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Modeling research on optimal allocation and regulation of exercise load parameters in physical fitness training based on genetic algorithm

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Abstract This paper collects physiological index data such as heart rate through real-time monitoring of wearable devices. Mining and extracting the relevant features of the physiological index data, we constructed a dynamic correlation model between the physiological indexes and the exercise load, and predicted the future physiological state of the athletes. The non-dominated sorting genetic (NSGA-II) algorithm is introduced to realize the multi-objective optimization and regulation of heart rate in the prediction of training load to enhance the training effect. The practical value of this paper's method of combining real-time monitoring and genetic algorithm modeling is verified through multiple sets of experiments. The results show that the physiological data of athletes can be monitored and collected in real time at a frequency of 1 time per second by using a wearable device, and the data have research value. During the 4 stages of incremental load exercise, the muscle oxygen saturation of different muscle parts showed a decreasing trend. Combined with the method of this paper, real-time regulation was performed to maintain the decreasing muscle oxygen saturation at the 4th stage. In the physical fitness training experiment, the real-time heart rate prediction error of the athletes was optimized by the algorithm and adjusted to be consistent with the actual monitoring value, so as to realize the real-time accurate regulation of the exercise load in the training process.

Index Terms NSGA-Ⅱ algorithm; exercise load regulation; physiological index monitoring; data mining; physical fitness training

I. Introduction

With the increasing emphasis on physical health, people began to gradually engage in different types of sports to improve their physical fitness. Fitness training is not only for athletes or fitness enthusiasts, it is applicable to people of all ages and different physical conditions, so it has been widely studied [1]. Through physical fitness training, all the physical qualities can be effectively improved, which can improve all the qualities of the body, such as endurance, strength, agility, flexibility, and so on, so as to improve the efficiency of work or study [2], [3]. At the same time, it can also prevent chronic diseases, such as aerobic exercise can reduce the occurrence of cardiovascular disease, and resistance training can help prevent and control diabetes [4], [5]. As well as can also promote the body's secretion of substances such as endorphins and dopamine, thus reducing negative emotions such as anxiety and depression, and improving self-confidence and mental toughness [6]. The core idea of physical fitness training is physical fitness, i.e., the ability of physical adaptation, and when performing physical fitness training, it is necessary to choose the appropriate training method and intensity according to the individual's physical condition and goals. Among the intensity requirements, exercise load is emphasized.

Exercise load is an important factor that mainly affects hereditary and qualitative changes in neurological function [7]. The appropriate load of exercise allows the exercise to develop positive effects, resulting in physiological and psychological changes in the body, such as strengthening muscle strength and aerobic capacity, and promoting a happy mood, thus achieving the goals of the exercise [8], [9]. From the athletic level, the human body in the quantitative load there is adaptability, if the same load is applied for a long time, the body will not appear corresponding changes, must increase the amount and intensity of the load, only in this way can be broken out of the balance of the body, promote the development of the body [10], [11]. The influence of exercise load on the effect of exercise increases with the increase of exercise intensity, and under the same intensity conditions, the load amount gradually decreases with the prolongation of exercise time [12]. However, non-professional athletes have a relatively vague understanding of reasonable exercise load, and sometimes they cannot master the intensity of exercise load well, and the exercise load is far beyond the tolerance range of the human body, which not only fails to achieve the effect of exercise, but also ultimately triggers the exercise injury [13]. Therefore, choosing the appropriate exercise load can improve the training effect and promote the health of the organism. In sports training, the level of exercise load can be adjusted to improve the performance and exercise effect. However, in traditional training programs, often the experience of the coach dominates and the underlying physiological situation, and does not take into account the physiological and psychological differences and needs of the individual, which is no longer adapted to the current development needs [14], [15]. Therefore, the importance of allocating and regulating exercise loads is becoming increasingly important.

Genetic algorithm is a search algorithm based on the mechanism of natural selection and population genetics, which simulates the phenomena of reproduction, hybridization and mutation that occur during natural selection and natural inheritance. When solving a problem using a genetic algorithm, each possible solution to the problem is encoded as a “chromosome”, i.e., an individual, and a number of individuals form a population [16]. This coding process can encode multiple possible solutions to form different solutions, which is logically similar to the assignment and regulation of exercise load parameters. A study has utilized genetic algorithms to provide a biomechanical analysis of injury prevention under proper training for free deep squatting, which provides a basis for scientific training [17].

Scientific quantification of the relationship between physiological indexes and exercise load and dynamic regulation is the key to improve the training effect and reduce the injury risk of athletes. In this paper, we use wearable devices to collect the characterization of exercise load in real time, such as step acceleration, to judge the physiological state of athletes. With the help of SVM algorithm in data mining, the athletes' exercise load is monitored in real time. Combining the physiological state and exercise load, an association model is established, which is used to calculate and predict the athlete's future fitness state. NSGA-Ⅱ algorithm is introduced to optimize the predicted heart rate and other physical state values, to solve the contradiction of the distribution of the exercise load in the process of physical fitness training, so as to maximize the training effect and minimize the physiological loss. Combined with experiments to judge the effectiveness of the co-optimization method in this paper.

II. Research on physiological indexes and exercise load balancing technology based on genetic algorithm

In this chapter, multi-dimensional physiological indicators such as exercise step acceleration, muscle oxygen saturation, heart rate, etc. are acquired in real time by wearable devices, and the data of these indicators are used as the basis of exercise load analysis and monitoring. Based on data mining technology, the dynamic association model between physiological index data and exercise load is established. Non-dominated Sorting Genetic Algorithm (NSGA-II) was introduced to use the real-time monitoring data of the model as input, and through multi-objective optimization calculation, the training load was appropriately adjusted to balance the fitness training effect and injury risk of the athletes.

II. A. Information Acquisition for Exercise Load Detection under Data Mining

II. A. 1) Motion Step Acceleration Calculation

As a characterization quantity of motion load, motion gait has a common point in the motion process of different targets, accordingly, by installing acceleration sensors at the waist, according to the acceleration change situation of the torso part, combined with software algorithms, the motion gait monitoring of the motion targets is accomplished.

The whole process of human walking is divided into four phases: stomping, stepping, landing, and supporting, and the torso part produces vertical and horizontal motions in each gait phase. The reason for the acceleration change in the vertical direction is the combined force of the ground on the foot and gravity, while the acceleration change in the horizontal direction is the friction between the ground and the foot.

The problem of monitoring the motion gait is converted into a problem of calculating the number of sine waves of the acceleration change curve. According to the periodicity law of sine-wave shaped curve of motion gait acceleration change, a dynamic threshold step monitoring strategy with adaptivity is designed. The threshold value is taken and updated by the extreme mean value of the torso acceleration collection samples.

Assuming that the acceleration extremes obtained after collecting a certain number of samples are $a_{\min}$ and $a_{\max}$, the formula for the dynamic threshold thr_d is shown below:

$$thr_d = a_{\min} + \left(a_{\max} - a_{\min}\right) * K \tag{1}$$

where K denotes the acceleration coefficient, and when taking the value of 1, the dynamic threshold is bipolar mean. The determination of the dynamic threshold step monitoring strategy is based on the fact that a step is completed once the acceleration profile makes one top-to-bottom or bottom-to-top crossing on the dynamic threshold.

II. A. 2) Oximetry-based exercise energy monitoring

Another key characterization of exercise load is exercise energy consumption, which is the portion of the load that is used to perform mechanical external work through muscle contraction, and can be obtained by using near-infrared spectroscopy to monitor blood oxygen saturation levels.

Assuming that the oxygenated hemoglobin is HbO_2 and the deoxyhemoglobin is Hb, the following formula is used to solve the oxygen saturation level SpO_2 as:

$$SpO_2 = \frac{HbO_2}{HbO_2 + Hb} * 100\% \tag{2}$$

Near-infrared spectroscopy for monitoring oxygen saturation is based on the fact that the two types of hemoglobin in blood have different absorption characteristics for light of the same wavelength. In order to reduce the difficulty and complexity of monitoring, a method for monitoring exercise energy consumption based on blood oxygen saturation content was designed according to Lambert's Beer's law.

When monochromatic light of intensity I_{in} is transmitted through a solution of absorbance A and concentration C, the transmitted intensity I_{out} of the light beam is solved by the following equation:

$$I_{out} = I_{in} * e^{-A} \tag{3}$$

where e is a constant. The absorbance A is calculated by the formula:

$$A = \varepsilon * C * D \tag{4}$$

Where ε indicates the solution absorption coefficient, depending on the wavelength of the incident light; D indicates the light propagation distance in the solution.

For the movement of the human body, if the blood concentration of deoxygenated and oxygenated two types of hemoglobin are C_1, C_2, λ wavelength absorption coefficient is ε_1, ε_2, respectively, then by the formula (3) deduced from the following human body transmittance of light intensity calculation formula for:

$$I_{out} = I_{in} * e^{-(\varepsilon_1 C_1 + \varepsilon_2 C_2)D} \tag{5}$$

where I_{in} represents the transmitted light intensity of arterial blood and its absorbance A is shown below:

$$A = \ln\left(\frac{I_{in}}{I_{out}}\right) = (\varepsilon_1 C_1 + \varepsilon_2 C_2) D \tag{6}$$

Arterial pulsation leads to changes in blood flow, and after the body tissues dissipate the beam, the light propagation distance increases by ΔD, and the light transmission intensity decreases by ΔI. The variable of absorbance ΔA is:

$$\begin{aligned} \Delta A = A_1 - A &= \ln\left(\frac{I_{in}}{I_{out} - \Delta I}\right) - \ln\left(\frac{I_{in}}{I_{out}}\right) \\ &= \ln\left(\frac{I_{out}}{I_{out} - \Delta I}\right) = (\varepsilon_1 C_1 + \varepsilon_2 C_2) * \Delta D \end{aligned} \tag{7}$$

Combining equation (2), the oxygen saturation was obtained as:

$$SpO_2 = \frac{C_1}{C_1 + C_2} = \frac{\Delta A}{(\varepsilon_1 - \varepsilon_2)(C_1 + C_2)\Delta D} - \frac{\varepsilon_2}{\varepsilon_1 - \varepsilon_2} \tag{8}$$

When the wavelength is λ', the corresponding absorption coefficients are ε_1' and ε_2', respectively, and the variable of absorbance is $\Delta A'$, then the oxygen saturation SpO_2' is:

$$SpO_2' = \frac{C_1}{C_1 + C_2} = \frac{\Delta A'}{(\varepsilon_1' - \varepsilon_2')(C_1 + C_2)\Delta D} - \frac{\varepsilon_2'}{\varepsilon_1' - \varepsilon_2'} \tag{9}$$

Substituting into equations (3) and (4) yields the following expression:

$$SpO_2' = \frac{\varepsilon_2 * \frac{\Delta A'}{\Delta A} - \varepsilon_2'}{(\varepsilon_1' - \varepsilon_2') - \frac{\Delta A'}{\Delta A}(\varepsilon_1 - \varepsilon_2)} \tag{10}$$

Let the wavelength satisfy $\varepsilon_1 \approx \varepsilon_2$ and the oxygen saturation be:

$$SpO_2' = \frac{\varepsilon_2}{\varepsilon_1' - \varepsilon_2'} * \frac{\Delta A}{\Delta A} - \frac{\varepsilon_2'}{\varepsilon_1' - \varepsilon_2'} = x * \frac{\Delta A'}{\Delta A} + y \tag{11}$$

where x and y are arbitrary constants.

After substituting the decompositions of absorbance ΔA and $\Delta A'$ corresponding to wavelengths λ and λ' into the above equation, due to $\Delta I \ll I$, the following approximate expression is obtained:

$$SpO_2 = x * \frac{\ln \frac{I_{out}'}{(I_{out}' - \Delta I')}}{\ln \frac{I_{out}}{(I_{out} - \Delta I)}} + y \approx x * \frac{\frac{\Delta I'}{I_{out}'}}{\frac{\Delta I}{I_{out}}} + y \tag{12}$$

In summary, the maximum transmitted intensity of different wavelength beams and their variables are measured to obtain the blood oxygen saturation, which achieves the purpose of exercise energy consumption monitoring.

II. B.Data mining based exercise load monitoring

Based on the above acquired heart rate feature signal, the exercise load is monitored with the help of SVM algorithm in data mining.

Assuming that there is currently k feature sample $G(g,t)$, the optimal hyperplane expression for the intensity of the exercise load volume is based on SVM for classification:

$$e + V^T G(g,t) = 0 \tag{13}$$

where V represents the normal vector of the optimal hyperplane and e represents the intercept of the optimal hyperplane.

The advantage of the optimal hyperplane is to ensure that the distance between the signal feature samples $G_i(g,t)$ and normal samples $G_j(g,t)$ is maximum, in the process of calculating the optimal hyperplane it must be ensured that the normal vector $\frac{1}{3}\|V\|^2$ is minimum, at this time, it is necessary to calculate the quadratic programming problem, the expression of which is:

$$\begin{cases} \min & \frac{1}{3}\|V\|^2 \\ s.e & o_j\left(e + V^T G(g,t)\right) \geq 1 \end{cases} \tag{14}$$

where o_j represents the support vector in the quadratic programming problem.

If the signal training sample contains linearly indivisible factors, the expression of the quadratic programming problem in this case is:

$$\begin{cases} \min_{V,e,\theta_j} \ E\sum_{j=1}^{k}\theta_j + \frac{1}{2}\|V\|^2 \\ s.t. \\ o_j\left(e+V^T G(g,t)\right) \geq 1-\theta_j \\ \theta_j \geq 0, j=1,2,\cdots,k \end{cases} \tag{15}$$

where θ_j represents the relaxation factor and E represents the penalty factor.

E balances the classification error as well as the generalization ability in the hyperplane quadratic programming problem, which is converted into a dyadic problem with the computational expression:

$$\begin{cases} \max_{l_j} \sum_{j=1}^{k} l_j - 1/2\sum_{j=1}^{k} l_j o_j \left(G_i(g,t)\cdot G_j(g,t)\right) \\ s.t. 0 \leq l_j \leq E, \sum_{j=1}^{k} o_j l_j = 0, j=1,2,\cdots,k \end{cases} \tag{16}$$

where l_j represents the Lagrange multiplier.

Suppose that the samples are projected directly into the high-dimensional characteristic linear space F, in which the optimal hyperplane is constructed, at which point the expression for the dyadic problem is:

$$\begin{cases} \max_{l_j} \sum_{j=1}^{k} l_j - 1/2\sum_{j=1}^{k} l_j o_j \lambda_i \lambda_j \\ s.t. 0 \leq l_j \leq E, \sum_{j=1}^{k} o_j l_j = 0, j=1,2,\cdots,k \end{cases} \tag{17}$$

where λ_i represents the Lagrangian multiplier for load intensity exceeding the standard and λ_j represents the Lagrangian multiplier for load intensity not exceeding the standard.

The inner product formula for the optimal hyperplane in the high-dimensional space F is given by:

$$k(i,j) = \left[\lambda_i, \lambda_j\right] \tag{18}$$

where $k(i,j)$ represents the kernel function.

The decision function of the feature sample is:

$$G(g,t) = \sum_{j=1}^{k} o_j l_j k(i,j) + e \tag{19}$$

According to this decision function, the classification of the amount of exercise load can be completed and the monitoring of the amount of exercise load can be realized.

II. C. Optimization algorithm design

The data captured in the real-time acquisition device will be used as inputs, including current fitness status, training intensity, and physiological metrics. These data will be associated with the previously established dynamic features to form an input feature vector. The prediction will be made using the association model of dynamic features and real-time monitoring to obtain the physical fitness state in the future period. This prediction will be used as the goal of the optimization algorithm, i.e. the objective function.

Suitable optimization algorithms, such as genetic algorithms, are introduced to adjust the training load by optimizing the objective function to make the predicted fitness state more consistent with the actual monitoring state. The goal of the optimization algorithm is to achieve the best results of physical training while reducing the risk of injury to the athlete.

The results of the optimization algorithm should be fed back to the trainer and the real-time acquisition device in a timely manner so that the load can be adjusted in real time during the training process. This real-time adjustment feedback mechanism can use intuitive graphical displays, alarm prompts, etc., so that the trainer can better understand the optimization results and take timely action.

II. D.Non-dominated Sorting Genetic Algorithm NSGA-II

II. D. 1) Overview of the NSGA-II algorithm

Genetic algorithm (NSGA) shows better optimization performance in sports load optimization with its unique optimization mechanism, which provides an effective means for the solution of complex problems. Non-dominated Sorting Genetic Algorithm (NSGA-II) is a genetic algorithm based on the concept of Pareto optimization, which searches for high-quality solutions adapted to multiple objectives based on the NSGA algorithm by improving the fast non-dominated sorting, crowding degree and elite strategy to reduce the computational complexity and maintain the diversity of populations to improve the algorithm performance. Specifically, NSGA is improved in the following three aspects:

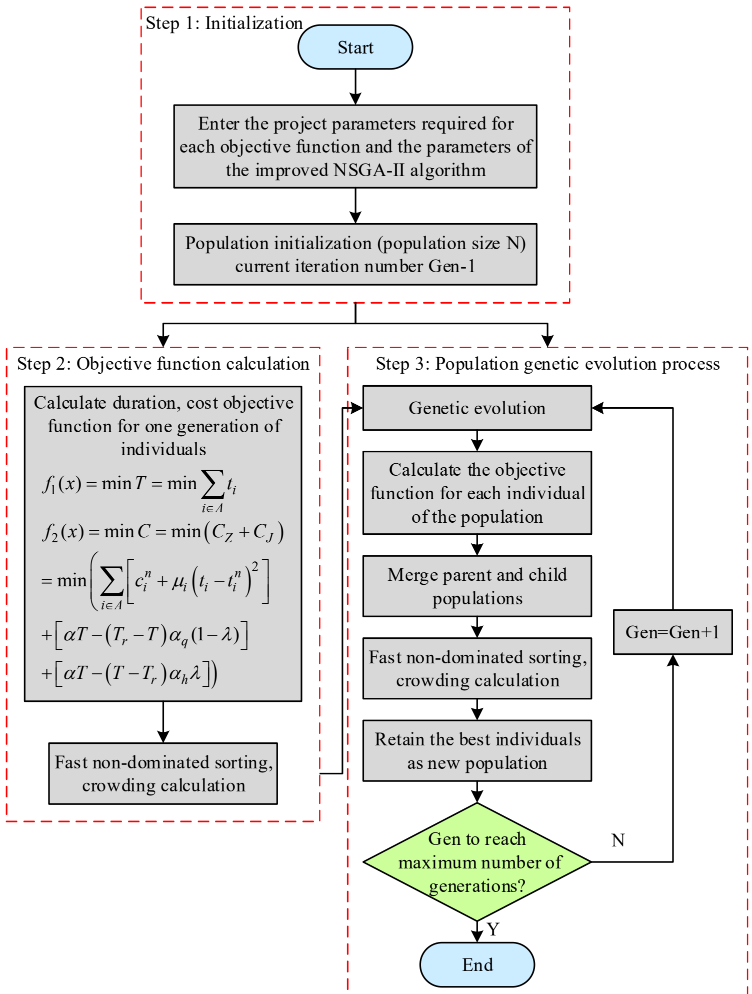

Figure 1: NSGA calculation flowchart

(1) To reduce the computational complexity of the algorithm, a fast non-dominated sorting method is introduced. This method significantly reduces the computational complexity of the algorithm from the original mN3 to mN2, making the algorithm more efficient in dealing with large-scale populations.

(2) NSGA-II also employs an elite strategy to expand the sampling space. By merging the parent and offspring populations and competing together to produce the next generation, it helps to retain the elite individuals in the parent generation and ensures that they can enter the next generation smoothly. Meanwhile, by storing the individuals in the population in layers, the best individuals are retained, which in turn rapidly improves the overall performance of the population.

(3) NSGA-II introduces the concepts of crowding degree and comparison operator, which effectively replaces the original fitness sharing strategy and avoids the tediousness of manually specifying the sharing radius. In the peer comparison after fast sorting, the crowding degree becomes a key factor in determining the winner. This

improvement enables individuals to be evenly distributed within the quasi-Pareto domain and extends to the entire Pareto domain, thus ensuring population diversity.

II. D. 2) NSGA-II algorithm computation flow

Figure 1 shows the NSGA computational flow. The specific flow of NSGA-II algorithm is:

(1) Initializing the population: in the solved duration cost objective function, the load variable is the underlying parameter of this objective function. Figure 2 shows the chromosome structure. Each chromosome is taken as a set of selection options, the chromosome coding method adopts decimal coding, the chromosome gene bit represents the coding serial number of the corresponding work, and the gene value is the corresponding duration of the corresponding work, which in turn randomly generates a set of initial solutions as the initial population in the search space.

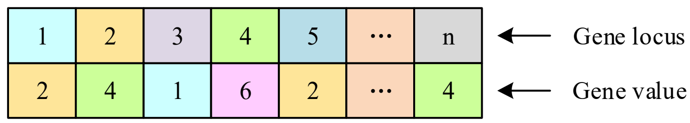

Figure 2: Chromosome structure diagram

(2) Constructing the non-domination layer: firstly, according to the selected fitness function that can reflect the comprehensive performance of the load cost, each individual of the population (load cost chromosome solution) is substituted into the fitness function to calculate its fitness value. Then non-dominated sorting is performed: the dominance relationship between each individual is determined based on the fitness function value. If neither the load nor the cost of one solution is inferior to another, the solution is said to dominate the other solution, and all the solutions are stratified according to the domination relationship to form multiple non-dominated layers.

(3) Calculate the congestion distance: the congestion distance reflects the degree of denseness between solutions in the same layer. For the solutions in each non-dominated layer, calculate the congestion distance between them. In the two dimensions of duration and cost, the distance between neighboring solutions is calculated separately, and these two distances are added to get the total congestion distance.

(4) Finally, a new offspring population is generated by the basic operation of genetic algorithm, and the parent and offspring are merged to form a new population, and the above operation is repeated until the condition of the end of the program is satisfied.

III. Application and analysis of correlation modeling with the introduction of the NSGA-II algorithm

After researching the related technology of balancing physiological indexes and exercise load based on genetic algorithm, this chapter applies the constructed association model introducing NSGA-II algorithm to athletes' physical fitness training. The physiological data of athletes during exercise were monitored by wearable real-time acquisition devices to judge the real-time and effectiveness of monitoring. The changes of muscle oxygen saturation with different incremental loads were used as an example to verify the optimization effect of the model. The experiments on the allocation and regulation of exercise load parameters in physical fitness training are set up to prove that the synergistic optimization model and method in this paper have application value.

III. A. Data acquisition and analysis

III. A. 1) Data acquisition process

Twenty athletes participating in physical fitness training were selected as research subjects, and the wearable device was used as a physiological state sensor to collect their physiological index data. Subjects wore wearable devices to continuously and dynamically collect their heart rate and respiratory rate in the exercise state, and subjects could exercise freely within the coverage of Wi-Fi signals. During the experiment, two groups of low-speed and high-speed exercise tests were conducted, low-speed exercise, i.e., subjects walked and jumped at their normal speed for 10 min, and high-speed exercise, i.e., subjects ran and rode at their maximum possible speed for 10 min, so as to monitor physiological parameters during exercise in real time. During the 2 sets of tests, the intensity of exercise load was categorized into 4 levels with 2.5, 5, 7.5 and 10 min as time points.

III. A. 2) Analysis of collected data

After wearing the wearable device, all subjects were able to move freely during the exercise training experiment time without any obvious discomfort. By reviewing the data, the heart rate and respiratory rate indicators of each subject could be captured and recorded. The physiological index data of subject A is used as a demonstration example. Figure 3 shows the cardiopulmonary physiological parameters of subject A under low-speed exercise acquired by the wearable device. Figure 4 shows the cardiorespiratory physiological parameters of subject A under high-speed exercise acquired by the wearable device. As can be seen from Figures 3 and 4, the athlete's heart rate was in the range of 45-85 beats/min-1 and respiratory rate was in the range of 90-130 beats/min-1 under the low-speed exercise condition, which fluctuated more gently; whereas under the high-speed exercise condition, the athlete's heart rate was in the range of 70-150 beats/min-1 and respiratory rate was in the range of 120-145 beats/min-1, which fluctuated more dramatically. The results of the analysis of basic cardiopulmonary physiological parameters were consistent with the actual physiological situation during low and high speed exercise. It indicates that the wearable devices are able to effectively collect basic human cardiopulmonary physiological parameters and reflect their developmental trends under different exercise training states. From the perspective of the monitored heart rate and respiratory rate indicators, the differences in monitoring indicators are not statistically significant ($P>0.05$). It can be seen that the selection of wearable devices as physiological state sensors in this paper can effectively collect continuous and dynamic data of heart rate, respiratory rate, muscle oxygen saturation and other indicators of athletes during physical fitness training, and the accuracy of the collection is high, so that these data can be used as physiological indicator data to participate in the subsequent modeling of exercise load.

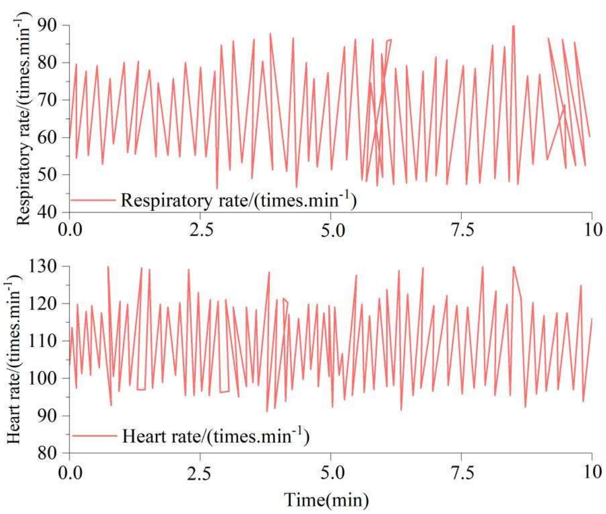

Figure 3: Changes of heart rate and respiratory rate during low-speed exercise

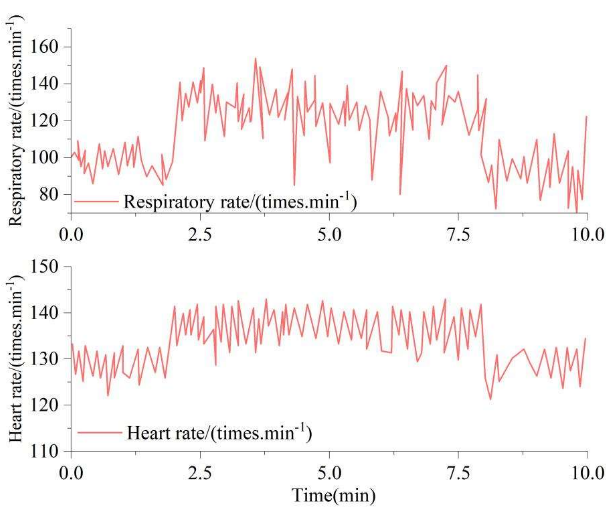

Figure 4: Changes of heart rate and respiratory rate during high-speed exercise

III. B. Changes in muscle muscle oxygen saturation with different incremental loads

III. B. 1) Analysis of changes in muscle oxygen saturation at incremental load intensities

The 2 sets of physiological index data collected by the device are input into the association model introducing the non-dominated sorting genetic algorithm NSGA-II for future physical state prediction, and the prediction results are optimized. Output the optimized results to the athletes, so that the athletes can adjust the exercise load independently according to the optimization results, so that their physiological state and exercise load can reach a balance and reduce the risk of injury. In order to analyze the data of 2 groups of physiological indexes re-collected after combining optimization and adjustment, the change of myocardial oxygen saturation with incremental load intensity was chosen as an example to demonstrate the effect of the association model introducing NSGA-II algorithm on the prediction and optimization of the relationship between myocardial oxygen saturation and exercise load.

During the actual incremental intensity exercise, the muscle oxygen content showed a decreasing trend with the incremental increase of exercise intensity. Figure 5 shows the trend of muscle oxygen saturation concentration of deltoid muscle with incremental load, which is consistent with the actual situation. That is, the gradual increase in the body's demand for oxygen during incremental load exercise is directly related to the increase in exercise intensity. The difference between body oxygen consumption and oxygen supply caused changes in muscle oxygen content, and the changes in muscle oxygen content during exercise were closely related to the level of intramuscular oxidative metabolism. At the 1st level of loading 55W power, deltoid muscle oxygen content was the highest, about 75%. With the gradual increase of exercise intensity, the muscle oxygen content gradually decreased, and reached the lowest at the 4th level of loading, which was about 50%. The range of variation in muscle oxygen content was around 25%. Although the body needs a large amount of oxygen supply in the final stage of the exercise load, the deltoid muscle muscle oxygen content did not appear deep hypoxia, indicating that the correlation model introduced into the NSGA-II algorithm can effectively calculate and optimize the future physiological state of the deltoid muscle of the athlete and give the results of regulation, so that the athlete does not suffer from hypoxia, and reduces the risk of physical fitness exercise training.

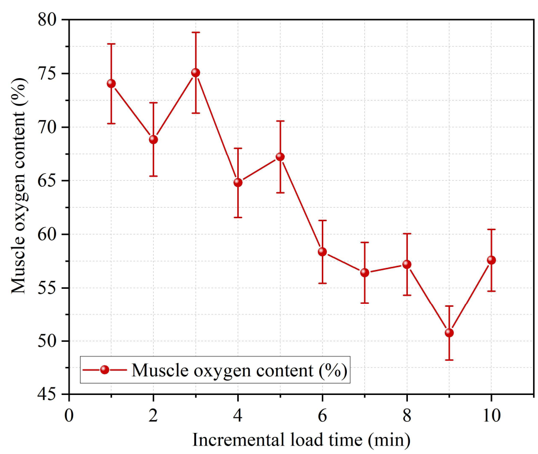

Figure 5: Change of deltoid muscle oxygen saturation concentration

III. B. 2) Changes in muscle oxygen saturation in the left lateral femoral muscle at increasing load intensities

Athletes performing incremental loading exercise on a power bike have higher muscle exercise intensity in the lower extremities and naturally consume more oxygen. Figure 6 shows the changes in muscle oxygen saturation of the left side of the lateral femoral muscle with incremental loading intensity. From Figure 6, it can be found that the muscle oxygen content of the left side of the lateral femoral muscle decreases very significantly with the increase of exercise intensity, and the muscle oxygen content at the beginning of the 1st level of loading 55W power is 66%, and at the end of the 1st level of loading the muscle oxygen content is 63.8%, which is a decrease of about 2.2%. The most pronounced decrease in muscle oxygen content was observed at level 2 load and level 3 load. At the end of level 3 loading, muscle oxygen concentration dropped to about 27%. The level 4 load remained until the end of the exercise, and the muscle oxygen was basically in a relatively stable state. It indicates that the correlation model introducing the NSGA-II algorithm outputs optimized regulation results in time to help the athletes adjust their exercise status after calculating the large decrease in muscle oxygen concentration and the possibility of future damage to the left side of the lateral femoral muscle, so that the muscle oxygen saturation of stage 4 loading until the end of the exercise can be maintained at a less depletion level and the possibility of loss can be reduced.

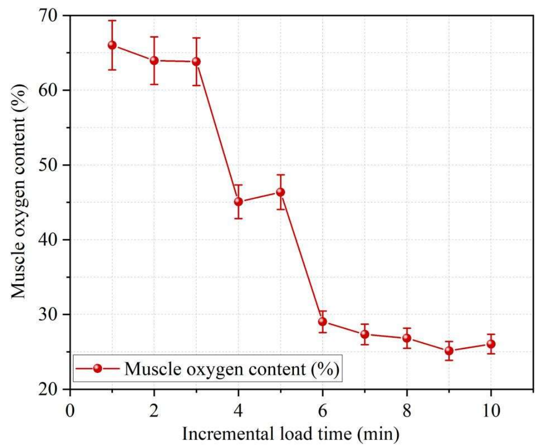

Figure 6: Change of oxygen saturation in the left lateral muscle of thigh

III. B. 3) Changes in myocardial oxygen saturation of the right lateral femoral muscle at incremental loading intensities

The stronger the muscle metabolism of oxygen, the more fully mobilized and utilized the local oxygen in the body, affected by the muscle utilization of oxygen by the type of muscle fibers and the number of mitochondria and the activity of oxidative enzymes within the muscle, muscle aerobic metabolism ability of the body's maximum oxygen uptake has a decisive role in the body's maximum oxygen intake, the higher the utilization rate of the local muscle oxygen, the larger the body's maximum oxygen uptake, such as the local muscle utilization of oxygen, the lower the rate of glycolysis supply situation occurs earlier when performing incremental load intensity exercise, which is detrimental to the continuation of exercise, affecting the exercise capacity. If the local muscle utilization of oxygen is lower, the earlier the glycolytic energy supply situation appears during the incremental load intensity exercise, which is not conducive to the continuation of the exercise and affects the exercise capacity. Figure 7 shows the change of muscle oxygen saturation of the right side of the lateral femoral muscle with increasing load intensity. From the graph in Figure 7, it can be seen that the muscle oxygen content of the right side of the lateral femoral muscle also decreases very significantly with increasing exercise intensity. At the 1st level of load 55W power to the 3rd level of load 155W power, the muscle oxygen content decreased from 76% to about 30%, and at this stage the muscle oxygen content was slightly higher than the left side, and then the muscle oxygen content was basically in a relatively stable state in the subsequent exercise load exercise. Similarly, according to the change of muscle oxygen saturation of the right side of the lateral femoral muscle, it can be judged that the correlation model introduced into the NSGA-II algorithm has a computational optimization effect between physiological state and exercise load, which helps the athletes to carry out effective regulation.

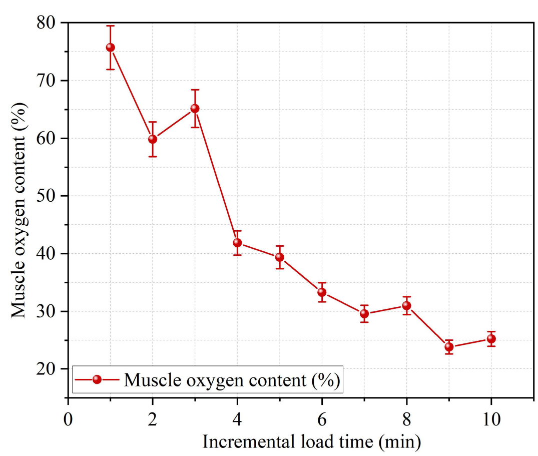

Figure 7: Change of oxygen saturation in the right lateral muscle of thigh

III. C. Pre-training Load Allocation and Regulation Experiment for Athletes

III. C. 1) Experimental setup

From the study in 3.2, it is found that the correlation model introduced into NSGA-II algorithm in this paper can effectively calculate the correlation between athletes' physiological state data and exercise load, predict the future physical state, and give the regulation scheme to assist the athletes to make optimized adjustments. This section further takes the pre-fitness training of ice dance athletes as an example to set up the experiment of pre-training load allocation and regulation of athletes. One of the important tasks of professional ice dance athletes in the pre-training period is to achieve a rapid and high-quality mastery of the techniques for completing each individual dance movement in the skating of a group, a part and a full set of dance movements. After studying the peculiarities of the pre-training structure of advanced ice dancers (ice training with integrated training of general physical functions and training for dance and performance), the following methods were used in the course of the research: pedagogical observation and experimentation, time measurement, mathematical-statistical processing of the obtained data.

Analyzing the changes in the training load of ice dance showed that the characteristics of solving the basic tasks and the need for a certain articulation should be taken into account in the preperiod. The preliminary stage should be reasonably divided into the following 4 stages: entering the preparatory state stage; familiarize with the mastery of the training content stage; monitoring training stage; pre-competition and final mastery of the training content stage. 4 stages of the intensity of the sports training load increases step by step.

Table 1 shows the different training load indicators of the 4 stages. The most important characteristic of stage Ⅰ is that it does not last long (2 weeks). In the 1st week, the main attention is focused on skating training, and in the 2nd week, the work practice for mastering the prescribed dances is started. During this time, athletes typically train once or twice a day. Phase II is the beginning of the prescribed training content - the number of dance drills increases to four. Operators train twice a day (in the morning and in the evening), and this is when the training load and intensity are increased. The duration is 3 weeks. Phase III continues with training to improve the completion of each set of dance slides, and the load should be increased according to the completion of the full set of dance slides. At this point, all efforts should be focused on monitoring the quality of mastery of the major new dance slides. Duration 6 weeks. In Phase IV before the competition, the load is increased in the practice of the prescribed dances and the choreographed dances, and the technique of the choreographed dances is gradually perfected. Duration 5 weeks.

Table 1: Training load change index

Training load index	Preparatory phase															
	Stage Ⅰ (2 weeks)				Stage Ⅱ (3 weeks)				Stage Ⅲ (6 weeks)				Stage Ⅳ (5 weeks)			
	Dance sequence															
	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
Number of moves (difficult, rotating moves)	58	60	44	-	160	181	96	95	240	277	196	154	310	205	181	190
The number of actions in a set	5	6	4	-	121	90	62	45	271	271	253	212	410	335	353	289
Number of sets	1	2	3	-	19	22	11	9	51	42	53	30	95	81	95	81
Number of free dance gliding moves	-	-	-	-	-	-	-	100	-	-	-	252	-	-	-	601
Total time required to complete required dance training (hours)	4	5	4	-	15	15	13	22	25	18	20	29	37	36	38	39
Pure time to complete training (hours)	3	4	5	-	3	11	10	3	21	15	18	24	31	30	29	32
Number of training sessions per session	14±3				50				65				89			
Daily training amount per session	12±3				25				31				50			

Note: The first week of phase Ⅰ - enter the preparatory training phase, 1 - the first prescribed dance, 2 - the second prescribed dance, 3 - the third prescribed dance, 4 – choreography

III. C. 2) Analysis of experimental results

With physiological indicators such as heart rate, respiratory rate, muscle oxygen saturation, etc., using wearable devices and well-trained correlation models introducing NSGA-II algorithms, real-time acquisition of athletes' indicator data under different training loads at a frequency of once per second, focusing on the dynamic feature extraction of load data, synergistically optimizing the error between real-time monitoring indicator data and the model's prediction data, and parameter regulation, so as to make the athletes' physical function maintains the excellent level in different training loads in the whole stage. Take heart rate as an example to analyze the experimental results. Table 2 shows the real-time output of the wearable device and the experimental results after optimization of the model prediction. In Table 2, the real-time heart rate is the data obtained by performing an acquisition every minute, the model-predicted heart rate is the prediction result obtained by the correlation model, and the optimized and adjusted heart rate is the adjusted heart rate under the guidance of the NSGA-II algorithm.

The real-time acquisition wearable device used in the experiment ensured that the heart rate data was transmitted in real time at a frequency of once per second. This ensured that the model was able to rapidly predict physiological changes in the athlete. Trainers and athletes were able to visualize the athlete's fitness status and take timely action. By establishing a correlation model between the dynamic features and the real-time monitored heart rate, the device is able to adjust the model parameters in real time based on the continuous collection of feature data in order to more accurately predict the future state of the heart rate.The NSGA-II algorithm, as an optimization algorithm, is able to optimize the error between the predicted heart rate of the model and the actual monitored heart rate in the experiments. This made the model's prediction more realistic.The results of the NSGA-II algorithm were fed back to the trainer and the monitoring device through real-time adjustments. For example, in the 4th minute of the experiment, the real-time acquisition device predicted a heart rate of 90, which was finally adjusted to 90 after the adjustment of the correlation model introduced into the NSGA-II algorithm, which was consistent with the actual monitored heart rate.

From the overall viewpoint, the synergy of dynamic feature extraction and real-time monitoring equipment enables the trainer to have a more comprehensive understanding of the athlete's physical condition, while the real-time adjustment through the introduction of the correlation model of the NSGA-II algorithm can realize the precise adjustment of the training load and improve the training effect. This synergistic optimization method provides a more scientific and intelligent monitoring and adjustment means for physical training.

Table 2: Experimental results

Time (minutes)	Real-time heart rate monitoring	Model predicted heart rate	Adjust heart rate after optimization
1	83	86	83
2	85	87	85
3	89	94	89
4	90	92	90
…	…	…	…
50	76	82	76

IV. Conclusion

Aiming at the dynamic balance between physiological state and exercise load in athletes' physical fitness training, this paper constructs an association model based on non-dominated sorting genetic algorithm for real-time collaborative optimization of athletes' training process. Through experimental verification, the model can effectively predict the change of muscle oxygen saturation under the incremental load in 4 stages. Among them, the muscle oxygen saturation of the left lateral femoral muscle rapidly decreased from 66% to about 27% under the incremental load in the first 3 stages. The muscle oxygen saturation of the right muscle of the lateral femoral muscle decreased rapidly from 76% to about 30% under the incremental load in the first 3 stages. Co-optimization by NSGA-II algorithm made the muscle oxygen saturation of the right and left lateral femoral muscles in the 4th stage keep a smaller decrease to ensure that the athletes would not be injured due to deep hypoxia. Take the pre-fitness training of ice dance athletes as an example to carry out the exercise compliance optimization and regulation experiment. It is verified again that the model of this paper also has good prediction and optimization effect in the real-time parameter allocation and regulation in the longer phase, and can optimize the heart rate prediction error to zero deviation in the real-time regulation. The model in this paper can significantly reduce the injury risk of athletes and improve the training science. In the future, genetic algorithm and multi-algorithm fusion can be explored in depth, as well as the modeling optimization of long-term training data, to improve the generalization ability of the model, and to provide athletes with better exercise load regulation for physical fitness training.

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