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A Neuromechanical Control Model For Rhythmic and Discrete Movements Based on Central Pattern Generator (CPG)

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Abstract— Movement is one of the essential characteristics of living beings. Despite the diversity of animal species and the apparent differences, standard features exist between their movement systems that follow a particular pattern. The movements can mainly be divided into discrete and rhythmic categories controlled by the central nervous system. Scientists usually consider these two types of motion separately in the control system and use different methods and resources to produce and model them. Proposing a unified and comprehensive model for generating and controlling rhythmic and discrete movement with the same control system is more valuable, albeit challenging. The present study provides a single neuromechanical control model for producing and controlling rhythmic and discrete movements. This model consists of a neural oscillator, the central pattern generator (CPG), coupled with inhibitory and excitatory paths to drive the flexor and extensor muscles. The computational model of this study follows the Hodgkin-Huxley (HH) equations. The structure of the model, the factors involved in creating the motion, and the oscillation were analyzed in great detail. It was found that supraspinal input and motor neuron feedback, as the motor control parameters, play an essential role in the activity and directly impact the production and control of rhythmic and discrete movements. According to these parameters, a neuromechanical model that can create both rhythmic and discrete movement is presented. The model also addresses the switching mechanism between rhythmic and discrete states.

Keywords— Rhythmic and Discrete movements, CPG, control, neuromechanical model, supraspinal drive, motor neuron feedback, sensory feedback.

I. INTRODUCTION

In neuroscience, the distinction between discrete and rhythmic movements is often studied in the context of motor control and motor learning [1]. Discrete movements are typically made up of a series of distinct, separate actions, such as reaching for a pen or writing on paper. In contrast, rhythmic movement is characterized by a repeated pattern or cycle of movement, such as the rhythm of running [2]. The interplay between rhythmic and discrete movements allows for the smooth, coordinated execution of complex actions, such as playing a musical instrument [3]. In the field of motor control, a discrete movement is a movement that is typically characterized by a distinct beginning and end, and it is often made up of a series of individual steps or sub-movements. On the other hand, rhythmic movement is characterized by repetitive motion patterns, often with a regular rhythm or beat.

The type of movement in every creature that can move is based on environmental conditions and body structures [4]. Various species' movement systems have standard features that follow a specific pattern [5]. The nervous system receives and processes multi-state motor neuron information and produces commands to control movement [6]. These commands are transmitted from the motor neurons in the spinal cord to the muscles and moving limbs, and through the motor neuron feedback, they return to the spinal cord for processing and completing actions [7]. Also, at the spinal cord level, some control operations are performed on the motor system, such as reflexes and adjustment of motor neuron weight to regulate the period, phase, and amplitude of the movement patterns [3].

Studying the neural basis of discrete and rhythmic movements can be helpful for various purposes, such as developing new technologies or therapies for people with movement disorders or improving human-machine interaction in robotics and other fields. Both discrete and rhythmic movements are essential in the field of motor control, and they are used in a variety of different contexts. The differences between these two types of movements can be helpful for researchers studying human movement and people interested in developing new technologies or devices that involve movement. The neural circuits involved in controlling and coordinating movement are complex and involve multiple brain and spinal cord areas. Understanding how these circuits work can help shed light on how the brain controls movement and learns and adapts to new motor tasks. Discrete movements, for instance, are thought to be controlled by the primary motor cortex and the supplementary motor area. In contrast, rhythmic movements are generated by central pattern generators (CPGs) in the spinal cord and brainstem. By studying the neural mechanisms underlying these movements, researchers can deeply understand how the brain controls and adapts movements to new motor tasks.

A central pattern generator (CPG) is a neural circuit that generates rhythmic patterns of movement and rhythmic activities, such as breathing, walking, and swimming, which do not require sensory input with timing information [8, 9, 10]. CPG is an oscillating network of different neurons found in animals’ spinal cords and brainstem [11]; it coordinates the activity of multiple muscles to produce the desired movement pattern. CPG's input is an elementary signal, but its output is complex, orderly, and coordinated. This point has received considerable attention in neuroscience for modeling motion [12]. The CPG-based model was also used as the controller of a humanoid robot to generate various walking patterns [13, 14]. Rhythmic movements
generated by CPGs are often repetitive and stereotyped and can occur even without input from the brain. CPGs are found in many animals, including invertebrates and vertebrates, and are thought to have evolved to produce coordinated movement patterns for survival and reproduction.

Indeed, CPG is a nonlinear oscillator as its primary function. It can only produce rhythmic motion and oscillations and send the output to the limb through flexor and extensor paths [15]. In other words, CPG outputs are usually rhythmic and repetitive activities. In this study, we have extracted both rhythmic and discrete output from the CPG model inspired by the model proposed by Markin et al. [16].

As mentioned earlier, in the proposed model, CPG is located at the spinal cord level; it is symmetrical, meaning that the muscles' structure, the flexor, and the extensor are similar but in the opposite phase. This symmetry leads to the same changes in the stationary vertical phases [17]. We used dynamic systems analysis to discuss how this model works, what factors play an essential role in the generation of movement, how it can produce rhythmic and discrete movements, the role of motor neuron feedback, and whether motor neuron feedback is involved in the production of oscillation or not. Furthermore, if the primary supraspinal input at the surface of the brainstem is lost, can movement occur by amplifying other model components? We added the roles of the basal ganglia and cerebellum in producing movement and their impact on the supraspinal input to control movement. Finally, we implemented the effect of different control parameters in a proposed model to extract discrete and rhythmic movements.

II. RELATED WORKS

Previous studies have proposed different views about the motor neuron and rhythmic and discrete movements. One model claims that discrete movement is the fundamental and rhythmic movement is the concatenation of discrete movements [18, 19]. Another model states that rhythmic movement is the principal movement, and discrete movement is a truncated rhythmic movement [20, 21]. A third viewpoint mentions that rhythmic and discrete movements represent two different movement categories produced by the separate sections [22, 23, 12]. The third viewpoint is more acceptable based on research on the nervous system and motor behavior [24, 25].

In addition to these various theories and models, the motor control system requires precise modeling for further study. Also, there are different ways and structures for modeling the motor neuron system to produce different movements. Fig. 1 demonstrates a model that combines electrical and mechanical systems to model rhythmic and discrete movements. This model uses a Matsuoka oscillator for the electrical part and a pendulum for the mechanical section [26].

![Fig. 1. A model for generating rhythmic and discrete movement by the Matsuoka oscillator [26].](image)

At the beginning of the last century, scientists offered two interpretations for the production of rhythmic movements. One of these interpretations was suggested by Charles Sherrington, based on reflex loops [27, 28]. Sherrington believed that rhythmic movements result from the stimulation of reflex loops by motor neuron feedback, so motor neuron feedback plays the role of igniting and switching between the different phases that make up a movement cycle. Another expression was proposed by Thomas Graham Brown, which was based on the centrality of rhythms [29, 28]. Although this theory was challenged at its emergence, today, scientists believe that the CPG as biological neural circuits can produce rhythmic output in the absence of rhythmic input [30]. For example, stimulating a paralyzed fish (with spinal cord injuries) electrically or chemically will result
in movement patterns called artificial movements, which are very similar to healthy movement [31]. Mock movements have also been observed in salamanders and adult frogs [32].

CPG has been seen in several animals, and research has shown that the CPGs are broad networks consisting of several paired oscillating centers that produce rhythm [10, 11]. Although there is no need for motor neuron feedback in the production of rhythmic output, this feedback plays an essential role in shaping the rhythmic pattern [33, 34]. The role of motor neuron feedback is critical for the CPG and body movements to be in harmony with each other.

In many vertebrates, electrical stimulation induces an area of the brain called the mesencephalic locomotor region (MLR), which is responsible for movement behavior [35]. At lower stimulation levels, a lower frequency of movements can be produced; correspondingly, higher stimulation levels result in a higher frequency of activities [36]. These observations show that CPG can generate complex movements by receiving simple inputs and switching between multiple phases.

CPG models are used in a wide range of robots and biomedical modeling [37]. Zhang et al. [38] proposed a new approach for designing a new actuator based on the CPG. The activity of the soft actuator is similar to octopuses’ muscles with no solid skeletal support. The authors simulated the gentle actuator activities under different conditions and controlled movements by adjusting the parameters of the CPG.

Moreover, CPG was used in designing six-legged Octopus robots [36]. It was also used in various swimming and crawling robots, such as snake robots [39, 40]. Furthermore, the CPG has been modeled in different levels of abstraction, from partial biophysical models to high-level abstract models. Partial biophysical models are based on the Hodgkin-Huxley model [41]. This neural model calculates how ions move within neural channels, how they affect the neurons' voltages and currents, and how nerve oscillations occur inside small neural circuits. While a large body of research has focused on the activity of single neurons, another group focused on the dynamic properties of larger neural circuits. Also, rhythmic models use simple modeling of neurons, including the leaky receptor integral [42]. These models focus on how oscillating activity causes the properties of the neural network and how inter-neural connections synchronize different neural circuits.

III. DESCRIPTION OF THE MODEL

The primary model in this study is a simple neuro-mechanical model consisting of several layers, including rhythm-generator neurons (RG-F and RG-E), pattern-formation neurons (PF-F and PF-E), motor neurons (Mn-F and Mn-E), interneurons (In-F and In-E), inhibitory interneurons (Inab-E and Int), feedback neurons (Ia-F, IaE, II-F, and Ib-E) and two flexor and extensor contraction muscles that attach to the limb (F and E) (Fig. 2).

![Neuromechanical model and the relationship between its components](image-url)

Each neuron in this model represents a population of nerve cells that show the voltage difference between its membranes, represented by $V$, and the output of each neural population in the CPG layers denoted by $f(v)$, which follows the nonlinear transformation below, where $V = -30 \text{ mV}$, $k = 3 \text{ mV}$ for motor neuron, $k = 8 \text{ mV}$ for other neurons, and $Vth = -50 \text{ mV}$ [17].
The internal neurons (first-order differential equations below (1) express dynamic relationships for rhythm-generator, pattern-formation, and motor neurons.

\[ C \dot{v}_i = -I_{\text{Nap}}(v_i, h_i) - I_k(v_i) - I_{\text{leak}}(v_i) - I_{\text{synE}}(v_i) - I_{\text{synI}}(v_i) \quad (1) \]

\[ \dot{h}_i = \frac{h_0(v_i) - h_i}{\tau_h(v_i)} \]

The internal neurons (In-F, In-E, Int, and Inab-E) equation is described by

\[ C \dot{v}_i = -I_{\text{leak}}(v_i) - I_{\text{synE}}(v_i) - I_{\text{synI}}(v_i) \quad (2) \]

where \( v_i \) is the voltage difference between the membranes of the neuron \( i \), \( C \) is the membrane capacitance, \( I_{\text{Nap}} \) is constant sodium current, \( I_k \) is potassium current, \( I_{\text{leak}} \) is leakage current, \( I_{\text{synE}} \) is the excitation input of the synapses entering neuron \( i \), \( I_{\text{synI}} \) is the inhibitory input of the synapses entering neuron \( i \), which follow equations below.

\[ I_{\text{synE}} = \sum_j a_j f(v_j) + c_i d + \sum_k w_{ik} f(bk) \quad (3) \]

\[ I_{\text{Nap}}(v_i, h_i) = \tilde{g}_{\text{Nap}} m_{\text{Nap}} h_i (v_i - E_{\text{Na}}) \]

\[ I_k(v_i) = \tilde{g}_k m_k^4 (v_i - E_k) \], \( m_k = m_k(v_i) \)

\[ I_{\text{leak}}(v_i) = \tilde{g}_{\text{leak}} (v_i - E_{\text{leak}}) \]

\[ I_{\text{synI}} = \sum_j b_{ji} f(v_j) \]

\( d \) is the supraspinal drive input to CPG neurons, \( c_i \) is a factor scaling the drive \( d \) to neuron \( i \), \( a_{ji} \) is the weight of the excitatory input from neuron \( j \) to neuron \( i \), \( b_{ji} \) is the weight of the inhibitory input from neuron \( j \) to \( i \), \( f(bk) \) denotes the \( k \)th feedback signal and \( w_{ik} \) is the weight of that feedback \( (kth) \) to neuron \( i \). More details and other parameters are provided in [17] and [43].

**IV. Investigating the effect of different factors on movement**

The supraspinal input and motor neuron feedback from the muscles are two critical inputs for CPGs [44]. Supraspinal drive refers to the input from higher brain centers that can modify the activity of CPGs, allowing for the initiation, termination, or modulation of rhythmic activity patterns [45]. These signals can originate from various brain areas, such as the motor cortex or the basal ganglia, and can contain information about movements the brain wants the body to perform. Feedback from the muscles, also known as sensory feedback, occurs when sensory receptors in the muscles and tendons send information about the position and movement of the body back to the central nervous system [46]. This feedback is vital for maintaining balance and coordinating movement. It can also help to initiate movement, as the brain can use sensory information to determine the starting position of a movement and plan the appropriate motor commands to execute the desired movement. Both supraspinal drive and sensory feedback are essential for proper functioning CPGs and coordinating rhythmic activity patterns [47].

In addition, motor neuron feedback stimulates rhythm-producing and pattern-generating neurons, which result in increased oscillations. When rhythm-producing neurons are active in the path of the extensor muscles, rhythm-producing neurons in the direction of the flexor muscles are silent because, as mentioned before, this model is symmetrical. This fact also works for other neural layers. Fig. 3 shows an example of rhythm-producing and motor neurons' activity. As shown in this diagram, when the

\[
f(v) = \begin{cases} 
1 & \text{if } V \geq V_{th} \\
0 & \text{otherwise}
\end{cases}
\]
neurons in the flexor muscle pathway (red line) are active, the neurons in the path of the extensor muscle are inactive (blue dashed line). This phase difference causes the extensor muscle to stop working while the flexor muscle starts working, and eventually, the limb begins to bend and contract. There are several models to create these symmetrical activities. For instance, a half-center oscillator CPG is commonly used to model the activation of opposing muscles. They are a specific CPG type consisting of two mutually inhibitory interneurons connected in a self-sustaining feedback loop. Each interneuron can alternately inhibit or excite the other, producing a cyclical pattern of neural activity that results in rhythmic motor output. The half-center oscillator CPGs can produce rhythmic muscle activation patterns without needing external stimuli or sensory feedback. They are also relatively simple to implement and can be used to investigate the basic principles of motor control.

![Figure 3](image-url)

Fig. 3. An example of the activity of rhythm-producing neurons (RG), motor neurons (Mn), and limb angle (bottom) in the path of the flexor (FL) and extensor (EXT) muscles, which also work in the opposite phase [17].

The CPG sends information to the limb muscles through the flexor and extensor pathways. The motor neuron feedback transmits information about the limb to the CPG, which indicates the angle of motion. It provides information to the nervous system to orient the body, regulate body movement, and communicate with the external environment. The supraspinal drive is a constant input from a higher level of the nervous system and primarily controls oscillation. The frequency fluctuations of CPG's output directly depend on this constant input strength.

In the following sections, we present the different parameters of this model that play an essential role in controlling and generating various movements applied to the neuromechanical system. Moreover, we examine the impact of multiple factors involved in the movement to indicate which factors could influence the fluctuation, period, and phase. Our study shows that the system could oscillate with proper supraspinal input and an adequate amount of motor neuron feedback from the muscles. To be more exact, if the system fails to receive sufficient information from the supraspinal drive, it will not generate oscillation or action with the same conditions as before (Fig. 4 and 5). Therefore, it is evident that the supraspinal input is essential in producing rhythmic information.
Fig. 4. Supernatural input with a value of 1.4 (less than the stimulation threshold of 1.5).

Fig. 5. Output (hand movement angle) for when we do not have proper supraspinal input in normal conditions. Therefore, there is no oscillation or rhythmic movement.

The remarkable point about the CPG is that simple signals are usually sufficient to stimulate and induct motion in the output [13]. Based on our research, the minimum amount of supraspinal input which can oscillate the system is 1.5, and higher values can lead to a higher frequency of movements. Likewise, low levels of stimulation reduce the frequency of movements (Fig. 6 and 7).

Fig. 6. The output angle in the rhythmic movement when the amount of supraspinal input is higher (4.7). Therefore, there is more oscillation.
In the absence of supraspinal input, the neurons cannot be activated; consequently, there is no motion in the limb. But could the motor neuron feedback be strong enough to move the motor limb? To answer this question, we removed the supraspinal input and set the system with an initial amount of motor neuron feedback in the normal state. We observed that without input and a minimum amount of motor neuron feedback, the neuromechanical model could not produce oscillation, and the limb could not have movements. So, after increasing the motor neuron feedback coefficient, we observed that the intermediate neurons could be activated; this makes it possible to produce fluctuations in the output, and some fluctuations can be returned to the system. As mentioned earlier, when the input is zero, with the same initial conditions, the rhythm-generating neurons cannot be released from the dormant phase, and no activity can occur. It’s important to note that the effects of feedback on a CPG can depend on the feedback’s specific type and timing and the CPG’s characteristics.

a. Examining the nullcline diagram of the model

The nullcline diagram in the phase space is an efficient mathematical concept used to analyze the dynamics of a system [48]. The phase space of a system is a representation of the state of the system in terms of its variables, such as position and velocity for a mechanical system or membrane potential and ionic concentrations for a biological system. The activity of neurons could be determined by their nullcline position in the phase space (V, h). In a biological system like a neuron, the nullcline position can be used to understand the equilibrium points and stability of the system. For example, when the nullcline position of the membrane potential intersects with that of a gating variable, it gives information about the system’s steady state. Additionally, the position of the nullcline can provide information about the system’s behavior, such as its stability and how it responds to perturbations.

The intersection of the nullcline diagram, which is related to the system's input, shows different neuron states [49]. The neurons are inactive when the information is such that the h-nullcline and v-nullcline intersect in the left branch of the v-nullcline, Fig. 8, C. When h-nullclines and v-nullcline cross in the central unit of the v-nullcline, the neuron begins to produce bursts, Fig. 8, B; the subsystem enters a limit cycle and has burst as long as it is in this state. By changing the input, when the h-nullclines in the right branch of the v-nullcline intersect, the neuron begins to oscillate tonically, Fig. 8, A. Therefore, neurons can observe different activities by changing the input values; as we increase the feedback, v-nullclines move to more positive voltages. Thus, activation in rhythm-generating neurons leads the intermediate neurons to exert a more robust input on the motor neurons, causing limb oscillations. When the information to the motor neurons is minimal, the oscillations disappear, and movement stops.
Rhythm-generating, pattern-generating, and motor neurons oscillate from their three input sources, including supraspinal input, interior neurons, and motor neuron feedback from the motor organ. If we remove one of these sources, the system will oscillate as long as the remaining two sources become more robust than in their normal state. So, rhythm-generating neurons could be activated with just two inputs, allowing intermediate neurons to exert more substantial input on motor neurons to produce oscillations in the limb. One of these two sources, the supraspinal information or motor neuron feedback, is always necessary to produce oscillations. However, these oscillations are not as strong as typical oscillations.

It is important to note that the nullcline diagram is just one aspect of the complex dynamics of a neuron, and other factors such as neurotransmitters, synaptic inputs, and intrinsic currents also play a role in determining the activity of a neuron.

b. Examining different values for supraspinal drive input

The supraspinal drive input is one of the most critical inputs to produce motion. According to this input, the neurons in CPG could be activated and run the motor control system, leading the system to oscillate. We observed constant fluctuations when we entered constant and stepped input to CPG as a supraspinal drive input. Also, when we applied the supraspinal input from the initial value of zero with a minimal step length (0.0001 ms), the system started oscillating as soon as the input's value (d) crossed 1.5. As time goes on, these inputs increase, and the output fluctuations also increase. Therefore, to change the output oscillation, we should change the amount of supraspinal drive input (Figs. 9 and 10).
c. **Checking the role of motor neuron feedback in the absence of supraspinal drive input**

When there is no supraspinal input, the system can only generate fluctuations in the output by increasing the motor neuron feedback strength. Still, as mentioned before, these oscillations are not as firm as they were in the normal state with supraspinal drive input (Fig. 11).

By examining the role of motor neuron feedback and its coefficient, we conclude that the most critical factor in motion is the motor neuron feedback coefficient. It can change the amplitude and frequency of movement and is an essential factor in controlling actions. The following section discusses the system dynamics scenarios through the bifurcation diagram.

**d. Investigation of the effect of supraspinal input and the gain of motor neurons in the occurrence of bifurcation**

Supraspinal input can influence the behavior of the nervous system and lead to changes in its activity. The increase in supraspinal input may lead to a bifurcation, which depends on a system’s limit cycle, input, and specific parameters, which is a sudden and dramatic change in the behavior of a system. This behavior is often seen in biological systems, such as the cardiac cycle, the neural activity that controls breathing, or rhythmic movements.

In the present study, the supraspinal input can lead the system to follow a bifurcation; when the input increases, the system enters the limit cycle at $d = 1.5$. More severe fluctuations can be achieved by increasing the value of this input to 3. Then by reducing this input with the same slight but negative slope (-0.003), the system at the point where $d = 1.0$ goes out of the limit cycle and reaches a steady state with different values than when it started to increase. Therefore, the system has a limit cycle in which hysteresis has occurred. Fig. 13 shows the bifurcation diagram of the system when the supra-spinal drive input ($d$) follows...
Another essential factor in the system’s bifurcation is increasing the motor neuron feedback coefficient, which leads to a significant decrease in the oscillation of the moving angle. Consequently, the bifurcation location will change, and the limit cycle will become smaller. As a result, when the amplitude of the oscillations decreases, the neurons enter and exit the limit cycle faster. (Fig. 13 and Fig. 14)
By increasing the value of the motor neuron feedback coefficient, neurons exit the limit cycle more quickly. So, in this study, by examining the bifurcation diagram, we could understand that the supraspinal input and the motor neuron feedback coefficient can be the control parameters to observe the desired dynamic behavior in the system. We should note that bifurcation diagrams are a tool for understanding the qualitative behavior of a system and may not capture all the details of the biological system, which is highly complex and multi-factorial.

V. Presenting a Controlling Model for Rhythmic and Discrete Movement

Linear controller methods are based on the basic assumption of small-scale performance. This kind of controller cannot compensate for nonlinear effects in the system. On the other hand, nonlinear controllers cannot be easily implemented in the natural system due to the complexity of their structure. All system parameters are known in our work, so nonlinear controllers are unnecessary. Therefore, we can control the system by changing the proportional linear controller structure. Since the physiological design of the nervous system can usually be influenced by strengthening or weakening its inputs, in this controller, there is a direct relationship between its inputs and outputs. In this system, the amplitude and the frequency of oscillations are limited. Therefore, we determined the maximum and minimum values of the movement’s range and used the control system parameters, supraspinal input, and motor neuron feedback coefficient to design a controller. So, according to the effect of these two parameters, we achieved an appropriate control model derived from a proportional linear controller. However, there is always a persistent error between the desired value and the actual output in the zero-order system in a proportional controller. This error can be significantly reduced by increasing the controller gain, but it causes delay, and the system returns to a steady state after a while. Therefore, we applied the exponential function to solve this problem. We then designed a training algorithm to adjust the amplitude and frequency of the system to reach the desired output. As a result, this controller leads the system to respond quickly, reduces its overload, and increases the result accuracy to 99%. The system achieves the desired output in this simple model with very little error (less than 0.001). The resulting rhythmic motion is demonstrated in Fig. 16.

Fig. 16. The output of the control model system reaches the desired amplitude and frequency after 2 seconds. It is noted that the amplitude and frequency decrease from 8 and 1.686 to 4 and 1.365, respectively.

Discrete movements can also be modeled with this controller to simulate a limb’s motion from a certain angle to another desired angle. In this case, the frequency of activity is zero, and the control model repeats its algorithm to reach the desired output. Fig. 17 shows an example of a discrete movement.
VI. CONCLUSION

Natural patterns always inspire researchers to design different systems. The movement of living organisms is a behavioral pattern considered in various studies. The central nervous system controls and produces motion activities through inhibitory and excitatory connections attached to muscles. This study examined the motor control system parameters through dynamics analysis and the bifurcation diagram. To this end, we evaluated the role of various components in the production and control of movement through bifurcation diagrams and system nullclines. Thus, we found that only two parameters, supraspinal input and motor neuron feedback gain, are directly involved in this purpose. Finally, we could extract rhythmic and discrete movement by applying our simple controller to CPG, a nonlinear oscillator that can only generate a rhythmic motion with its initial structure. This study would be the first step in constructing robots with a single control system to produce rhythmic and discrete movements.

VII. REFERENCES


