

## Research Article

# Cyclic Anaerobic Exercise Performance and Neuromuscular Activity Based on Artificial Intelligence Genetic Algorithm

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Anaerobic exercise capacity and neuromuscular activity research is an important content and an emerging research field in sports training research. At present, the understanding of anaerobic exercise ability in academia is still at the general and overall cognitive level, and the understanding and application of anaerobic exercise ability cannot fully meet the needs of competitive sports practice. In order to solve these problems, this paper proposes a cyclic anaerobic exercise performance and neuromuscular activity based on artificial intelligence genetic algorithm, aimed at studying the theory and application mechanism of anaerobic exercise capacity and neuromuscular activity and its application characteristics in competitive sports practice. The approach in this paper is to design genetic operators, compare artificial intelligence genetic algorithms, and test neuromuscular movements. The purpose of these methods is to provide exercisers with a feasible and more effective new method of daily training and to investigate whether this new training method can optimize anaerobic exercise in humans. In this paper, by studying the kinematic basis of anaerobic exercise capacity and the mechanism of neuromuscular regulation, a model of muscle neuron population in anaerobic exercise is established. The results showed that the CMC of the beta band was significantly higher than that of the alpha band at the same strength level, with a difference of 0.03.

## 1. Introduction

In the continuous development of sports training, the research on human exercise capacity, especially the research on anaerobic metabolism and aerobic metabolism, the basic pathways of material metabolism and energy metabolism in the body's exercise process, has always been the focus of debate and hot issue. Under normal circumstances, aerobic metabolism cannot meet the needs of the body at this time, so sugar undergoes anaerobic metabolism to quickly generate a large amount of energy. Exercise in this state is anaerobic exercise. From the point of view of material metabolism and energy metabolism, the exercise performance of the human body consists of the corresponding aerobic and anaerobic exercise performance. The performance of the human body in various sports or technical movements is nothing more than aerobic, anaerobic, or a combination of aerobic and anaerobic exercise. A detailed and systematic study of the theoretical mechanisms, basic characteristics,

and application characteristics of human aerobic and anaerobic exercise capacity will be the core of future exercise training research. In this paper, an example of finger movement is selected to study the characteristics of anaerobic exercise and neuromuscular activity. The realization of human finger movement function is closely related to the control of cranial nervous system movement. From hand projection areas to motor cortex, this paper found that the brain's control mechanism of finger movement is very complex. At present, research on the neural regulation mechanism of the human hand mainly focuses on cortical neural activity, electromyography, and muscle strength.

At the same time, this research can reveal the improvement of the anaerobic exercise ability of the athletes by the optimal training method, provide certain theoretical guidance for the coaches and athletes to improve the training methods in training and competition, and promote the better development of sports. Different types of anaerobic fitness have their own basic characteristics and practical

significance, and different types of anaerobic fitness have sports advantages, technical movements, unique training methods and other characteristics and means, and the basic requirements of unique training. This paper redefines the concept of anaerobic exercise capacity in the theoretical system of sports training by studying the theory and application mechanism of anaerobic exercise capacity and the actual effect of sports training and discusses it from the perspective of biology and training. This paper studies neuromuscular activity in depth and can propose effective measures to prevent and treat neuromuscular junction, peripheral nerve, and muscle diseases. Anaerobic exercise performance of various types and forms of the human body in competitive sports practice has important theoretical significance and practical value for in-depth understanding of the theory and application mechanism of the body's anaerobic exercise ability in academics and disciplines, as well as the effective grasp and application of anaerobic exercise ability in sports training practice.

In this study, the anaerobic training method was applied to the stage training to improve the athletes' special anaerobic exercise ability, and a better training effect was obtained. This study is the first to design and analyze the characteristics of different anaerobic exercise capacity requirements and the relationship between anaerobic exercise capacities of the same athletes, so as to provide a reference for the evaluation of anaerobic exercise capacity. The implementation of the training tasks provided in this study is simple and convenient, and the requirements for the venue are not high. During the training process, various index data of athletes can be automatically recorded directly through software and training tools. By observing the surface EMG of lower limb muscles, this paper confirmed the effect of 30% 1RM weight-bearing additional vibration stimulation on the activation of lower limb muscles during finger movement, perfected the theory of weight-bearing vibration training, and provided a basis for the frequency selection of weight-bearing vibration training.

## 2. Related Work

Paying attention to the neuromuscular changes in anaerobic exercise is of great significance for improving human movement patterns and exercise outcomes. Tsujimura believes that genetic algorithms are one of the most powerful tools for solving job shop scheduling problems, especially for large-scale real-world problems. He demonstrated its performance through a standard benchmark for job shop scheduling problems with two different fuzzy subset ranking methods, where he fused a genetic algorithm, where the processing time is represented by a fuzzy number [1]. Qiang studied a global optimization method combining genetic algorithm and Hooke-Jeeves method to solve a class of constrained optimization problems. The method he proposed significantly improves the accuracy and convergence speed of genetic algorithms. He has studied many classic test problems through precise penalty functions [2]. Yoshitomi proposed a modified genetic algorithm called Genetic Algorithm in Uncertain Environments, in which objective

function constraints fluctuate according to the distribution functions of their random variables. The algorithm is applied to the stochastic optimal assignment problem, the stochastic knapsack problem, and the newly formulated stochastic image compression problem [3]. Tayebi designed to investigate the acute response of athletes to three types of aerobic, anaerobic, and wrestling sports. He randomly divided 24 volunteers into three groups and gave them three nonconsecutive exercise programs. To study acute responses, blood sampling was performed after the first and third exercise sessions; study shows exercise type has no effect on serum iron [4]. The purpose of Kang was to measure the muscle function and anaerobic exercise capacity of the knee joint according to three exercise programs. He selected 21 athletes as research subjects. The results demonstrated that the tested athletes performed better than their peers on almost all metrics, including body composition, physical fitness factors, isokinetic muscle function, muscle strength, and anaerobic capacity [5]. Park proposed that the need for lactate cycling after aerobic exercise eliminates lactate produced during exercise, a process that requires energy expenditure. Supplementation with D-ribose increases muscle cell energy, promotes PRPP synthesis in cardiac and skeletal muscle, and eliminates pentose phosphate within the lower limit of glucose 6-phosphate dehydrogenase activity [6]. Morana designed to detect and determine the ability of RQA-sensitive fatigue components. He analyzed muscle activity with RQA to obtain percent certainty, and at the onset of exercise, a significant increase in Pt was observed in both groups [7].

## 3. Artificial Intelligence Genetic Algorithm

*3.1. Design of Genetic Operators.* Genetic operations include three genetic operators: selection, crossover, and mutation. Each operator in the group first performs a selection operation. The process of selecting excellent individuals from a population and excluding inferior individuals is called selection and replication. The selection operation is an operation used to determine how to select which individuals are inherited from the parent group to the next-generation group according to a specific method, and its main purpose is to avoid the loss of useful genetic information and improve global convergence and computational efficiency. The quality of the selection operator directly affects the calculation result of the genetic algorithm. If the operator makes an improper decision, it will lead to the increase of individuals with similar similarity values in the group, making the offspring individuals similar to the parent individuals, and the evolutionary stagnation. Or the value of the fitness function increases, which leads to the loss of the formation of genetic diversity and the problem of precocious puberty in the process of group development. The selection operation is based on an assessment of the suitability of the individuals in the group. Commonly used selection operators are fitness ratio method, optimal personal preservation method, sorting selection method, league selection method, etc. In addition, there are other selection options, such as exclusion method and expected value method. Each method has a different

impact on the search efficiency of the genetic algorithm. Among many selection operations, the fitness proportional selection method is the most basic and most commonly used method, but it is prone to large selection errors. The optimal individual preservation strategy ensures that the final result of the iteration is the individual with the highest fitness function value in the past generations. Then, after choosing the best individual preservation strategy, the fitness ratio method is used for the modern population [8]. Assuming a population size of  $n$ , the probability of individual  $i$  being selected is as follows.

$$P_i = \frac{f_i}{\sum_{j=1}^n f_j}. \quad (1)$$

In the formula,  $f_i$  represents the fitness function value of the  $i$ th chromosome. In this method, each chromosome is selected with probability  $P_i$ ; it reflects the ratio of the individual's fitness to the individual's overall fitness. Arithmetic crossover refers to the creation of a new individual from a linear combination of two individuals. Assuming an arithmetic crossover between two objects  $x_1$  and  $x_2$ , the two new individuals after the crossover are

$$\begin{cases} X'_1 = ax_1 + (1-a)x_2, \\ X'_2 = ax_2 + (1-a)x_1. \end{cases} \quad (2)$$

Among them,  $a \in [0, 1]$ ,  $a$  is a real number.

As one of the control parameters of genetic algorithm, population size also affects the performance of genetic algorithm. This paper needs to increase the population size so that genetic engineering is more likely to process more patterns, generate meaningful gene blocks, and gradually evolve into optimal solutions. But the size of each group is too large, which increases the computational complexity of the algorithm and increases the convergence time [9]. The size of the group can be selected from 10 to 200 according to the actual situation.

During the optimization process, the crossover probability  $P_c$  always controls the dominant crossover operator. Inappropriate crossover probabilities can lead to unintended consequences. A high probability of crossover results in complete crossover every generation, but too high  $P_c$  is more likely to destroy good individuals and randomize search trends. Also, if  $P_c$  is too small, more individuals may go directly to the next generation and the search may stall. In general, it is recommended that the value of  $P_c$  be in the range of  $[0.5, 1]$ . The mutation probability  $P_m$  controls how often the mutation operation is used. A larger  $P_m$  can generate more individuals and increase the diversity of the group, but it can also destroy good individuals, making the performance of the genetic algorithm approximate to random search.

In order to avoid the tedious work of determining the crossover probability  $P_c$  and the mutation probability  $P_m$  by repeated experiments, this paper adopts an adaptive genetic algorithm in which  $P_c$  and  $P_m$  can change with the

fitness value, as shown in the formula.

$$P_c = \begin{cases} (f_{\max} - f') / (f_{\max} - f_v), & (f' \geq f_v), \\ 1, & (f' < f_v), \end{cases} \quad (3)$$

$$P_m = \begin{cases} \frac{1}{2} * (f_{\max} - f) / (f_{\max} - f_v), & (f' \geq f_v), \\ (f_v - f) / (f_v - f_{\min}), & (f' < f_v). \end{cases}$$

In the formula,  $f_{\max}$  is the maximum fitness value of the previous group,  $f_{\min}$  is the minimum fitness value of the previous group,  $f_v$  is the average fitness value of the current group, and  $f'$  is the fitness value of the two chromosomes participating in the crossover and is the fitness value of the chromosome with a high-order value. Figure 1 shows the training target curve of the pure genetic algorithm.

As can be seen from Figure 1, the genetic algorithm can converge to the error target value of 0.002 at step 815. After initializing the coding, calculating the objective function, transcoding the binary numbers and programming the decimal numbers, and then passing through inheritance, crossover, and mutation, the maximum fitness value and the optimal individual in the population are finally obtained, as shown in Figure 2.

It can be seen from Figure 2 that the genetic algorithm has found the global maximum point of the nonlinear function. The importance of each node in the network depends not only on its own objective function value but also on the number of adjacent nodes and the ranking of the objective function value in adjacent nodes [10]. To assess the importance of nodes, this chapter provides the following definition of the node consistency NF of an exponential network.

$$NF = \left( \frac{1}{k+1} \right)^{R-1}, \quad (4)$$

where  $R$  is the rank of the objective function value of nodes near  $k$ .  $R=1$  means that the objective function value of the node is lower than that of all neighboring nodes. Therefore, the goodness-of-fit value of this network node is 1. With the increase of  $R$ , the rank of the node's objective function value on the adjacent nodes also increases so that the node's network node fitting degree decreases. In this paper, a fitness calculation method is proposed, which is defined as follows.

$$NF = \frac{k - R + 1}{k}. \quad (5)$$

There are still some problems with this definition; the fitness value of some nodes is equal to 0, which cannot reflect the difference between nodes. Figure 3 shows how the fitness of network nodes changes with the change of topology. When the connecting edges of nodes change, the fitness of network nodes also changes [11].

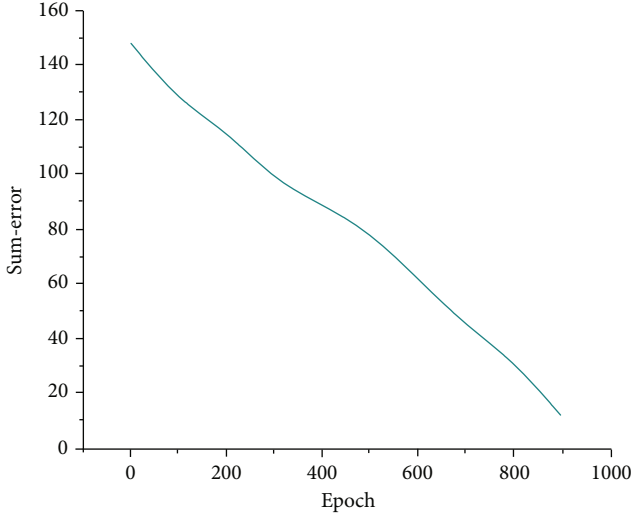


FIGURE 1: Target curve for standard algorithm training.

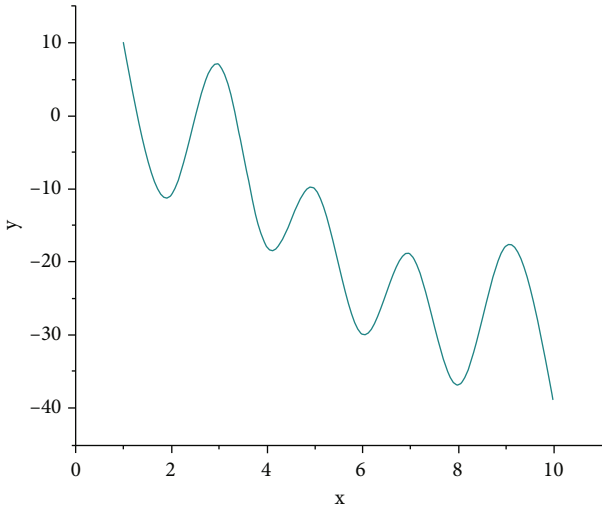


FIGURE 2: Simulation diagram.

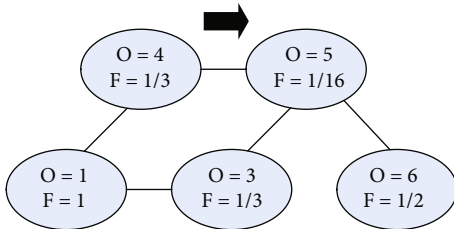


FIGURE 3: Network node fitness change graph.

The network in Figure 3 consists of 5 nodes and edges, where  $O$  is the objective function value of the node and  $F$  is the fitness value of the network node. The arrows on each graph point to nodes with lower network node fitness; if it is a horizontal line, the network node fitness of the top two nodes is equal.

The five genetic algorithm test functions used in this chapter are as follows.

Rosenbrock function:

$$f_1(x) = \sum_{i=1}^{30} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]. \quad (6)$$

Ackley function:

$$f_2(x) = -20 \exp \left( -0.2 \sqrt{0.5 \sum_{i=1}^2 x_i^2} \right) - \exp \left( 0.5 \sum_{i=1}^2 \cos(2\pi x_i) \right) + 20 + e. \quad (7)$$

Schwefel's function:

$$f_3(x) = \sum_{i=1}^{30} |x_i| + \prod_{i=1}^{30} |x_i|. \quad (8)$$

Rastrigin function:

$$f_4(x) = \sum_{i=1}^{30} [x_i^2 - 10 \cos(2\pi x_i) + 10]. \quad (9)$$

Sphere function:

$$f_5(x) = \sum_{i=1}^{30} x_i^2. \quad (10)$$

**3.2. Comparison of Artificial Intelligence Genetic Algorithms.** This section compares SWGA (small-world genetic algorithm) with SODNGA (self-organizing dynamic network genetic algorithm) and SGA (standard genetic algorithm) [12]. The SODNGA parameters were set as follows: population size  $M = 50$ , each algorithm was independently run 10 times and run for 500 generations, crossover probability  $P_c = 0.7$ , and mutation probability  $P_m = 0.06$ . The parameters of the SWGA and SGA algorithms are the same as those of the SODNGA algorithm. First calculate the Hamming distance between individuals as follows:

$$H(i, j) = \sum_{g=1}^W (1 - \beta(x_i, y_i)). \quad (11)$$

The population diversity is then calculated as follows:

$$D = \frac{\sum_{i=1}^M \sum_{j=1}^M H(i, j)}{M(M-1)(W/2)}. \quad (12)$$

Among them,  $W$  refers to the gene string length of the individual, and  $x_i$  and  $y_i$  represent the  $i$ th gene of individual  $x$  and  $y$ , respectively. If  $x_i = y_i$ , the function  $\beta(x_i, y_i)$  is 1;

otherwise, it is 0, and  $M$  is the population size. The results of the population diversity experiment are shown in Figure 4.

In the early days, the population diversity of the three algorithms was similar. With the increase of evolutionary generation, it is difficult for standard genetic algorithms to maintain population diversity. Compared with the standard genetic algorithm, the small-world genetic algorithm can better maintain the population diversity. Genetic algorithms that organize dynamic networks are ideal for maintaining population diversity [13].

When the three functions take different crossover probabilities to reach the iteration termination condition, the test results of the average running time and the average running algebra of the traditional evolutionary strategy genetic algorithm and the improved evolutionary strategy genetic algorithm are shown in Table 1.

As can be seen from Table 1, for the 3 functions, when the crossover probability is taken as 1, the average running time and the average running algebra are the least for any test function. And the average running algebra and average running time gradually decrease with the increase of the crossover probability. Self-organizing topology not only has the above advantages for genetic algorithm but also can significantly improve the convergence speed and accuracy of genetic algorithm. Figure 5 depicts the experimental results of the algorithm's convergence performance, each algorithm is run independently 10 times and run for 500 generations, the population size  $M = 100$ , and the network node fitness is defined by formula (4).

As can be seen in Figure 5, compared with the other two algorithms, the genetic algorithm based on self-organizing dynamic network is not accurate; the standard genetic algorithm can easily perform locally optimal classification. At the same time, the convergence performance of small-world genetic algorithm is better than that of standard genetic algorithm, but the convergence speed is slow [14].

**3.3. Neuromuscular Motor Testing.** Two test modes with isokinetic motion at  $60^\circ/s$  were used: isokinetic centrifuge/centrifuge and isokinetic centrifuge/centrifuge. At weekly intervals between the two test modes, the order of the two muscle fatigue tests and the two ankle joints was randomly determined. The experiments in this study were single-blind, and subjects were required to do their best while testing all of the above indicators and were often verbally encouraged. After the test, subjects were asked to perform stretching and relaxation exercises [15]. The criterion for neuromuscular fatigue is to change the test process to the proprioceptive test mode after the ankle plantar flexion and dorsiflexion moments are lower than 50% MVC for 3 consecutive times and perform a postfatigue proprioceptive test.

In the proprioceptive test, the three actual measurements are  $a_1$ ,  $a_2$ , and  $a_3$ , and the target is  $a$ . The three errors are calculated as constant error (CE):

$$CE = \frac{\sum_{i=1}^3 (a_i - a)}{3}. \quad (13)$$

It is represented by CEJPS in position sense and CEFS in

force sense. In this study, the relative value (RC) of the constant error is used to express

$$RC = \frac{CE}{0.25 * M}, \quad (14)$$

where  $M$  is the maximum isometric force and the standard deviation of three repeated measurements of proprioception is expressed as variable error (VE):

$$VE = \sqrt{\frac{\sum_{i=1}^3 a_i^2 - \left( \left( \sum_{i=1}^3 a_i \right)^2 / 3 \right)}{2}}. \quad (15)$$

It is represented by VEJPS in position sense, VEFS in force sense, and in this study by the relative value of variable error (RV):

$$RV = \frac{VE}{0.25 * M}. \quad (16)$$

Calculating the mean of the absolute values of the differences between the three target and test values, the absolute error (AE)

$$AE = \frac{\sum_{i=1}^3 |a_i - a|}{3}. \quad (17)$$

It is expressed as AEJPS in position sense, AEFS in force sense, and in this study the relative value of absolute error (RA):

$$RA = \frac{AE}{0.25 * M}. \quad (18)$$

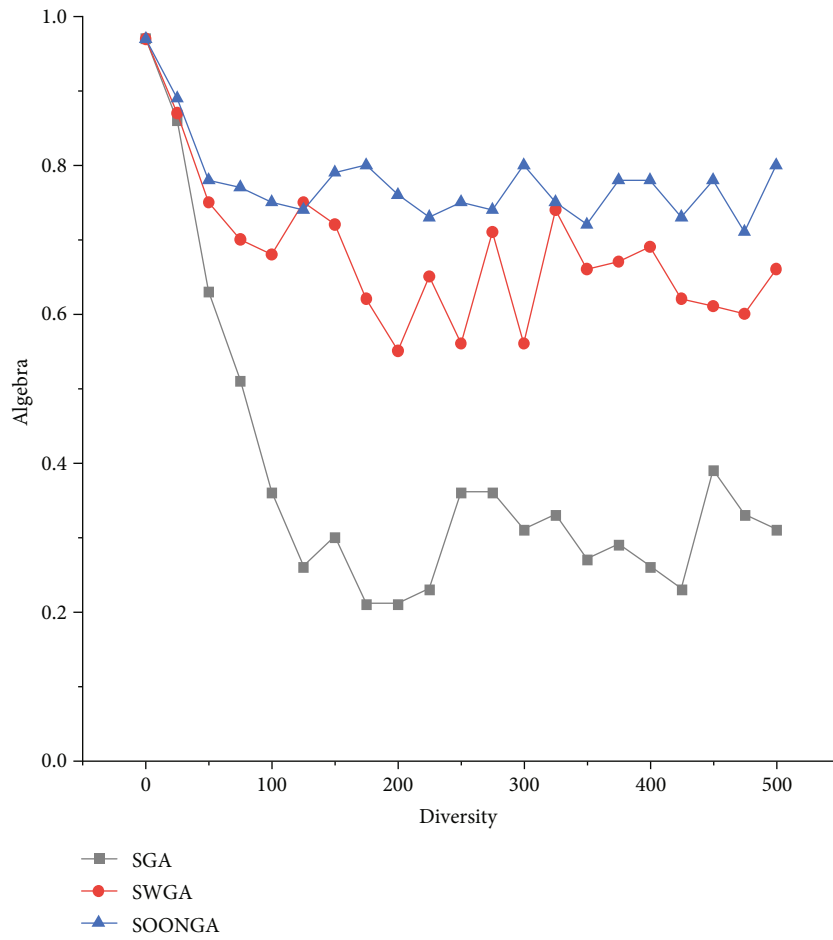
In this paper, test-and-retest reliability and standard deviation of measurements were calculated, and the intra-class correlation coefficient (ICC) was used to measure test-retest reliability.

$$ICC = \frac{BM - EM}{BM + (k - 1)EM + k[(TM - EM)/n]}. \quad (19)$$

Among them,  $k$  is the number of tests,  $n$  is the sample size,  $TM$  is the mean square of the test,  $EM$  is the mean square error, and  $BM$  is the mean square between groups.

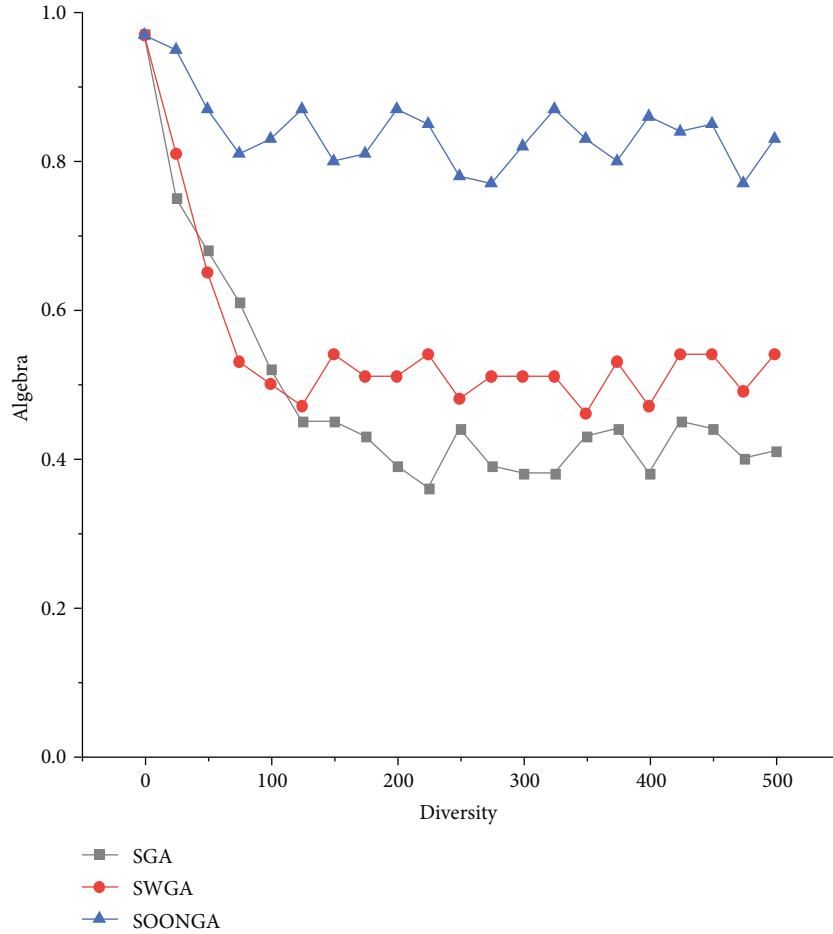
## 4. Anaerobic Exercise and Neuromuscular Activity Experiment and Analysis

**4.1. The Kinematic Basis of Anaerobic Exercise Capacity.** Exercise capacity is the concentrated expression of various functional activities of the body. The metabolism of substances and energy is the basis for the functional activities of various tissues and organs. In the practice of sports training, understanding and mastering the laws of material and energy metabolism in sports to arrange and adjust training, mastering and following the body's recovery process, and



(a) Rosenbrock

FIGURE 4: Continued.



(b) Rastrigin

FIGURE 4: Population diversity.

TABLE 1: Average runtime.

Function	Method	Crossover probability				
		1	0.9	0.8	0.7	0.6
SOONGA	Traditional GA	59.9	53.52	59.58	51.06	56.72
	Improved GA	6.93	7.28	7.01	7.43	7.01
SWGA	Traditional GA	15.93	13.72	15.51	15.48	16.27
	Improved GA	7.78	6.87	6.39	7.21	6.87
SGA	Traditional GA	24.94	19.22	17.01	24.89	21.91
	Improved GA	13.72	13.19	10.8	10.99	10.65

rationally adjusting nutrition are effective ways to scientifically and safely improve athletes’ athletic ability [16].

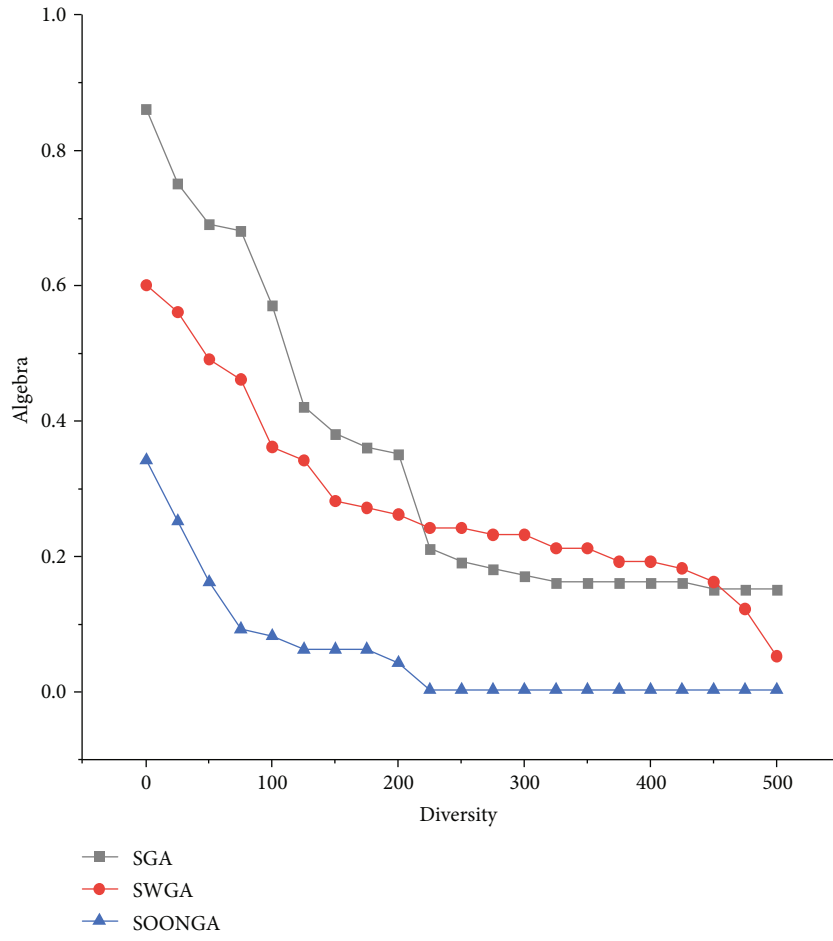
The basic process of energy output during human exercise is anaerobic metabolism process and aerobic metabolism process. The relationship between metabolic processes and exercise performance conforms to the rules of anaerobic exercise. In short, different sports require different metabolic processes as the main basis for energy supply, and different metabolic capacities directly affect different sports performance.

Aerobic and anaerobic metabolism of athletes depends on three aspects. One is the storage of energy substances,

that is, the amount of ATP and CP muscle glycogen in skeletal muscle. The second is the ability to regulate metabolic processes, including changes in enzyme activity during metabolic processes under the influence of training, regulation of metabolism by nerves and hormones, acid-base balance, and regulatory changes between various organs in the internal environment. Third is the metabolic capacity of the recovery process after exercise. The postexercise recovery process is not a simple adverse reaction to the consumption process during exercise. Scientific and rational arrangements for rest, nutrition, and various means of relieving fatigue can speed up the recovery process. The comprehensive performance of human skeletal muscle metabolic capacity is shown in Table 2.

In various sports, after ATP is depleted, the body needs to restore the amount of ATP as soon as possible to maintain sports performance. Enzymes and hormones, such as creatine kinase, phosphofructokinase, and epinephrine, which are required to restore ATP to accelerate the rate of ATP resynthesis and metabolic regulation, are also very important. Table 3 shows the corresponding percentages of muscle energy requirements.

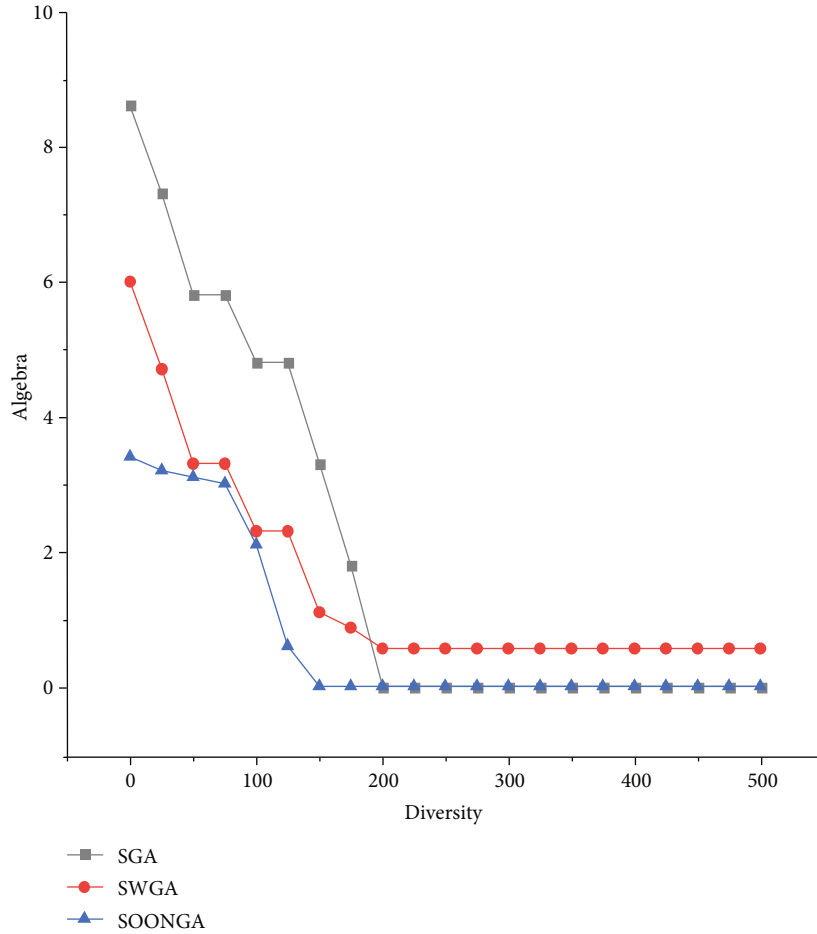
It can be seen that the energy system relies on the glycolysis system in addition to phosphate during the 200 m



(a) Schwefel's

FIGURE 5: Continued.





(b) Ackley

FIGURE 5: Convergence performance graph.

TABLE 2: Metabolic capacity of human skeletal muscle during exercise.

Metabolic process	Reserve	Amount of ATP synthesized	Available time for exercise	
			Extreme exercise	70%VO <sub>2max</sub> intensity (min)
<i>Anaerobic metabolism</i>				
ATP	29	261	6 s-9 s	0.21
CP	67	198	6 s-10 s	0.05
<i>Glycolysis system</i>				
Muscle glycogen	425	1024	3 min-5 min	0.84
<i>Aerobic metabolism</i>				
Muscle glycogen	463	13502	1 h-1.5 h	0.93
Fat	65	65214	1 h-2 h	1.62

running. During the 400 m running and the 100 m swimming, the anaerobic metabolic systems of phosphate and glycolysis interact with each other. But in the 800 m and 1500 m run and most swimming events, the glycolysis and aerobic metabolic systems are clearly dominant, and the aerobic metabolic system is dominant in the 1500 m swimming and marathon running [17].

Sustained anaerobic exercise ability reflects the energy supply capacity required by the body in short-term extreme

sports, is the embodiment of the body’s ability to maintain extreme exercise, and reflects the ability of the body to maintain speed and maintain load intensity. The ability to maintain anaerobic exercise mainly reflects the ability of the body to complete extreme or submaximal exercise within 30-180 seconds in competitive competitions and training. The energy supply of the maintenance anaerobic exercise ability reflects a kind of maintenance ability of the body’s limit energy supply and the body’s ATP-CP energy supply

TABLE 3: Energy requirements and available quantities and rates for different distances.

Project	Energy requirements		Available energy and speed	
	Rate	Quantity	Maximum rate	Quantity
100 m run	1.84	1.48	2.44	0.67
400 m run	1.48	2.89	3.51	5.26
800 m run	1.75	3.1	3.08	1.5
1500 m run	3.12	3.25	2.75	86
Marathon	1.52	1.89	1.67	1250

ability and glycolysis energy supply ability. If the neurological anaerobic exercise ability and the primary anaerobic exercise ability are both critically restricted by the genetic factors of the exerciser, then the maintenance anaerobic exercise ability is mainly obtained through the acquired scientific training of the exerciser. Therefore, this study believes that acquired scientific exercise training has a decisive role and significance in improving the maintenance anaerobic exercise ability of exercise individuals [18].

According to the characteristics of the energy supply basis of continuous anaerobic exercise ability defined in this paper, as well as the theoretical mechanism of continuous anaerobic exercise ability and the characteristics in sports training practice, sustained anaerobic exercise capacity corresponds to extreme sports within 15 minutes. The sports items corresponding to the sustained anaerobic exercise capacity defined in this study include 3000-meter running, 5000-meter running, 5000-meter speed skating, 10,000-meter speed skating, 400-meter swimming, 800 swimming, middle distance cycling, and middle and long distance racing rowing. In the past sports training theory, there are different opinions on the sports ability corresponding to these sports items. In the past, it was believed that these sports items lasted for a long time, and the dominant sports ability of the sports individual should be aerobic exercise ability. But the characteristics of these sports today in competitive competitions are obviously contrary to aerobic fitness. Because with the increasingly fierce competition in modern competitive sports, the level is getting higher and higher, and the ability of sports individuals is getting stronger and stronger; in order to win the competition in these competitive sports, the sports body is required to exercise close to the extreme intensity from the beginning of the competition. And it is required that the sports body must be able to maintain extreme sports, high-speed, high-intensity, and high-load sports for a long time in order to win the game [19].

**4.2. Mechanisms of Neuromuscular Regulation.** FCMC is considered a classic and commonly used method for assessing functional connectivity between neural signals and associated somatic muscles. FCMC analysis was initially implemented based on magnetoencephalography (MEG) and EMG. It was subsequently generalized to local field potential (LFP) electroencephalography (EEG), electrocorticography (ECoG), and surface electromyography (sEMG)

TABLE 4: CMC peak mean and standard deviation in alpha band at different strength levels.

Strength level	CMC peak mean $\pm$ standard deviation
<i>I</i> 10% MVC	2.067 $\pm$ 0.106
<i>I</i> 20% MVC	2.246 $\pm$ 0.113
<i>I</i> 30% MVC	2.282 $\pm$ 0.103
<i>I</i> 40% MVC	2.008 $\pm$ 0.109
<i>I</i> 50% MVC	2.239 $\pm$ 0.108

and validated in multiple methods and species. This paper takes finger strength as a practical example to study the neuromuscular regulation mechanism [20].

To explore the effect of finger strength level on CMC, one-way ANOVA was performed on 50 groups of coherence data at two strength levels, *I* 20% MVC and *I* 40% MVC. One-way ANOVA and *T*-test were performed on the CMC in the alpha band under the two strength levels of *I* 20% MVC and *I* 40% MVC, and it was found that the peak CMC in this band was significantly different at the two strength levels. The results are shown in Table 4.

At the *I* 20% MVC strength level, the CMC of the alpha and beta bands were compared and found to be significantly different ( $P < 0.05$ ) between the two different bands. Similarly, the CMC in the alpha and beta bands at *I* 40% MVC strength level was compared, and the results were also significantly different ( $P < 0.05$ ).

In order to make an intuitive comparison of the effect of the finger strength level on the alpha and beta frequency bands, a box plot of the obtained results is made, as shown in Figure 6.

As can be seen from Figure 6, both  $\alpha$  and  $\beta$  band CMCs increased with increasing intensity levels. In addition, at the same strength level, the CMC of the beta band is significantly higher than that of the alpha band, with an average of 0.231.

There are three explanations for the current mechanism of the effect of increased strength levels on beta-band CMC. (1) At lower strength levels, in order to make movements with less error, a large number of corrective movements are involved, thereby reducing the CMC at lower strength levels. (2) The tuning effect of the firing rate of the motor unit to the beta band enhances the CMC at greater force levels. (3) The increase in CMC in the beta band at higher force levels compared to lower force levels indicates stronger binding between cortex and motor neurons. It is generally accepted that CMC reflects the direct connection between the brain and muscles, which is thought to be related to force control. In addition, some studies have found that the oscillatory activity in the lower beta frequency band and multiple cortical areas combine to form a network structure in visual guidance tasks, thereby effectively promoting neurophysiological processes [21].

**4.3. Muscle Neuron Population Model.** The essence of FCMC is the transmission of information in the corticospinal pathway between the primary motor cortex and the muscles, as shown in Figure 7.

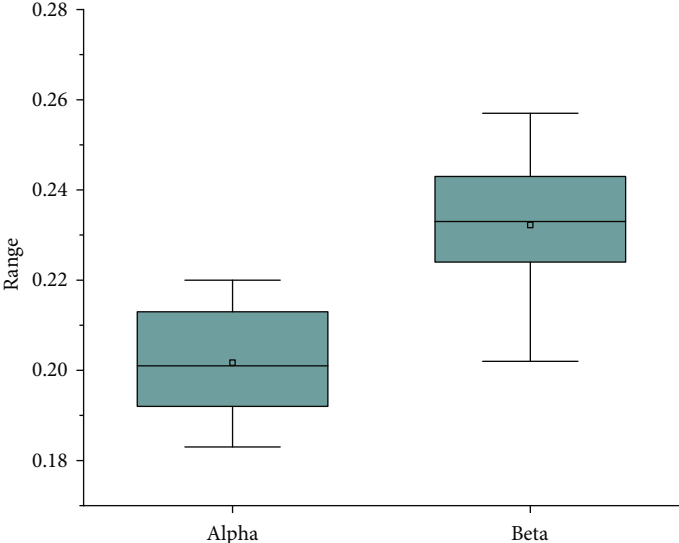


FIGURE 6: Box plots of alpha and beta band CMCs at different strength levels.

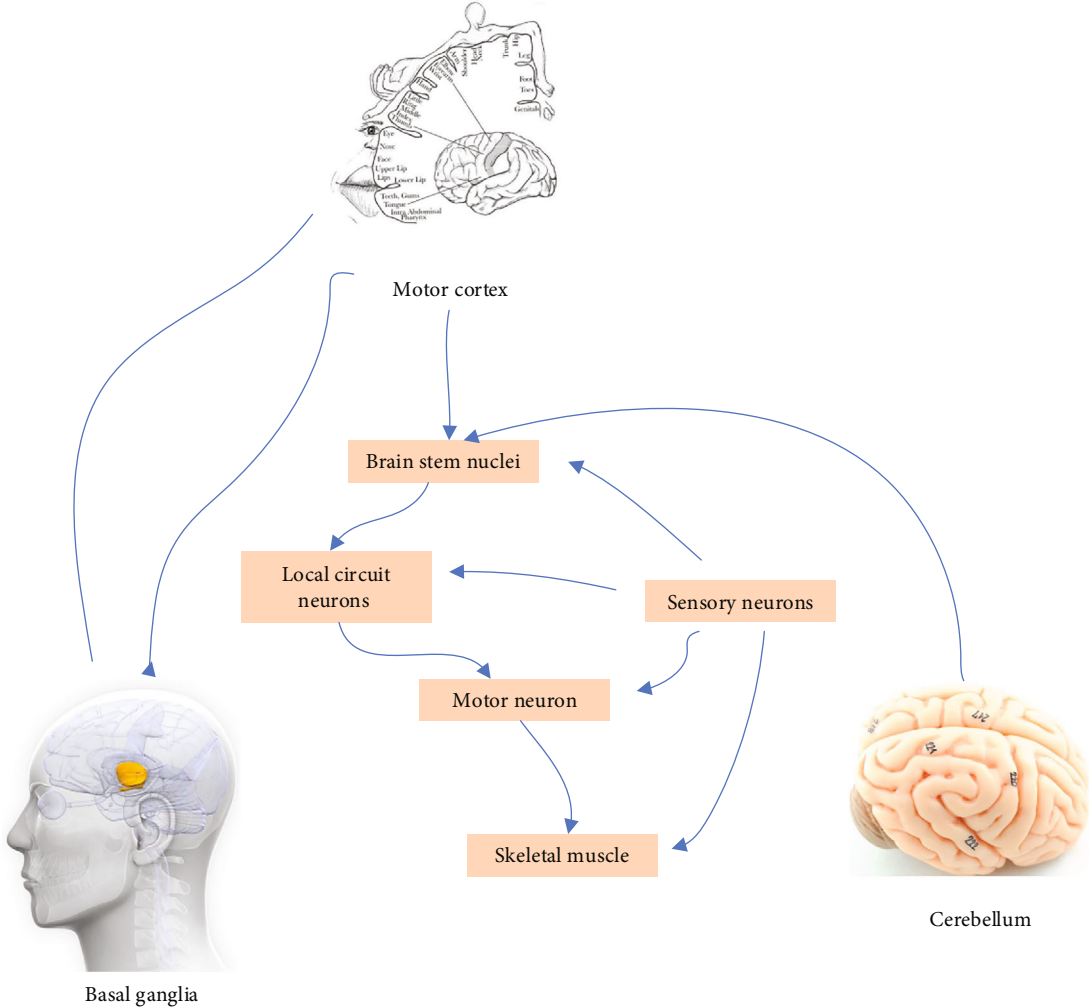


FIGURE 7: Neuromuscular information transmission pathway.

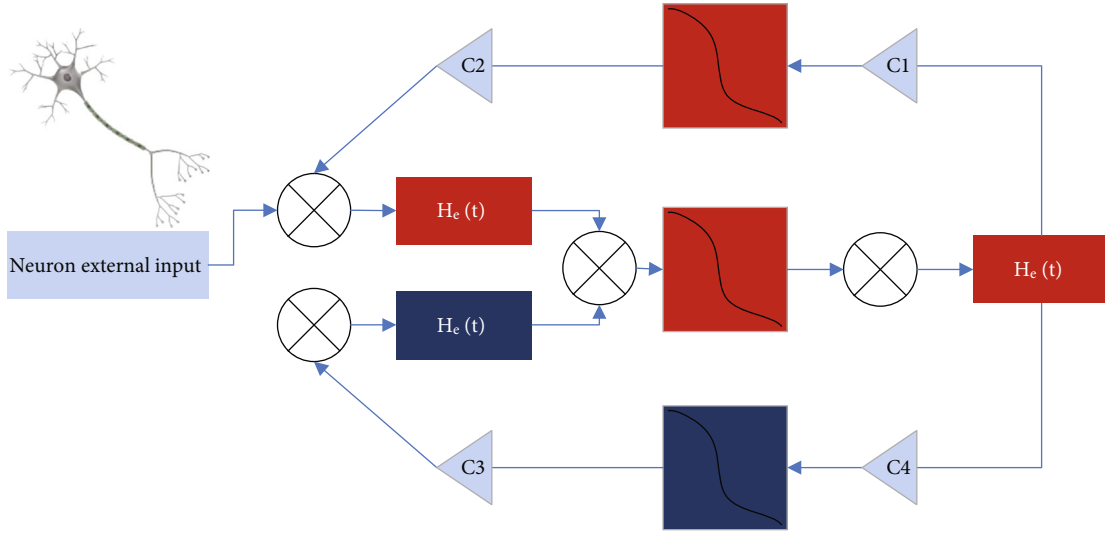


FIGURE 8: Schematic and equations of JR-NMM.

FCMC studies can reflect the interaction between the brain and muscles. It represents information transfer within the neuromuscular system and is related to the transmission of commands from the brain to the muscles and the upward feedback of muscle contractions [22]. As such, it contributes to understanding the mechanisms by which the brain controls muscle activity, the impact of muscle movement on brain function, and the underlying causes of certain physiological and pathological conditions.

The Jansen-Rit neuron population model (JR-NMM) can model the activity of neuron populations aggregated in local neural circuits by simulating pyramidal neuron population activity. This pyramidal neuron can receive both inhibitory and excitatory feedback from local neurons as well as excitatory input from nearby or distant neuronal populations. Figure 8 shows a schematic diagram of the overall structure of the JR-NMM used to simulate UER in this study.

JR-NMM contains three neuronal population structures, namely, pyramidal neuron population, excitatory interneuron population, and inhibitory interneuron population. They are connected by excitatory synaptic impulses in response to  $H_e(t)$  and inhibitory synaptic impulses in response to  $H_i(t)$  [23].

In order to confirm that the passive membrane time constant of JR-NMM can be used as an identification parameter to simulate the rhythmic characteristics of UER, in this study, different brain rhythms were simulated by adjusting the passive membrane time constant, and the relationship between the passive membrane time constant and the frequency band distribution characteristics of JR-NMM (from alpha band to ripple band) was analyzed, and Figure 9 is obtained.

Figure 9(a) shows the simulated brain rhythm waveforms in the alpha frequency band. The results show that JR-NMM can simulate brain rhythm waveforms in different frequency bands by adjusting the excitatory and inhibitory passive membrane time constants. Figure 9(b) shows the dis-

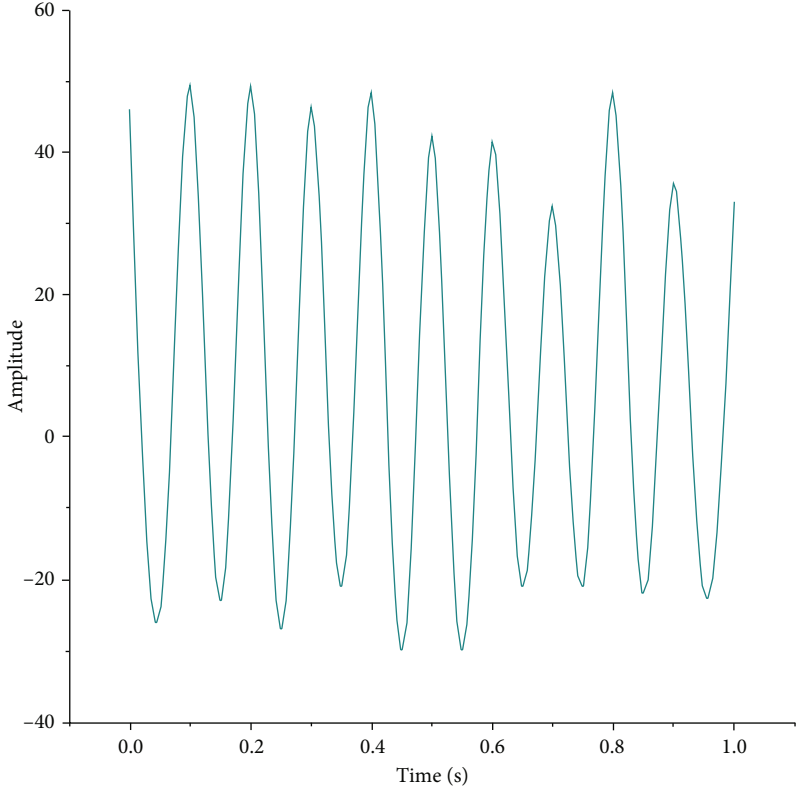
tribution relationship between passive membrane time constants and simulated brain rhythms in JR-NMM. Among them, the  $x$ -axis is the excitatory passive membrane time constant, the  $y$ -axis is the inhibitory passive membrane time constant, and the color scheme represents the frequency peaks of the simulated brain rhythm. The results show that the frequency peaks of the simulated brain rhythms increase with increasing passive membrane time constants. Therefore, the passive membrane time constant in JR-NMM can be used as an identification parameter to simulate the brain rhythm characteristics of UER. Moreover, according to the results of isolated neurons of ultrasound neuromodulation, ultrasound-regulated neuronal firing is caused by the change of the passive membrane time constant under the action of ultrasound radiation force [24]. Therefore, in this study, the passive membrane time constant was used as a “biological effector” for the neuronal firing activity induced by ultrasonic radiation force.

First, this paper uses the short-time Fourier transform (STFT) method to estimate the time-frequency characteristics of the LFP signal and the EMG signal in the frequency range of 5~200 Hz under a single ultrasound stimulation, as shown in Figure 10.

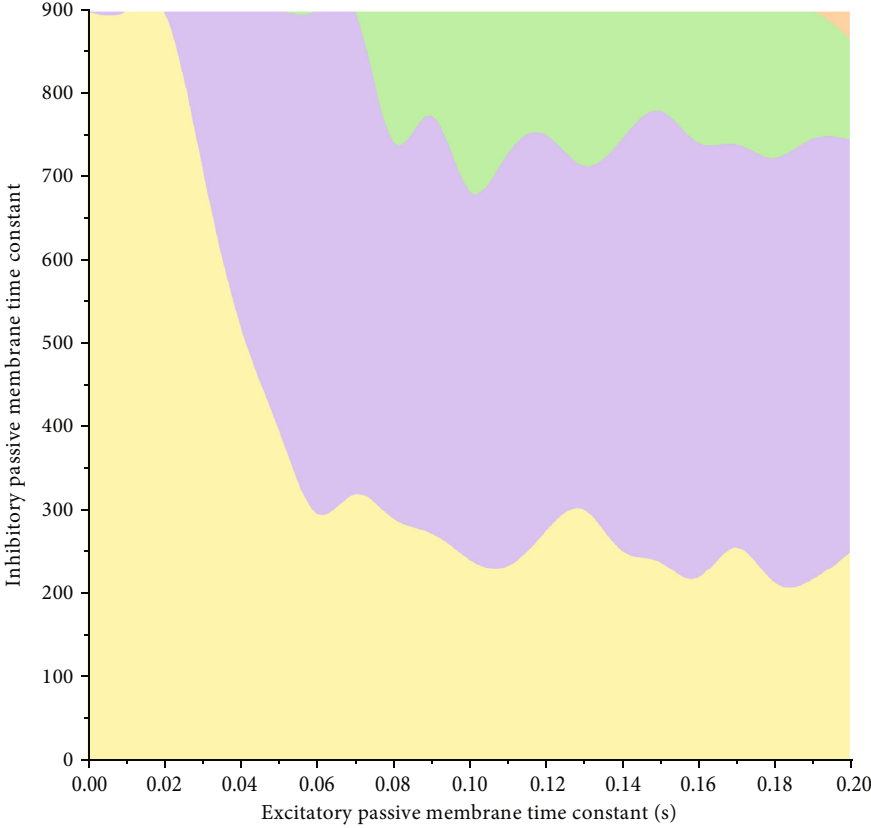
Figure 10 shows the waveforms and time spectra of the LFP and EMG signals for the next stimulation cycle with a duration of 4 s in the next stimulation cycle at this ultrasound parameter ( $0.20 \text{ W/cm}^2$ , 50% DC, 400 ms). Among them, 0~2 s of the  $x$ -axis is the nonstimulation period. In the waveform diagrams of the LFP and EMG signals, it can be clearly observed that the signal amplitude during the stimulation period is higher than that in the nonstimulation period.

## 5. Discussion

There are still shortcomings in this paper, and it is recommended that researchers supplement the data later and increase the sample size. The rhythmic keystrokes discussed

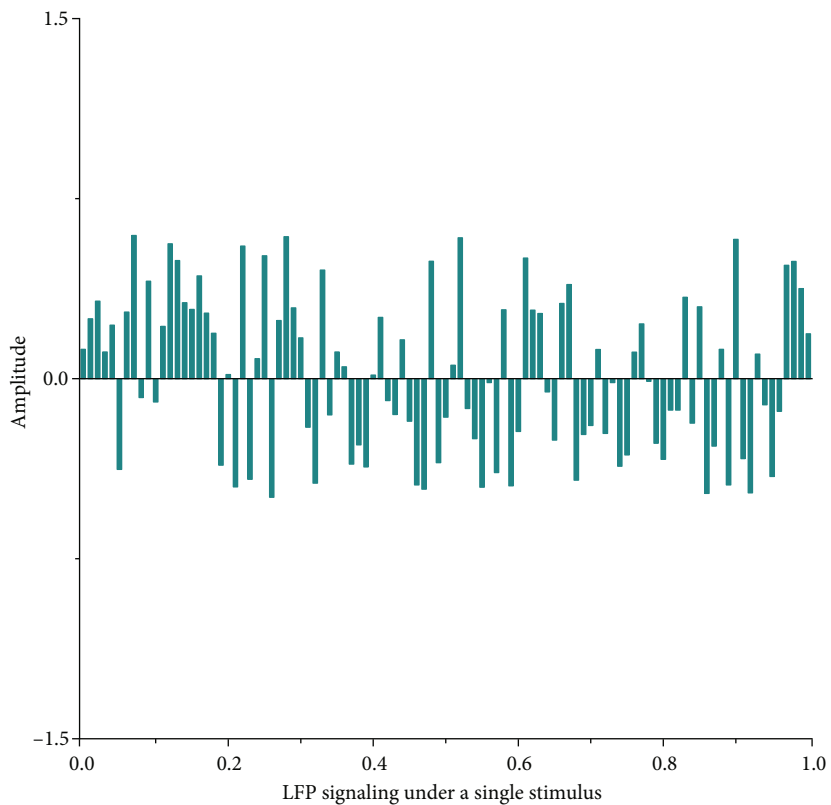


(a) Simulated membrane rhythm

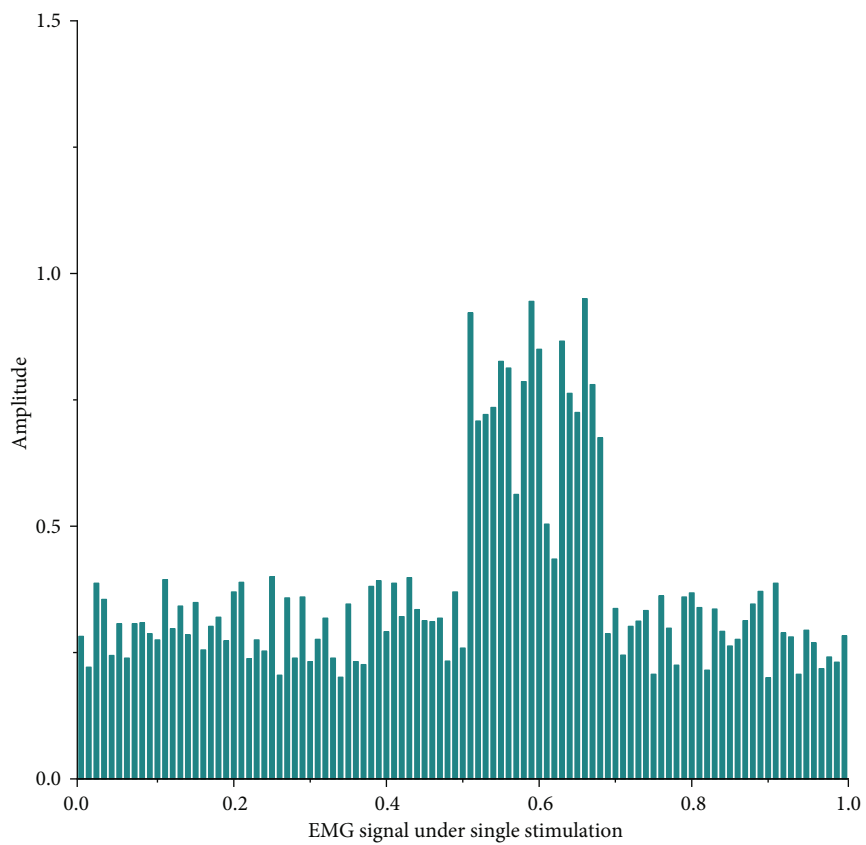


(b) Passive membrane time constant

FIGURE 9: Brain rhythms simulated by tuning the passive membrane time constant of JR-NMM.



(a) LFP



(b) ENG

FIGURE 10: LFP and EMG signals and their corresponding time-frequency plots under a single stimulus.

in this work only took the data of one healthy subject, and the MEG, SEMG, and finger strength signals of five healthy subjects were collected in the visual-guided finger force tracking task. However, relatively speaking, the sample size is still small. In order to avoid errors caused by insufficient samples in the statistical analysis of the characteristic information of cortical neural activity, the sample size needs to be increased in the future. The cause of exercise-induced fatigue is unknown, and the hydrogen ion theory is one of the generally accepted theories. Due to insufficient oxygen supply in the body during high-intensity exercise, skeletal muscle cells need to perform contraction through glycolysis, but at the same time as producing ATP, they also produce a large amount of lactic acid. In a short period of time, the body's own buffering system becomes difficult, and the lactic acid produced by the body is completely buffered, resulting in the accumulation of lactic acid and an increase in the concentration of hydrogen ions.

## 6. Conclusions

Based on the results of expert interviews and the basis of biology and sports training, combined with the characteristics of finger movement, this paper mainly studies three types of anaerobic exercise capacity, maintenance anaerobic exercise ability, and continuous anaerobic exercise ability. Different types of anaerobic fitness have their own basic characteristics and practical significance, and there are also different training characteristics in competitive sports practice, such as training content characteristics, methods, and basic requirements. In this paper, we investigated the effects of weight-bearing loading and vibrational stimulation on the activation of the subjects' finger muscles by analyzing electromyography and identified the vibrational frequency that caused maximal muscle activation by different frequencies of vibrational stimulation. In this paper, a specific vibration training program was developed, and through an 8-week training intervention, the effects on maximal strength, rapid strength, H-reflex, and T-reflex of the subjects' finger muscles were observed, and the differences were compared. This article analyzes the neuromuscular effects of weight-supported vibrational strength training, modulates properties, and explores its possible mechanisms. This study improves the theoretical system of weight-bearing vibration training and provides a reference for the public and athletes to formulate vibration strength training programs.

## Data Availability

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

## Conflicts of Interest

The authors state that this article has no conflict of interest.

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