the modulation of rhythmic patterns and the effect of the sensing loop via sensory neurons during the locomotion task. Some good examples of employing sensory feedbacks in the CPG control to improve robotic locomotion can be found in [118] and [119].

B. Parameter Tuning

One drawback of the CPG-based control is that there are too many parameters to be set for achieving a desired locomotor pattern within a broad search space. To obtain a full understanding of how control parameters can tune quantities such as frequency, amplitude, phase lags, or waveforms usually constitutes a tremendously difficult task.

As there is no sound methodology for CPG parameter tuning, two main alternative methods, i.e., the trial-and-error method and the learning and optimization method, are currently used [4]. In the former method, the control parameters are obtained by intuitive principles and refined by trial and error with the aid of simulators or physical experiments. An example of setting the CPG parameters by tactile interaction with the user is also reported in [120]. Two major disadvantages of the trial-and-error method are that it is tedious and inefficient and the obtained parameters are only applicable to a specific robotic system under specific conditions. As for the latter method, the parameter tuning problem is converted to an optimization problem with constraints. Many early methods relied heavily on the evolutionary computation method (e.g., genetic algorithm, genetic programming, and particle swarm optimization) [121]–[123]. In recent years, supervised and unsupervised learning techniques increasingly played a large role in CPG parameter search [124], [125]. For example, with the help of statistical learning techniques, oscillator and attractor models have been designed exactly with the goal to facilitate the process of tuning multiple movement primitives [26]. For an in-depth discussion of the learning techniques in the CPG-based control, please refer to [4].

Furthermore, there are two ways to optimize CPG parameters for a robot, i.e., online optimization (e.g., in [126]) and offline optimization. The online optimization evolves the control parameters directly on a real robot, whereas the offline optimization relies on a simulator for parameter search. Nowadays, it is common to use simulation to speedup the learning process; however, simulations are normally achieved from arbitrary offline designs, rather than from the result of embodied cognitive processes. So, the reality gap problem occurs, meaning that the optimized control parameters obtained from the offline optimization usually do not lead to the same locomotion effect as they do on simulators [127]. One of the main reasons for this phenomenon is that simulation models are only simplifications of the real world. Incidentally, the circuit implementation of CPG parameter tuning is possible now. As an example, Li *et al.* successfully used aVLSI floating gates to implement modulation of CPGs [128].

C. Gait Transition

Different gaits in animals are achieved via appropriate initialization and parameterization of the CPG network. From a dynamical systems perspective, successive bifurcations result in gait transitions [129]. To interpret and imitate the biological transition mechanisms underlying CPGs, different approaches have been proposed and further applied to robots, most of which fall into four broad types.

1) Changing the pattern of connectivity. This is the major way to switch gaits. Considering that a gait corresponds to a template comprising a set of CPG control parameters, the transition task can be fulfilled by a mechanism like finite state machine. Typically, Arena *et al.* proposed a multitemplate approach for the implementation of several possible connections among cells in CNN CPG [110]. Kimura *et al.* achieved gait transitions from trotting to pacing via walking in a quadrupedal robot with various connecting weights [33] or by changing the gain of the controller [32]. With a focus on three problems (i.e., breakpoint, phase lock, and oscillation stop) during transition, Zhang *et al.* adopted an approach of directly replacing the connecting weight matrices for gait transition [130].
2) Varying the properties of the oscillators themselves. This approach seems to be more like a sort of CPG reconfiguration [25]. As most engineered CPG models are modularly constructed based on a single oscillator, this transition approach is rarely used in robotics.
3) Altering the driving signal to the CPG. Using neural computation as a tool, Collins and Richmond first explored this transition mechanism with a hard-wired CPG model producing walk, trot, and bound [131]. Nishii proposed a learning model for coupled oscillators, in which the intrinsic frequencies of the component oscillators and the coupling strength between them are adjusted in accordance with the changes in the input signals [132]. In practical applications, this drive signal can be specified according to sensory information or set *a priori*. For example, Santos and Matos applied a brainstem-like modulation approach to achieve CPG-based gait transition and modulation for a quadruped robot, where a driving signal that encodes the required activity and/or modulation is incorporated [133].
4) Using a transient perturbation. This transition mechanism is often practically interpreted as environmental adaptability. In simulations of CPGs, for instance, Canavier *et al.* demonstrated that the timing and synaptic characterization of the switch signal that is induced by a transient perturbation can be adjusted to produce the desired amount of phase resetting for pattern switching in ring circuits of oscillators [134]. Following this switching strategy, Luo *et al.* explored the mechanisms of rapidly and effectively switching between gait modes in a four neuron ring circuit [135].

Besides these four major transition approaches, gait modes can be regulated via the variation of sensory input or its effects. For the purpose of establishing stable gaits during the gait transition, sensory inputs are usually required to be integrated so as to close the control loop. For example, Ijspeert *et al.* explored the effect of incorporating sensory feedback in different CPG configurations and tested the transition from aquatic to terrestrial locomotion with a salamander robot [47], [136]. They suggested that sensory feedback may be a potential explanation for the transition from a traveling wave for swimming to a standing wave for walking. With the aid of visual feedback responsible for modifying the control parameters, Santos and Matos developed a CPG-based locomotion controller that is able to generate omnidirectional quadruped locomotion [137]. This paper was performed on a real-AIBO platform, offering a paradigm for achieving flexible and adaptive goal-directed vertebrate locomotion within the framework of CPG-based control. In addition, for quadruped and biped robots, the transition from a static posture into the pattern and from stopping back to a static posture poses a great challenge to modeling and control. If the transition does not occur in an appropriate context, the robot will fall over easily.

V. System Implementation

Although most modeling into biological rhythmic pattern generation uses computer simulations, the CPG-based robotic

TABLE II
SUMMARY OF REPRESENTATIVE HARDWARE CPGS

Hardware CPG Type	Year	Reference
Custom aVLSI CPG chip (four neurons)	2000	[138]
Analog CMOS CPG (Amari-Hopfield model)	2003	[77]
VLSI CNN CPG chip	2005	[111]
VLSI CPG chip (four oscillator circuits)	2006	[139]
Pulse-type hardware CPG	2006	[140]
Low-power CMOS CPG (lobster circuitry)	2007	[141]
FPGA-based CPG (Amari-Hopfield model)	2008	[142]
FPGA-based CPG (van de Pol model)	2010	[143]
FPGA-based CPG using distributed arithmetic	2011	[144]
FPGA-based CPG controller	2011	[145]
VLSI-based adaptive-frequency Hopf oscillator	2011	[146]
Analog CMOS CPG (hybrid Matsuoka oscillators)	2012	[147]

locomotion control is programmed in software and running on a CPU/microcontroller, or in a pure hardware. In this section, a brief description of CPG implementation both in software and hardware is given.

A. Software Implementation

Almost all software implementations involve some sort of coupled differential equations, which are numerically integrated on a general-purpose processor or microcontroller. Building an intelligent robot that can flexibly achieve its goals in changing environments requires a blending of real-time computing and intelligent algorithms. Along with the fast development of the hardware of embedded systems, the software CPGs can be embedded as a locomotion control subsystem, offering a system-on-chip solution for embedded control. Especially, in contrast to the hardware CPGs, the software CPGs that are independent of hardware architecture and operating systems allow for much more freedom in modulating CPG parameters.

B. Hardware Implementation

With the rapid development of electronic technology in miniaturization, energy saving, and powerful computation, efforts have been devoted to implement CPGs in pure hardware in recent years. It is expected that hardware CPGs will increase the computation speed and simultaneously minimize the power consumption of the control system, and eventually make the CPG-based locomotion control faster and smoother. Table II lists the representative hardware CPGs applied to real robots successfully. They can grossly be divided into two classes, those that are built as silicon chips [77], [111], [138]–[141], [146], [147] and those that are implemented through field programmable gate arrays (FPGAs) [142]–[145].

1) Silicon-Chip-Based CPGs: Considering that the physics of silicon is in many ways analogous to the biophysics of the nervous system [148], silicon-based integrated circuit technology is used to construct CPG chips. A CPG chip is usually compact and small, and consumes less power. These prominent features are crucial for autonomous robots whose size, power consumption, and payload are usually limited. Lewis *et al.* gave an implementation example of an adaptive aVLSI neural chip in the early 2000s [138]. Nakada *et al.* designed an Amari–Hopfield-neuron-based CPG controller with complementary metal–oxide–semiconductor (CMOS) analog circuits [77], whereas Zhang *et al.* realized a neuromorphic pattern generator model synthesizing the Matsuoka model and the resonate-and-fire model with CMOS circuits [147]. Similarly, Hata *et al.* gave a pulse-type hardware CPG model using coupled oscillator composed of pulse-type hardware neuron models [140]. Lee *et al.* used CMOS subthreshold circuit techniques to achieve low power consumption of the CPG-based analog controller [141]. In addition, Arena *et al.* [111], Still *et al.* [139], and Ahmadi *et al.* [146] implemented VLSI CPG chips based on nonlinear oscillators or CNN. Although the CPG chip offers a portable computation- and power-efficient solution, its disadvantages of lacking flexibility and dynamics as well as of long design cycles should not be ignored. It means that once the CPG chip has been built, there is no way to make small alterations but to redesign the whole hardware CPG.

2) FPGA-Based CPGs: The other solution to hardware CPGs is using FPGAs as the hardware platform. An FPGA is an integrated circuit designed to be configured by a customer or a designer after manufacturing—hence field programmable. FPGAs can be used to implement any logical function that an application-specific integrated circuit could perform. The ability to reconfigure by programming rather than redesigning the physical hardware offers advantages for many applications. In particular, FPGAs are suitable for neural processing that mixes real-time or low-power constraints with a need for flexibility [149]. Thereby, the FPGA-based CPGs provide an embedded, flexible, and expandable solution for generating periodic rhythmic patterns in robot control applications. For instance, Torres–Huitzil and Girau gave an implementation case of the fundamental Amari–Hopfield CPG in an FPGA-embedded system providing performance and flexibility to generate rhythmic patterns suitable for mobile robotic applications [142]. Similarly, Barron–Zambrano *et al.* explored the FPGA-based implementation of van de Pol oscillators coupled with a CPG controller to generate adaptive gait patterns for quadruped robots [143]. From the perspective of algorithm design, Li and Li exploited an improved distributed-arithmetic algorithm to maximize the usage of lookup tables in an FPGA-based CPG implementation [144]. Barron-Zambrano *et al.* presented an FPGA-based embedded control scheme to connect the visual perception and the CPG-based locomotion [145]. It should be remarked that the FPGA-based CPGs will work well with a real-time constraint only if the control hardware is embedded in the FPGA. This hardware constraint partly sacrifices the energy performance and also restricts the application and extension of the FPGA-based CPGs.

VI. FUTURE DEVELOPMENTS

In the previous sections, we have reviewed the state-of-the-art of CPG-based locomotion control for various robots sorted by locomotion type. Along with theoretical and practical explorations, although an enormous amount of work has been done in bioinspired CPG-based control, many issues are still open and deserve further research, especially in the following areas.

A. CPG Model Handling

The bioinspired CPG-based locomotion control draws nourishment from the neurobiological research. However, the specific intrinsic neural mechanisms involved in the generation of locomotor oscillations in most CPGs, especially in mammals, remain largely unclear nowadays. The CPG is increasingly being dissected using novel tools, techniques, and approaches but is still, in most parts, a black box for which many of the components are incompletely characterized. To transfer the advantages of biological CPGs to robotic locomotion control, the primary question is to extract the most appropriate representations for engineered CPG models. A natural avenue to investigate the network is to find out every individual cell, to explore its structures, coupling styles, and influences on other cells, and ultimately to obtain the whole structure and the working mechanism. This analytical approach hardly takes effect in that CPG is a very complicated neural network. Hence, approximate ways to simplify the biological CPG without losing its traits such as modularity and stability should be sought. Interesting progress is being made using physiological findings regarding living CPGs to create hybrid CPG control paradigms for robots [108], [115], [150]. Perhaps the most promising practical approach for handling the CPG model problem is through tight interaction between the bioinspired design strategies and the robotic locomotion requirements.

B. Bridging the Reality Gap During CPG Evolution

An important problem in the CPG-based locomotion control is to evolve the control parameters for a particular locomotor gait. In addition to conventional computer simulations, robots have become effective tools for testing hypotheses of locomotor mechanisms and control methods by demonstrating real-world dynamic characteristics. Although evolving gait directly in real robots is an intriguing target with certain advantages, it usually consumes more time and computational resources. To bridge the reality gap between computer simulations and robot experiments, a possible scheme is to integrate offline and online evolution into a staged evolution. This staged method evolves the gait by simulation first so as to accelerate the preliminary evaluation, and then the simulation results are transferred to the real robot where the process of evolution is continued under actual running environments. A general multistage process synthesizing offline optimization and online adjustable parameters for biped gait generation has been reported in [151]. In addition, with the advent of multicore processors or hybrid processors (e.g., CPU + FPGA and CPU + DSP), the CPG controllers will become building blocks embedded into the dynamic systems, which will be more powerful than any on considering computation speed and real timeness.

C. Replicating Environmental Adaptability

Another remaining challenge is to design control architectures able to exhibit adaptive and multimodal motor skills. A general biological view holds that adaptive behavior depends on interactions among the nervous system, body, and environment: sensory preprocessing and motor postprocessing filter inputs to and outputs from the nervous system; coevolution and codevelopment of the nervous system and periphery create matching and complementarity between them; body structure creates constraints and opportunities for neural control; and continuous feedback between the nervous system, the body, and the environment are essential for normal behavior [152]. Following this principle, the CPG-based hierarchical control architecture to implement the autonomous locomotion has been adopted in robotics [116]. To guarantee the mutual entrainment between the CPG and the mechanical body, sensory feedback should be included to close the control loop. In addition to closed-loop CPGs, greater importance should be attached to stable and continuous gait transition in changing environments. Considering that the adaptive behavior of robots can be regarded as an emergent property of an agent embedded in an environment with which it must continuously interact, the reflex-based closed-loop CPG method can be an alternative to continuous and rapid gait transitions.

D. Combination of Perception and CPG-Based Navigation

Though locomotion and perception are usually treated as separate problems in robotics, these two components can be tightly integrated for CPG-based navigation tasks. Examples of a low-level CPG-based locomotion mechanism and a high-level visual perception-based reaching mechanism for autonomous navigation have been reported in [137] and [153]. The terrestrial/underwater visual perception not only serves to modulate the CPG parameters, but also contributes to navigation tasks including target acquisition and obstacle avoidance. Undoubtedly, the successful implementation of perception-aided and goal-oriented locomotion tasks will substantially expand the use of CPG controllers.

E. Combining CPG and Brain–Computer-Interface Technology for Locomotion Rehabilitation

Recent years have witnessed an increasing interest in the use of adaptive oscillators for assistance of cyclical movements in assistive and rehabilitation robotics [154]–[156]. As suggested in [157], targeting intrinsic spinal circuits by stimulating or engaging remaining pathways and sensory afferents should be a focus for rehabilitative strategies in humans with spinal cord injury, where the spinal locomotor CPG is indispensable in understanding the locomotor recovery. Harkema *et al.* demonstrated that stimulation of the injured spinal cord in a human can significantly contribute to the ability to walk [158]. From an engineering standpoint, as shown in Fig. 7, a hybrid locomotion rehabilitation system can be built based on brain–computer interface (BCI) technology and artificial CPGs. Similar to the general nervous structure of human beings, the BCI aims to establish a direct link for transmitting information between the brain and external devices; the artificial CPGs are triggered by the BCI command and generate rhythmic motor patterns for assistive devices (e.g., prosthetics,

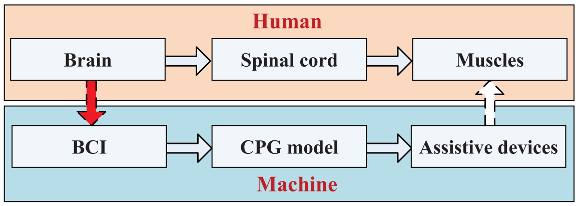

Fig. 7. Block diagram of a hybrid locomotion rehabilitation system based on the BCI–CPG technology.

orthotics, exoskeletons, robots, or functional electrical stimulations); thus a neuroprosthetic bridge can be constructed to restore mobility in paralyzed limbs by electrically stimulating muscles [159]. Currently, the BCI technology can merely recognize limited states of human intention, failing to provide continuous control inputs for the assistive devices directly. Thanks to the merit of CPGs that only need simple commands from higher centers (e.g., brain) for rhythmic locomotion generation and modulation, the BCI–CPG technology offers a functionally integrated solution to locomotion rehabilitation in practice. More remarkably, a new study in Nature reports that two people with tetraplegia were able to reach for and grasp objects in 3-D space using robotic arms that they controlled directly with brain activity [160]. This latest breakthrough in the BCI field shows significant promise for people with brain injuries and disorders. In the longer term, wireless applications of the CPG and BCI technology are expected, which will greatly expand the range of communication functions of the BCIs and help enhance locomotion after neurological injury in humans.

VII. Conclusion

As a bioinspired neural network, CPGs have been deployed to provide control solutions, especially during the last 20 years. Besides various practical applications, advances in the CPG-inspired locomotion control contribute in understanding the mechanisms underlying locomotor deficits after spinal cord injury and help the development of rehabilitation strategies. In this paper, we have presented an overview of recent developments of CPG-based locomotion control, primarily involving CPG modeling and analysis, CPG modulation, as well as CPG implementation. The state-of-the-art of existing methods in each key issue is described with the focus on the robotics-related applications. In addition, we have given some detailed discussions on future directions, such as CPG model handling, CPG evolution, replicating environmental adaptability, combination of perception and CPG-based navigation, as well as combining CPG and BCI technology for locomotion rehabilitation.

At present, the biggest impediment to the CPG-based control technology is the lack of a solid theoretical foundation for designing and fine-tuning CPGs. However, it will be a gradually advancing process for the improvement of the CPG-based control, which is well nourished by the neurobiological progress on biological CPGs. With the advent of component-based software frameworks (e.g., Open-RTM, ROS, OPRoS, and SmartSoft) that support the development and reuse of large grained pieces of robotics software, the CPGs are promisingly built as an optional locomotion control component. It is also concluded that studies on the CPG-based locomotion control should concentrate more on solving urgent problems like parameter tuning, environmental adaptability, and locomotion rehabilitation-oriented applications.

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