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A Bionic Control Method for Human–Exoskeleton Coupling Based on CPG Model

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Abstract: Exoskeleton robots are functioning in contexts with more complicated motion control needs as a result of the technology and applications for these robots rapidly developing. This calls for novel control techniques to accommodate their employment in a range of real-world settings. This paper proposes a bionic control method for a human–exoskeleton coupling dynamic model based on the CPG model, utilizing a model on the dynamics of the human–exoskeleton interaction. The CPG network is established as an oscillator by two neurons inhibiting one another, which approximates the torques simulated in the inverse dynamic analysis as the input to the exoskeleton robot. The findings of the simulation assessment suggest that the bionic control strategy may improve the robot’s ability to move quickly and steadily, as well as better adapt to challenging environments.

Keywords: exoskeleton; CPG; bionic control



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1. Introduction

An exoskeleton robot is a type of integrated human–machine equipment that supports the human body in accordance with user demands. It is utilized as an adjunct rehabilitation tool in the field of medical rehabilitation to carry out rehabilitation training for patients [1], as well as to lessen the stress on the human body [2] in the civil realm. As a wearable human mobility aid and function-augmentation equipment, exoskeleton robots have recently been a research hotspot due to their wide range of potential applications. Since the exoskeleton system is designed to reduce the unnecessary physical consumption of the human body during exercise, motion control is a key technology in the research and application fields of exoskeleton robots [3].

The traditional approach of motion control involves manual planning [4], which necessitates extensive online computation and measurement to make the robot move in accordance with the predetermined motion mode [5,6]. The controllers are typically viewed as external agents with the intention of moving in coordination with the human in robotic exoskeleton control systems [3]. For the exoskeleton robot system with multiple degrees of freedom, it is quite challenging to realize real-time multi-degree-of-freedom coordinated control in this conventional way [7]. The exoskeleton controller should ideally work in tandem with the human, according to embodiment principles, so that the nervous system can accurately simulate the input–output dynamics of the exoskeleton controller. Exoskeleton development and prototyping procedures should include measuring the embodiment of exoskeletons [8,9]. The working environment of the robot is becoming increasingly complicated, and motion control needs are escalating as a result of the exoskeleton robot technologies and applications quick growth. To address the needs of the robot in varied practical contexts, more succinct and organic motion control approaches are required [10,11]. It has been discovered via observation that creatures exhibit a wide variety of fixed periodic motions, including limb movements and physiological actions, known as rhythmic

movements. There is currently no robot that can match the steadiness and flexibility of this rhythmic movement. Therefore, applying the rhythmic movement control mechanism of animals to exoskeleton robots is a promising research direction [12].

The central pattern generator, which is located in the spinal cord, plays a crucial role in the striking similarities between biological locomotion gaits and the evolution of phase patterns in linked oscillatory networks [13]. It is generally believed by biologists that the rhythmic movement of animals is a self-excited behavior of the lower nervous center, which is controlled by CPG located in the spinal cord of vertebrates or the thoracoabdominal ganglion of invertebrates [14–17]. CPG is a distributed oscillatory network composed of intermediate neurons, which realizes self-excited oscillations through mutual inhibition between neurons, generates multi-channel or single-channel periodic signals with stable phase locking, and controls the rhythmic movement of limbs or related body parts [18,19]. The synaptic connections between neurons in the CPG are plastic and can produce different output modes, allowing animals to exhibit a variety of rhythmic motor behaviors. The activity of the CPG can be triggered by the descending signal from the brainstem mesencephalic locomotor region (MLR) to produce a stable rhythmic output. The continuous oscillation of the CPG does not depend on the commands of the high-level nerve center, nor on the peripheral sensory signal; however, the oscillation mode can be adjusted by the upper command and the peripheral feedback signal to make appropriate changes and adapt to the external environment [20].

CPG itself can produce stable rhythm signals. Through the coupling with the physical system of the mechanical body controlled by it, the rhythm is transmitted between the nervous system and the physical system, and a stable limit cycle can be formed in the state space. Different from the motion obtained by traditional one-cycle planning [21], the motion generated by CPG control is continuous. Moreover, the nonlinearity of CPG itself and the existence of a state limit cycle make the system have a certain anti-interference ability and can enter stable operation from any random state. The CPG network produces self-organizing characteristics through the coupling connection between its internal functional units, which can homogenize errors and coordinate multiple degrees of freedom. This is fully reflected in the multi-joint limb movement coordinated by animals in nature [22].

Robot biological control is an engineering application technology based on biological control theory, which belongs to a research direction in the interdisciplinary field of biology, physiology, robotics, mathematics and so on. The biological control method is to use the entire biological nervous system model as a mapping approach, and the core is the introduction of the CPG neural circuit model. The biological control of the robot is to realize the rhythmic motion with environmental adaptability as the control target. Through the mathematical modeling or engineering simulation of some biological models or control mechanisms, such as biological CPG, high-level control center, reflection mechanism, etc., and simplification and improvement, as the control model of the robot, it is applied to the motion control of the robot to improve the motion performance and practicability of the robot [23].

The 1980s saw the emergence of the CPG-centered strategy for the biological control of robots in the USA and Japan. Numerous academic institutions and research centers have recently carried out in-depth investigations on theoretical methods for the biological control of robots. For example, a CPG-based gait theory for multipedal robots and a biological control technique for quadrupedal robots was presented [11]. A novel biological control approach on how to fully utilize the properties of the CPG mechanism to improve the environmental adaptability in the walking control of a bipedal robot was described in [12]. In addition, many attempts to use dynamically coupled systems to create CPGs for humanoid robots [24] and lower-limb exoskeleton control [25] have been made. However, none of them incorporate particular robot mathematical dynamic modeling techniques with control methods. They also did not evaluate control approaches using human–robot coupling moments as a reference.

As discussed above, the wearable lower limb exoskeleton robot is taken as the research object, the influence of the wearer on the exoskeleton is taken into account, and the human–exoskeleton interaction force is modeled by linear damped springs to establish the dynamic model of the coupling of the human body and the exoskeleton in this paper. Based on the human–exoskeleton coupling dynamic model, the CPG model is constructed as a signal generator that can generate stable rhythm output, which is used as the motion controller of each degree of freedom of the robot. Then, a CPG network composed of multiple oscillators is established to realize that changing the topology of the network can change the output mode of the coupled oscillation signal. By introducing the feedback mechanism into the CPG model, the output of the rhythm signal is adjusted to make the exoskeleton robot adapt to the changes of the external environment and generate adaptive motion. The derived theoretical findings are then compared, demonstrating consistency in the tracking errors and coupling forces of the exoskeleton robot.

2. Materials and Methods

2.1. Human–Exoskeleton Coupling Dynamics Model

During the rehabilitation process, there is a complex physical coupling between the patient and the exoskeleton, and this behavior is concentrated in the human–exoskeleton interaction forces. The proper evaluation of patient recovery, comfort, and exoskeleton performance depends on a thorough investigation of the dynamics of human–exoskeleton interaction [10]. The interaction behavior between the patient and the exoskeleton cannot be accurately modeled by a straightforward kinetic model of the exoskeleton or human body. Therefore, it is essential to create a dynamic model that considers the behavior of the human–exoskeleton connection. It is then necessary to develop a dynamic model that takes into account the coupled human–exoskeleton behavior.

In order to simplify the issue, several assumptions are made. Since the sagittal plane accounts for the majority of typical human motion, only that motion is preserved. The geometric lengths of the human and exoskeletal lower limbs are considered to be the same. These presumptions lead to a simplification of the swing models of the exoskeleton and the human lower limb to a planar system made up of two homogenous connecting rods [26].

In Figure 1, a wearer’s thigh and shank are attached to a lower-limb exoskeleton with two actuated degrees of freedom (DoF). Where l_{i_1,i_2} , c_{i_1,i_2} , s_{i_1,i_2} , m_{i_1,i_2} and I_{i_1,i_2} ($i_1 \in \{h, r\}$ and $i_2 \in \{t, s\}$) are, respectively, the lengths, the position coordinates of the rods’ center of mass, the locations of human–exoskeleton linkage connection, the weights and the moments of inertia of human ($i_1 = h$), and exoskeleton robot’s ($i_1 = r$) thigh ($i_2 = t$) and shank links ($i_2 = s$). θ_{i_1,i_3} ($i_1 \in \{h, r\}$ and $i_3 \in \{h, k\}$) are the angles of the human ($i_1 = h$) and exoskeleton ($i_1 = r$) hip joints ($i_3 = h$) and knee joints ($i_3 = k$), which with respect to the direction of gravity (i.e., vertical) in the former, the later with respect to the thigh links, and the positive direction of the angles are set to be counterclockwise. Additionally, based on the presumptions before, we also have

$$s_{h,t} = s_{r,t}, \quad l_{h,t} + s_{h,s} = l_{r,t} + s_{r,s} \quad (1)$$

This schematic illustration shows how the human–exoskeleton coupling swing dynamics in sagittal plane work. An equation for the position coordinates of the human–exoskeleton linkage connection may be written using this double-joint coupling model. The coupling position in task space has coordinates $\mathbf{p}_{i_1,t}$ at the thigh and $\mathbf{p}_{i_1,s}$ at the shank of human ($i_1 = h$) and exoskeleton robot ($i_1 = r$)

$$\begin{aligned} \mathbf{p}_{i_1,t} &= \begin{pmatrix} s_{i_1,t} \sin(\theta_{i_1,h}) \\ -s_{i_1,t} \cos(\theta_{i_1,h}) \end{pmatrix} \\ \mathbf{p}_{i_1,s} &= \begin{pmatrix} l_{i_1,t} \sin(\theta_{i_1,h}) + s_{i_1,s} \sin(\theta_{i_1,h} + \theta_{i_1,k}) \\ -l_{i_1,t} \cos(\theta_{i_1,h}) - s_{i_1,s} \cos(\theta_{i_1,h} + \theta_{i_1,k}) \end{pmatrix} \end{aligned} \quad (2)$$

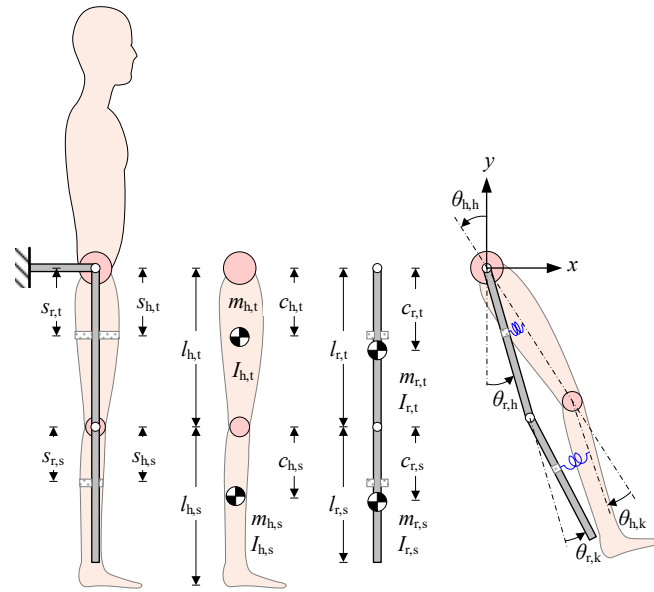


Figure 1. Schematic of the 2-DoF exoskeleton supporting the swinging motion of the human lower limb.

For the coupling position, the wearer's tissue, such as skin, fat, and muscle, is particularly soft in comparison to the stiff exoskeleton and human skeleton. By choosing the inertia necessary for the lower limb's inherent inertia in the current state, the control goal, i.e., the interaction force between the wearer and exoskeleton F_{i_2} at the thigh ($i_2 = t$) and the shank ($i_2 = s$), is calculated without the need for force feedback in the control loop [27]. Therefore, in accordance with the above rationale, the connection between the human limb body and the exoskeleton is equated in this paper to the linear damped spring model as

$$\mathbf{F}_{i_2} = -k_{i_2} \Delta \mathbf{p}_{i_2} - b_{i_2} \Delta \dot{\mathbf{p}}_{i_2} \quad (3)$$

where k_{i_2} and b_{i_2} denotes the stiffness coefficient (or elasticity coefficient) and the damping coefficient between the human and the robot, $\Delta \mathbf{p}_{i_2}$ and $\Delta \dot{\mathbf{p}}_{i_2}$ is the displacement difference between the human and the robot coupling and the derivatives with respect to the time of it, respectively.

By deriving the coupling positions for $\theta_{i_1,h}$ and $\theta_{i_1,k}$, respectively, the conversion from task space to joint space can be achieved, from which the Jacobians matrix of the coupled position coordinates of the linkage in human ($i_1 = h$) and exoskeleton robot's ($i_1 = r$) thigh and shank is derived as follows

$$\begin{aligned} \mathbf{J}_{i_1,t} &= \begin{pmatrix} s_{i_1,t} \cos(\theta_{i_1,h}) & 0 \\ s_{i_1,t} \sin(\theta_{i_1,h}) & 0 \end{pmatrix} \\ \mathbf{J}_{i_1,s} &= \begin{pmatrix} l_{i_1,t} \cos(\theta_{i_1,h}) + s_{i_1,s} \cos(\theta_{i_1,h} + \theta_{i_1,k}) & s_{i_1,s} \cos(\theta_{i_1,h} + \theta_{i_1,k}) \\ l_{i_1,t} \sin(\theta_{i_1,h}) + s_{i_1,s} \sin(\theta_{i_1,h} + \theta_{i_1,k}) & s_{i_1,s} \sin(\theta_{i_1,h} + \theta_{i_1,k}) \end{pmatrix} \end{aligned} \quad (4)$$

Using the Jacobians, the coupling forces that are applied to the joints of human ($i_1 = h$) and exoskeleton ($i_1 = r$) during interactive torques $\tau_{i_1}^i$ may be mapped onto joint space

$$\begin{aligned} \tau_h^i &= \begin{pmatrix} \tau_{h,h}^i \\ \tau_{h,k}^i \end{pmatrix} = \mathbf{J}_{h,t}^T \mathbf{F}_t + \mathbf{J}_{h,s}^T \mathbf{F}_s \\ \tau_r^i &= \begin{pmatrix} \tau_{r,h}^i \\ \tau_{r,k}^i \end{pmatrix} = -\mathbf{J}_{r,t}^T \mathbf{F}_t - \mathbf{J}_{r,s}^T \mathbf{F}_s \end{aligned} \quad (5)$$

The exoskeleton and the lower limb of a human may be simulated using the same dynamics. The dynamics model of human–exoskeleton can be represented with the external torques by the following equation, which uses Lagrange’s equation

$$\begin{cases} \mathbf{M}_h(\theta_h)\ddot{\theta}_h + \mathbf{C}_h(\theta_h, \dot{\theta}_h)\dot{\theta}_h + \mathbf{G}_h(\theta_h) = \tau_h \\ \mathbf{M}_r(\theta_r)\ddot{\theta}_r + \mathbf{C}_r(\theta_r, \dot{\theta}_r)\dot{\theta}_r + \mathbf{G}_r(\theta_r) = \tau_r \end{cases} \quad (6)$$

For human ($i_1 = h$) and exoskeleton robot ($i_1 = r$), $\mathbf{M}_{i_1}$ is the symmetric positive definite inertia matrix, $\mathbf{C}_{i_1}$ is taken into account as the centripetal and Coriolis matrix, $\mathbf{G}_{i_1}$ is the gravity matrix, and τ_{i_1} is the total joint torque. The exact shape of each matrix in the human–exoskeleton coupling model may be stated in this instance by concentrating the joint masses on the position of the connecting rod’s center of mass

$$\begin{aligned} \mathbf{M}_{i_1}(\theta_{i_1}) &= \begin{pmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{pmatrix} \\ \mathbf{C}_{i_1}(\theta_{i_1}, \dot{\theta}_{i_1}) &= m_{i_1,s}l_{i_1,t}c_{i_1,s}\sin(\theta_{i_1,k}) \begin{pmatrix} -\dot{\theta}_{i_1,k} & -\dot{\theta}_{i_1,k} - \dot{\theta}_{i_1,h} \\ \dot{\theta}_{i_1,h} & 0 \end{pmatrix} \\ \mathbf{G}_{i_1}(\theta_{i_1}) &= g \begin{pmatrix} m_{i_1,t}c_{i_1,t}\sin(\theta_{i_1,h}) + m_{i_1,s}l_{i_1,t}\sin(\theta_{i_1,h}) + m_{i_1,s}c_{i_1,s}\sin(\theta_{i_1,h} + \theta_{i_1,k}) \\ m_{i_1,s}c_{i_1,s}\sin(\theta_{i_1,h} + \theta_{i_1,k}) \end{pmatrix} \end{aligned} \quad (7)$$

where gravitational acceleration $g = 9.8 \text{ m/s}^2$, and each exact element of $M_{i_1}(\theta_{i_1})$ is

$$\begin{aligned} M_{11} &= I_{i_1,t} + m_{i_1,t}c_{i_1,t}^2 + m_{i_1,s}l_{i_1,t}^2 + 2m_{i_1,s}l_{i_1,t}c_{i_1,s}\cos(\theta_{i_1,k}) + I_{i_1,s} + m_{i_1,s}c_{i_1,s}^2, \\ M_{12} &= M_{21} = m_{i_1,s}l_{i_1,t}c_{i_1,s}\cos(\theta_{i_1,k}) + I_{i_1,s} + m_{i_1,s}c_{i_1,s}^2, \\ M_{22} &= I_{i_1,s} + m_{i_1,s}c_{i_1,s}^2. \end{aligned} \quad (8)$$

For human joints, the total torque is made up of the following active and interacting components

$$\tau_h = \begin{pmatrix} \tau_{h,h} \\ \tau_{h,k} \end{pmatrix} = \tau_h^a + \tau_h^i \quad (9)$$

where τ_{h,i_3} is the joints torque at the human hip ($i_3 = h$) and knee joint ($i_3 = k$), τ_h^i is the vector of interactive torque given in Equation (5), τ_h^a is the vector of active torque produced by muscular contraction. An individual without human–exoskeleton contact ought to optimally offer the following active joint torques from inverse dynamics analysis (IDA) for recording the ideal reference joint trajectory θ_d

$$\tau_h^a = \tau_h^{\text{ida}} = \begin{pmatrix} \tau_{h,h}^{\text{ida}} \\ \tau_{h,k}^{\text{ida}} \end{pmatrix} = \mathbf{M}_h(\theta_d)\ddot{\theta}_d + \mathbf{C}_h(\theta_d, \dot{\theta}_d)\dot{\theta}_d + \mathbf{G}_h(\theta_d) \quad (10)$$

where $\tau_{h,i_3}^{\text{ida}}$ is the active torques from IDA at the human hip ($i_3 = h$) and knee joint ($i_3 = k$).

For an exoskeleton robot, the total moment always contained the input moment (i.e., the control moment), the moment created during the interaction task with the environment (or human), and the frictional moment as follows

$$\tau_r = \tau_r^c + \tau_r^i + \tau_r^f \quad (11)$$

where τ_r^c is the control torque and τ_r^i is the interaction torque specified in Equation (5). The friction torque τ_r^f includes Coulomb dry friction and viscous friction, which can be written as

$$\tau_r^f = \begin{pmatrix} -\text{sgn}(\dot{\theta}_{r,h})k_{v,h} - k_{s,h}\dot{\theta}_{r,h} \\ -\text{sgn}(\dot{\theta}_{r,k})k_{v,k} - k_{s,k}\dot{\theta}_{r,k} \end{pmatrix}, \quad (12)$$

where $\text{sgn}(\cdot)$ is the sign function of $\cdot$, k_{v,i_3} and k_{s,i_3} is, respectively, the dry friction and the viscous friction coefficient at the robot's hip ($i_3 = h$) and knee ($i_3 = k$).

For the control moment delivered by the robot's servo motor, we expect a simple controller. Instead of the use of PID control, PD control will be adequate for the aforementioned system to meet our control needs and achieve steady state performance. Therefore, we choose a straightforward PD controller that can compensate for the robot's gravity, as follows

$$\tau_r^c = \mathbf{G}_r(\theta_r) + k_p \mathbf{e}_r + k_d \dot{\mathbf{e}}_r \quad (13)$$

where k_p and k_d is the parameters of the proportional element and differential element of the PD controller, and

$$\mathbf{e}_r = \begin{pmatrix} e_{r,h} \\ e_{r,k} \end{pmatrix} = \theta_d - \theta_r \quad (14)$$

is defined as the robot's tracking error, $\dot{\mathbf{e}}_r$ is its derivatives with respect to time.

2.2. CPG Model and Its Characteristics

The study of the anatomical makeup and neural regulatory mechanisms of the animal motor nervous system serves as the foundation for the biological control approach of the robot. The corresponding physical or mathematical model is developed by the simplification of the animals' brain structure and simulation of the control mechanism; then, it is implemented by the computer or electronic control system to accomplish robot motion control. According to biological research, the animal's motor control system is constructed in this paper as a complex network that includes the central nervous system, receptors, sensory organs, and skeletal-muscular executive system [28], as shown in Figure 2.

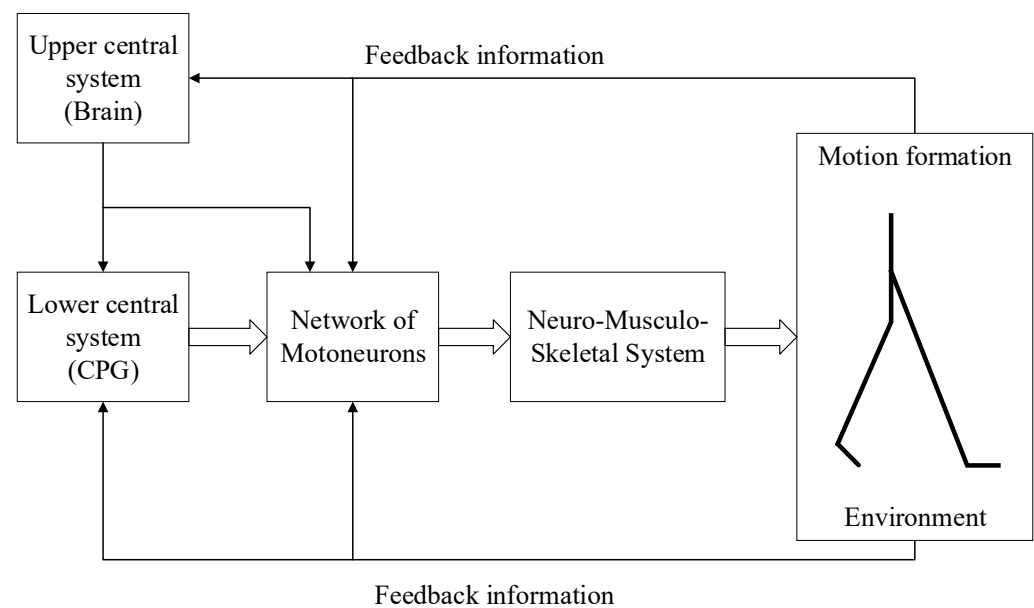


Figure 2. The basic network structure of animal walking control.

Based on the system block diagram, there is a broad consensus among biologists that the rhythmic movement of animals is caused by the lower nerve center's self-excited behavior, which is managed by the spinal cord's central pattern generator (CPG). A local network of intermediate neurons makes up the CPG, which may achieve self-excited oscillation, produce a stable phase interlock connection, and then activate the rhythmic movement of limbs. CPG plays the role of the basic control signal generator of the "muscle bone" system in motion generation. It creates adaptive control signals by fusing peripheral feedback data with high-level center control directives. Motion control signals generated by CPG activate motor neurons to control every muscle in the "muscle bone" system to

achieve real-time control of the limb. The motion control of a robot can be improved by applying the animal motion control concept based on the CPG mechanism.

In order to recreate the mechanism of animal rhythmic movement, an effective mathematical model of CPG is a necessity and a basis. The behavior of animal CPG has so far been simulated using VLSI hardware circuits, artificial neural networks (such as cellular neural networks, CNNs), and topological nonlinear oscillators. In this paper, an oscillator is created by two neurons inhibiting one another [29] as in Figure 3.

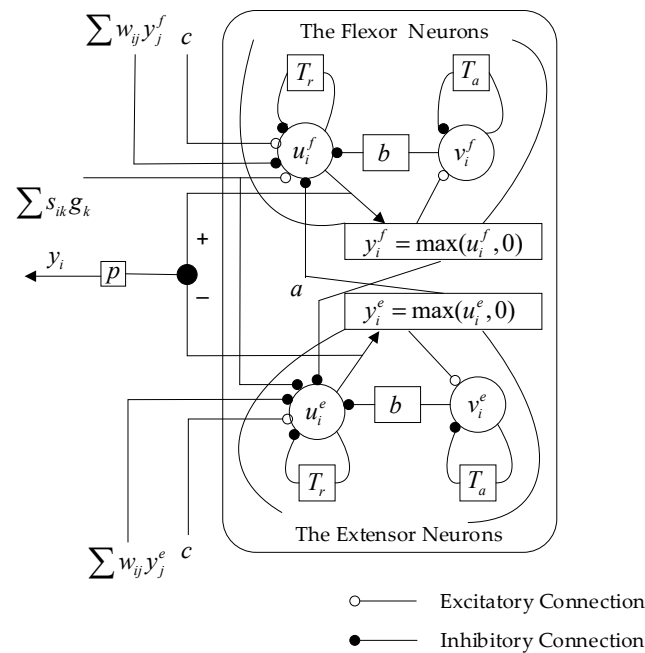


Figure 3. CPG model.

The CPG neural circuit is then thought of as a distributed system made up of a collection of mutually matched nonlinear oscillators. The two neurons represent, respectively, the flexor and extensor control neurons in animals. By altering the coupling connection between the neurons, sequence signals with various phase relationships can be produced to actualize various motion modes. The output of the oscillator is linearly synthesized by the state term of neurons, which can express the biological characteristics of CPG well [22].

$$\begin{cases} T_r \dot{u}_i^f + u_i^f = b v_i^f + a y_i^e + \sum_{j=1}^n w_{ij} y_j^f + \sum_{k=1}^m s_{ik} g_k + c, \\ T_a \dot{v}_i^f + v_i^f = y_i^f, \\ T_r \dot{u}_i^e + u_i^e = b v_i^e + a y_i^f + \sum_{j=1}^n w_{ij} y_j^e - \sum_{k=1}^m s_{ik} g_k + c, \\ T_a \dot{v}_i^e + v_i^e = y_i^e, \\ w_{ij} = \begin{cases} \pm 1, & (i \neq j), \\ 0, & (i = j), \end{cases} \\ y_i^{f,e} = \max(u_i^{f,e}, 0), \\ y_i = p(u_i^f - u_i^e), \\ (i, j = 1, 2, \dots, n; k = 1, 2, \dots, m), (\bullet = d/dt). \end{cases} \quad (15)$$

In the equation, i, f, e stand in for the oscillator, flexor, and extensor neurons, respectively. n stands for the number of oscillators and m stands for the quantity of feedback terms. The left side of the formula represents the cell state term, where u_i represents the internal state of the neuron. The first term on the right side is the intracellular fatigue term, v_i indicates the level of neuronal exhaustion (self-inhibition), and b is the fatigue coefficient,

which shows the extent to which the fatigue term has an impact on the internal state of cells; the second term is the coefficient of reciprocal inhibition between cells, a is often known as the coupling term; the third term is the coupling term between oscillators, where w_{ij} stands for the connection weight between oscillators i to j and $y_i^{f,e}$ denotes the output of neurons; the fourth term is the CPG control network's external feedback term, where s_{ik} stands for the reflection information which represents the k -th feedback input from the oscillator i , and g_k is the coefficient of reflection; the fifth component c is the continuous excitation input from the upper level; T_r is the rise time constant, which represents the rise time under step input; T_a represents the fatigue time constant, which is the lag time of the fatigue effect; y_i , the output of the i -th oscillator, is synthesized from the states of the flexor and extensor neurons, which may be utilized as position or torque control signals for robot joints; p is the limiting coefficient used to alter the oscillator output to make it equal to the DC input c .

The differential equations mentioned above are represented by the matrix form as follows

$$\begin{cases} T_r \dot{\mathbf{U}}^{f,e} + \mathbf{U}^{f,e} = b\mathbf{V}^{f,e} + a\mathbf{Y}^{f,e} + \mathbf{W} \cdot \mathbf{Y}^{f,e} + \mathbf{S} \cdot \mathbf{G}^{f,e} + c\mathbf{E} \\ T_a \dot{\mathbf{V}}^{f,e} + \mathbf{V}^{f,e} = \mathbf{Y}^{f,e} \\ y_i^{f,e} = \max(u_i^{f,e}, 0) \\ \mathbf{Y} = p(\mathbf{U}^f - \mathbf{U}^e) \\ \mathbf{U}^{f,e}, \mathbf{V}^{f,e}, \mathbf{Y}^{f,e}, \mathbf{Y} \in R^n, \mathbf{W} \in R^{n \times n}, \mathbf{S} \in R^{n \times m}, \mathbf{G} \in R^m \\ \mathbf{E} = \underbrace{[1, 1, \dots, 1]^T}_n, i = 1, 2, \dots, n \end{cases} \quad (16)$$

The terms $\mathbf{S} \cdot \mathbf{G}$ and the parameters $\mathbf{W}(w_{ij})$ are quite important. $\mathbf{W} = \begin{pmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{pmatrix}$

stands for the connection weight matrix of the CPG network, which establishes the CPG model's output mode and directs the robot to move in various ways. The CPG model's feedback term, $\mathbf{S} \cdot \mathbf{G}$, regulates how the CPG model interacts with the outside world to produce biological reflex function. The reflection information matrix $\mathbf{S}(s_{jk})$ and the reflection coefficient vector $\mathbf{G}$ make up the feedback term. Rows in the reflected information

matrix, $\mathbf{S} = \begin{pmatrix} s_{11} & \cdots & s_{1m} \\ \vdots & \ddots & \vdots \\ s_{n1} & \cdots & s_{nm} \end{pmatrix}$, stand in for each leg, and columns for each input signal

from feedback. Each leg of the n -legged robot receive m feedback data, which is combined to generate the $n \times m$ order reflection information matrix. The gain from incorporating the matching reflection data into the CPG model is represented by each element of the reflection coefficient vector $\mathbf{G} = [g_1 \cdots g_m]^T$. A regular expression and unambiguous implementation strategy may be obtained by using the reflection information matrix and reflection coefficient vector for the CPG model's feedback terms.

The output of CPG exhibits a wide range of events, including divergence, sluggish start and stop, high-order resonance phase-locking and oscillations of identical amplitude. These phenomena are obtained from the significant nonlinearity, output coupling, parameter coupling, and starting value dependency of the CPG differential equations, which are complex dynamic properties. The CPG equation can, however, provide a stable limit cycle for a given set of parameters, causing the system to generate steady oscillation output. The CPG model is capable of transmitting the external signal's mode and producing the appropriate output in response to it. These are the basis of engineering applications.

Aspects such as amplitude, period, phase, waveform, and others can be used to define periodic signals. The CPG equation's parameters may be categorized into four groups based on their primary uses: the amplitude influence parameter c , period influence parameter T_r , T_a , waveform influence parameter a , and phase influence parameter $\mathbf{W}$. The effect of

CPG equation parameters on output and the coupling relationship between parameters are depicted in Table 1 and Figure 4, respectively. The succinct summary of the effect on output can be written as follows

$$\begin{cases} A = f(c, b, a, T_a, \mathbf{W}) \\ T = f(T_r, T_a, a, b, \mathbf{W}) \end{cases} \quad (17)$$

In other words, the output amplitude A is dependent on five factors, c , a , b , T_a , $\mathbf{W}$, namely c , and the oscillation duration T is dependent on five parameters, T_r , T_a , a , b , $\mathbf{W}$, primarily T_r . The corresponding CPG signal can be produced by determining the aforementioned parameters.

In addition, the phase of the CPG-generated signal needs to be selected. In this paper, the phase of the CPG signal is ascertained using an optimization approach, the genetic algorithm. This is due to the great degree of optimization capabilities and adaptive optimization technique of the genetic algorithm. In this paper, an improved genetic algorithm is used [12], which is mainly developed by improving and optimizing the basic genetic algorithm. This algorithm primarily increases search efficiency and optimizes results by revising crossover and genetic methods that are better suited for CPG signals.

Table 1. CPG model parameter-coupling relationship.

	T_r	T_a	a	b	c	$\mathbf{W}$
T_r	T	bounded T_a/T_r	value ranges	value ranges	—	—
T_a	bounded T_a/T_r	T, A	value ranges	value ranges	slope of $c-A$	—
a	slope of $(T_a, T_r)-T$	slope of $(T_a, T_r)-T$	T, A waveform	—	slope of $c-A$	phase sequence
b	slope of $(T_a, T_r)-T$	slope of $(T_a, T_r)-T$	—	T, A	slope of $c-A$	phase sequence
c	—	—	—	—	A	—
$\mathbf{W}$	value ranges	value ranges	value ranges	value ranges	slope of $c-A$	T, A gait

— represents no influence or weak influence, T is the impact duration and A is the impact amplitude.

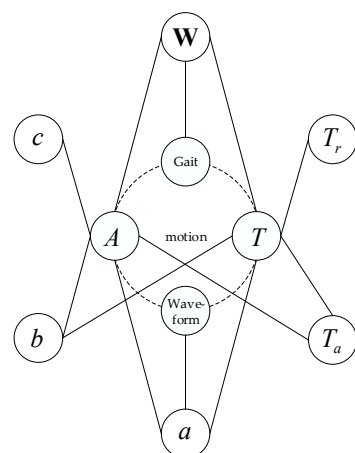


Figure 4. Parameter relationship of CPG model.

3. Experimental Validation

In order to validate the model put forth above, we constructed an experimental lower-limb exoskeleton with two degrees of freedom (DoF) and its hip fixed to a rigid frame.

As seen in Figure 5, the primary construction was built of steel, and two servo motors (GDM1- 100N2/120N2) were used to move the hip and knee joints. The robot's joint angles are monitored by two absolute encoders, the INC-4-150 and INC-3-125, while the forces that interact with the human exoskeleton are measured by four 3D force sensors (JNSH-2-10kg-BSQ-12). The sampling frequency of the platform is 100 Hz.

In this section, a 55 kg/1.7 m healthy adult female served as the data-acquisition experiment's subject. The subject was standing during the trial, enabling the entire leg to swing and the knee to be in a natural posture. The support leg was raised by putting a plate beneath the wearer's foot in order to prevent contact between the swing leg and the ground. Only when the subject could maintain the stability of her support leg were data obtained. Once the subject began to feel fatigued or when data clearly indicated non-periodicity, she was urged to take a break. The human body swing data set was then established by gathering the real-time angle, angular velocity, and angular acceleration information of the subject's lower limb joints during single leg swings.

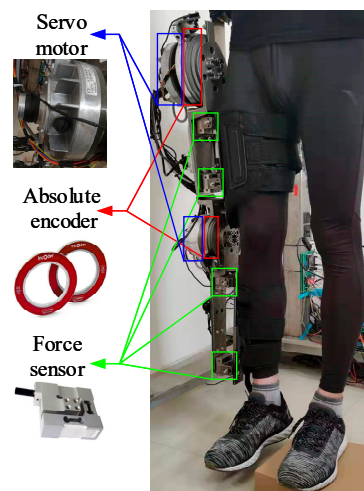


Figure 5. The exoskeleton platform.

The parameters of the exoskeleton and human limb are estimated based on the two-joint dynamic model of the exoskeleton robot and human lower limb coupling in Figure 1. The unknown parameters matrices provided in Equation (7), which can be written as non-linear groups, and the frictional force coefficients listed in Equation (12), are identified using the offline least squares optimization method. Notably, this identification can only retrieve the values of the parameter as groups in Tables 2 and 3. For the model-based dynamics design, Neighborhood Field Optimization (NFO) is suggested as a way for parameter identification, and more details are given in [30].

Table 2. Parameters of exoskeleton.

Parameter Groups	Values [Unit]
$m_{r,t}c_{r,t}^2 + I_{r,t} + m_{r,s}l_{r,t}^2 + m_{r,s}c_{r,s}^2 + I_{r,s}$	5.00175 [kg m ²]
$m_{r,s}c_{r,s}^2 + I_{r,s}$	2.0653 [kg m ²]
$m_{r,s}c_{r,s}$	0.52645 [kg m]
$m_{r,t}c_{r,t} + m_{r,s}l_{r,t}$	2.3319 [kg m]
$k_{v,h}$	31.38 [N m]
$k_{v,k}$	43.67 [N m]
$k_{s,h}$	15.55 [N m s ⁻¹]
$k_{s,k}$	27.51 [N m s ⁻¹]

Table 3. Parameters of human body.

Parameter Groups	Values [Unit]
$m_{h,t}c_{h,t}^2 + I_{h,t} + m_{h,s}l_{h,t}^2 + m_{h,s}c_{h,s}^2 + I_{h,s}$	5.29985 [kg m ²]
$m_{h,s}c_{h,s}^2 + I_{h,s}$	0.9504 [kg m ²]
$m_{h,s}c_{h,s}$	1.73995 [kg m]
$m_{h,t}c_{h,t} + m_{h,s}l_{h,t}$	3.2035 [kg m]

4. Results

4.1. The Performance of CPG Controller

In the first step, the performance of the CPG model is tested. For the design of the CPG network, several steps are considered as follows: Firstly, for the unit model, the CPG model is constructed as Equation (15). When it comes to the coupling technique of the CPG units, or the design of the network architecture, the connection weight matrix is made to be equal to one another in accordance with the inhibition relation regarding the swing motion examined in this study. The relatively independent parameters indicated in Table 1 and their impact on the output form the basis of the mathematical connection between parameters and output. According to the relationship, the prime parameter can be determined. The mathematical explanation of CPG above is provided in Table 4.

Table 4. Parameters of CPG models.

Parameters	Values
T_a/T_r	10
a	−1
b	−2
c	0.23
$\mathbf{W}$	$\begin{bmatrix} 0 & -1 \\ -1 & 0 \end{bmatrix}$

In this instance, CPG generated the two joint torques with inverse dynamic analysis. The basic parameters of the CPG model were derived from Table 4. The torques of the hip joint and knee joint in a swing routine for both the CPG control model and the subject are illustrated in Figure 6. It can be seen that the moment information predicted by CPG fits the joint torques calculated by the inverse dynamic analysis accurately.

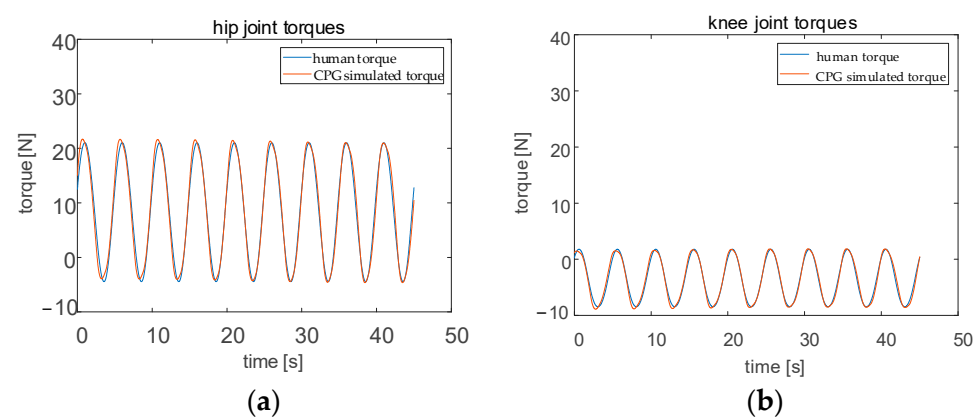


Figure 6. The joint torques of two joints generated from CPG controller and the subject: (a) Hip joint; (b) knee joint.

4.2. Tracking Error

The ranges of human joint flexion and extension are constrained. For instance, the hip can bend at a maximum angle of 90° with the knee extended and at a maximum angle of 10° . To ensure the wearer's safety, the desired trajectory, θ_d , should be constrained [26]. In this section, a straightforward sinusoidal trajectory that indicates the desired trajectory was used as follows

$$\theta_d = \begin{pmatrix} 25^\circ + 21^\circ \sin(\omega t) \\ -43^\circ + 21^\circ \cos(\omega t) \end{pmatrix} \quad (18)$$

where the swing frequency is $\omega = 0.4\pi$.

In this section, the impact of the proportional gain of the PD controller, set previously on the control effect, is discussed using the control variable technique. Through simulation, we determine the ideal differential gain value. For $k_d = 100$, Figure 7 compares the joint angles in the swing period acquired from simulation with the required trajectories. As comparing Figure 7a–c, further improving the tracking accuracy in both hip and knee joints is raising the proportional gain, k_p , from 300 to 3000. We give here only the results for $k_p = 300$ and $k_p = 3000$. The exoskeleton may overcome friction for higher tracking accuracy by injecting human force.

The tracking errors for both the human and the robot in each swing period are gathered and presented in Figure 8. To provide a clearer overview of the accuracy, the root mean squared tracking errors in every swing period are collected and plotted in Figure 9 as functions of the proportional gain. According to the simulation results in Figure 9, raising the proportional gain can reduce error, but its effectiveness becomes less significant as the gain is increased.

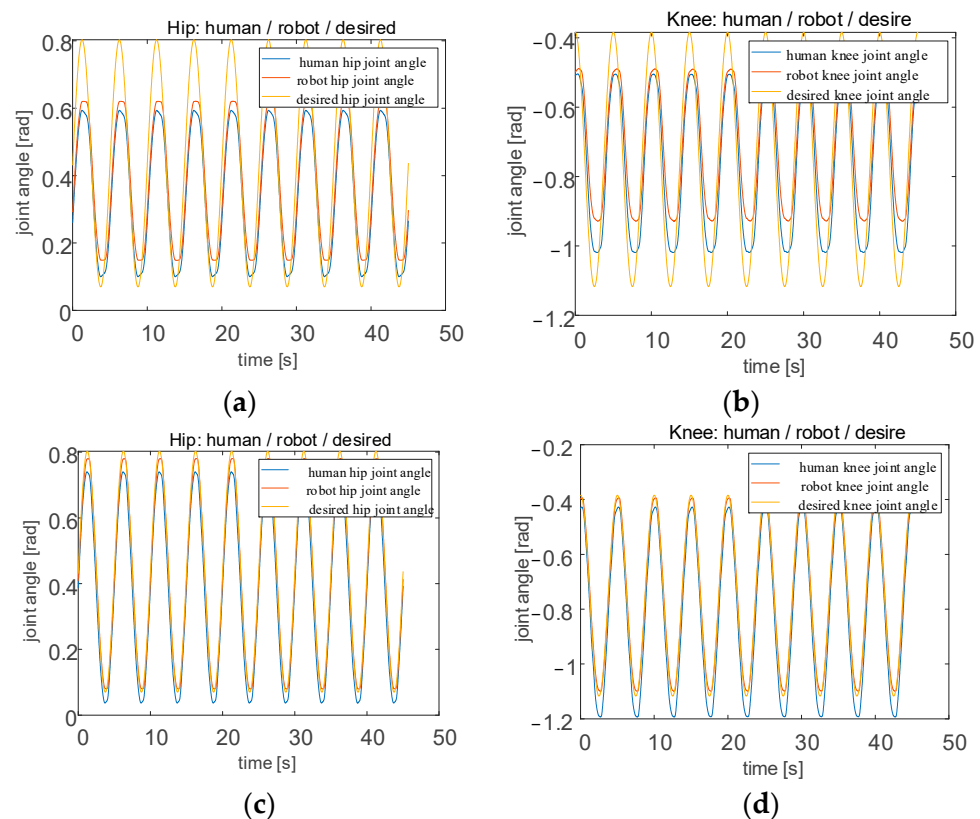


Figure 7. Exoskeleton's desired trajectories (yellow line), simulation results including human trajectories (blue line) and exoskeleton robot's trajectories (orange line): (a) hip and (b) knee angles for $k_p = 300$, and (c) hip and (d) knee angles for $k_p = 3000$.

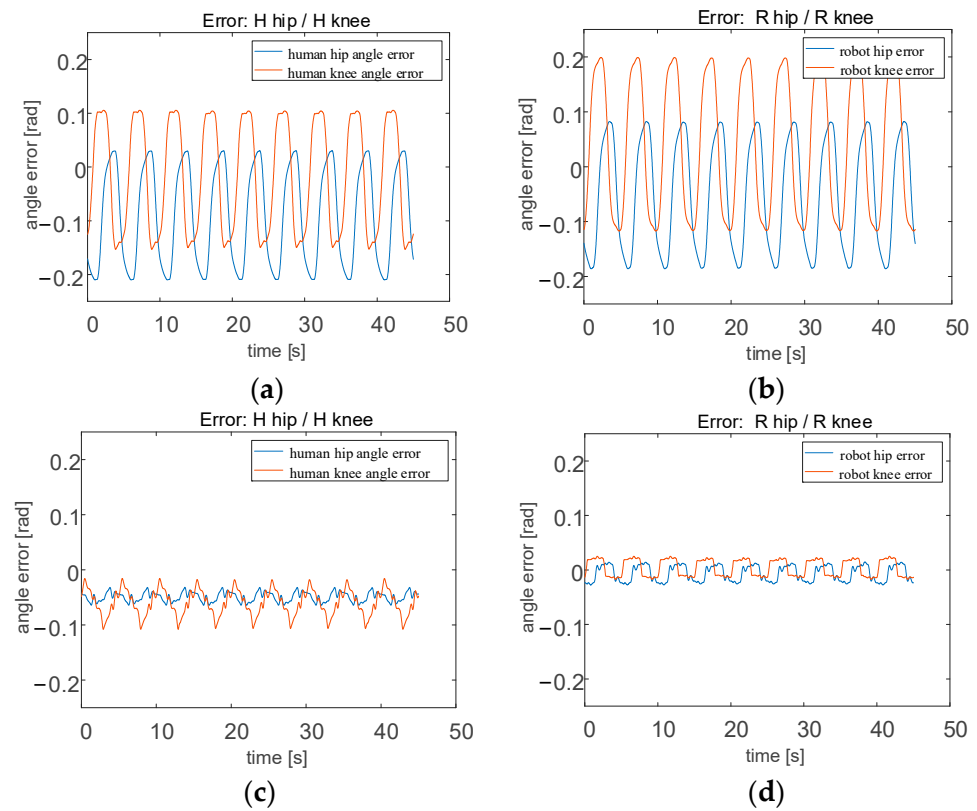


Figure 8. Tracking errors in human body (blue line) and the exoskeleton robot (orange line): (a) hip and (b) knee for $k_p = 300$, and (c) hip and (d) knee for $k_p = 3000$.

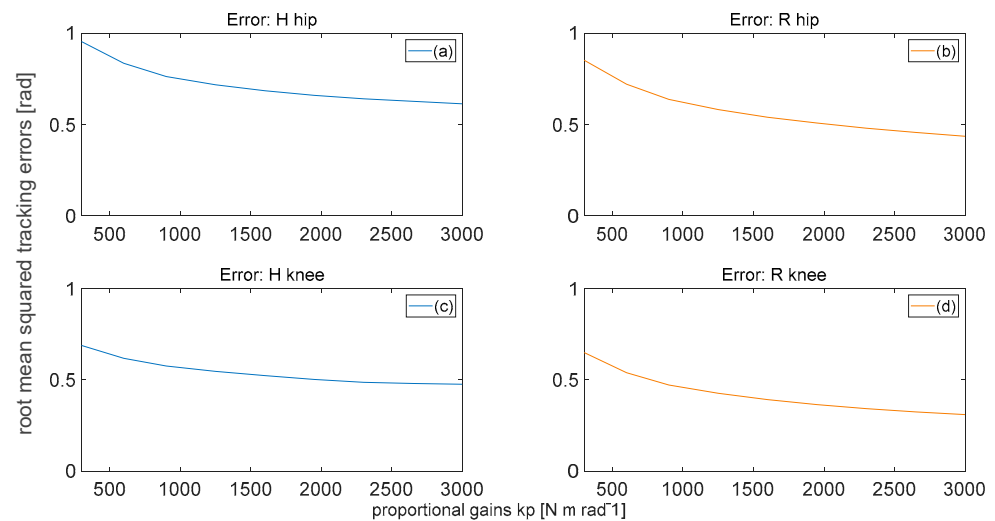


Figure 9. Root mean squared tracking errors in human body (blue line) and the exoskeleton robot (orange line) about proportional gains: (a) hip and (c) knee in human body, and (b) hip and (d) knee in robot.

4.3. Coupling Force

Plotted in Figure 10 are the magnitudes of the coupling forces that correspond to the movements in Figure 7. As seen in Figure 10, the coupling forces oscillate around a comparable level of magnitude when k_p climbs and the fluctuation amplitude is noticeably bigger.

Figure 10a,b provide the coupling forces both at the thigh and the shank, $|\mathbf{F}_t|, |\mathbf{F}_s|$, for $k_p = 300$ and 3000. In particular, when k_p increases, the coupling force at the thigh increases along with the oscillation amplitude, which results in a reduction in $|\mathbf{F}_t|$ from around 30 N

for $k_p = 300$ to 35–40 N for $k_p = 3000$; the coupling force at the shank has an insignificant change in magnitude but an increase in oscillation amplitude.

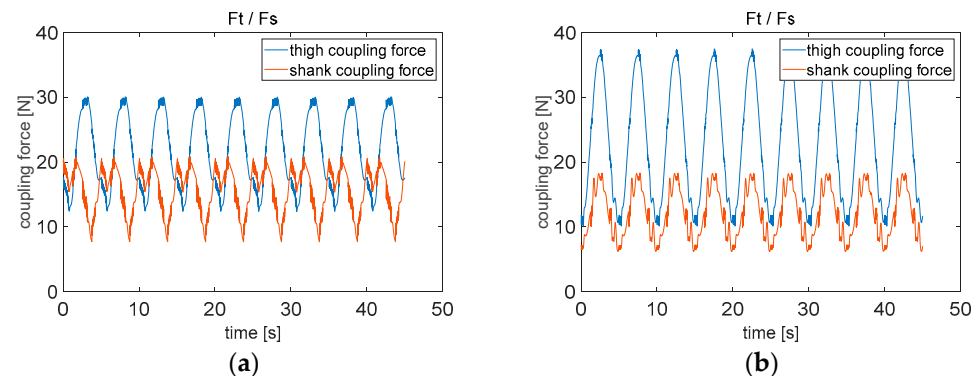


Figure 10. Magnitude of human–exoskeleton coupling forces at thigh (blue line) and shank (orange line) for: (a) $k_p = 300$, and (b) $k_p = 3000$.

5. Conclusions

This study, utilizing a model of the dynamics of human–exoskeleton interaction, proposed a new control method for the human–exoskeleton coupling dynamic model, which is based on the CPG model. The output of the complete CPG network approximates the torques as the input to the exoskeleton robot, which is computed by inverse dynamic analysis in human motion, in the way of examining the coupling of the oscillators and modifying the system setting parameters.

The experimental evaluation results show that the biological control approach may enhance the robot’s motion performance, create quick and steady motion, and have a better capacity to adapt to complicated settings. A considerable improvement in tracking accuracy is also found as the proportional gain rose, but with coupling forces in the hip joint increasing.

Based on the self-excitation of the CPG network, CPG may be used as a motion control mechanism in open-loop or closed-loop adaptive control with feedback and high-level modulation. By modifying the network settings, CPG provides distributed control of various motion modes. The standard modeling–planning–control technological approach is distinct from the biological control technique for robots. It does away with the time-consuming and difficult dynamic modeling and moves past the incompatibility of single-cycle planning and continuous control.

However, the application of the existing bionic control system based on the CPG mechanism has several issues. One of these is the non-linear coupling between the mechanical system and the CPG network, where the dynamic properties of the mechanical system interact with the control system’s features. The second is that sinusoidal signals cannot adequately control joints for movements with high walking needs, such as exoskeleton robots. The CPG network’s ability to create precise control signals will be crucial in enabling the robot’s walking to be as flexible as possible. Therefore, this may be our future research.

Additionally, our dynamic model still has significant limits. Only a very basic PD control was used, which has little potential to increase tracking precision or reduce coupling force. The experimental exoskeleton’s hip is fixed to a hard frame, allowing researchers to focus solely on the swing action. In order to study the entire walking dynamics, we will attempt to present a high-dimensional model that is relevant for both the swing and stance phases.

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