ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

Mobile technology applications in sports training: sensor-based adaptive environment optimization for motion data

Qiubin Chen[1,*]

[1] Physical Education Institute, Jimei University, Xiamen, Fujian, 361021, China

SUMMARY: *This paper proposes a set of adaptive environment optimization system based on digital filtering technology, feature extraction technology and as a basis for the optimization of athletes' sports training, which adopts a multi-level feedback control architecture, with the environment perception layer responsible for data acquisition, the decision analysis layer executing intelligent algorithms, and the executive control layer, realizing intelligent recognition of sports status and quantitative assessment of training effect. The empirical results show that the athletes in the experimental group improved their specialized skills by 12.7% and their physical fitness composite index by 15.3%, which are significantly better than the control group. Physiological monitoring shows that the average heart rate in the optimized environment is reduced by 9.1%, and the recovery time is shortened by 26.2%, indicating that the system can effectively reduce the load and promote the recovery, providing an effective technical solution for the scientific and personalized sports training.*

KEYWORDS: *digital filtering technology; sports training; adaptive environment optimization; exercise state; intelligent recognition*

1 Introduction

With the continuous progress of science and technology, the application of mobile technology has brought unprecedented changes in the field of sports training, especially the application of sensor technology, which not only improves the training efficiency of athletes, but also greatly improves their competitive performance and health [1-4].

In sports training, the monitoring of physiological indicators is crucial for assessing athletes' physical status and training load [5, 6]. Sensor technology is capable of monitoring physiological parameters such as heart rate, blood pressure, and oxygen saturation of athletes in real time [7]. By wearing a heart rate monitoring bracelet or chest strap, coaches can keep track of the athlete's heart rate variations during training to ensure that the training intensity is within the appropriate range [8, 9]. If the heart rate is too high, it may mean that the training intensity is too high, which may easily lead to fatigue and injury, while too low a heart rate may indicate a poor training effect. In addition, the oxygen saturation sensor can reflect the oxygen supply of the athlete and help the coach to judge whether the athlete is in the best physical condition [10, 11]. Through the analysis of these data to achieve the adaptive optimization of the training environment, coaches can more scientifically formulate training plans and programs to improve the relevance and effectiveness of training [12-14]. At the same time, virtual reality technology can be utilized to provide a more realistic training environment and improve the training effect and competitive level of athletes [15]. In addition, the intelligent

*qiubinchen2023@163.com
https://doi.org/10.65102/is2026723 Published: 30 April, 2026

training system can automatically generate personalized training plans and programs according to the characteristics and needs of the athletes to improve the personalization and specialization of training [16, 17].

According to the sensor data-driven adaptive environment optimization method proposed in this paper, the method can be divided into three levels, the perception layer composed of multiple sensors is responsible for acquiring movement information about the athlete and sending it to the processing layer; the data information obtained is used in the processing layer to judge the current state of the athlete and fed back to the relevant devices in the optimization layer; finally, corresponding changes are made in the optimized environment to adapt to the The optimization layer is mainly composed of various types of sensing layers. The sensing layer mainly consists of various types of sensors to collect real-time data on the athlete's body information and movement status, among which the acceleration sensor measures the acceleration of each point of the human body in three different directions at a speed of 100 times per second, and the results of each measurement are accurate to centimeters per second, so as to record the athlete's movement distance and speed. The data preprocessing layer filters and reduces the noise of the collected data to remove the noise information; the feature extraction layer uses PCA analysis and time frequency domain analysis to extract the effective information in the action sequences, i.e., the main characteristic factors; the pattern recognition layer utilizes the SVM and BP neural network model to complete the discrimination of the action categories and make the corresponding evaluation of the student's learning situation.

2 Research methodology

2.1 Sensor technology

For sports training monitoring, the application of sensing devices has evolved from single-element detection to a diversified overall detection mode; while the inertial navigation module can be combined with a three-direction gravitational accelerometer, three-direction velocity-torque meter, and three-direction magnetometer to form a nine-dimensional space to accurately record subject spatial coordinates, rate, acceleration, and angular information.

Acceleration sensor is based on Newton's law F = ma physical principles to work, it can feel the acceleration of a sensitive element (made of silicon micromachining a cantilever beam or mass block - spring) to determine the acceleration, when the sensitive element by the external acceleration of the role of its internal mass block will produce movement, within a certain range, the size of the acceleration is directly proportional to the distance of the mass block movement. The relative displacement of the inertial mass in the sensing element is converted into a corresponding electrical signal and output via the capacitive, piezoresistive or piezoelectric principle. The linear relationship between the output voltage of a capacitive acceleration sensor and the acceleration can be expressed as follows:

$$V_{out} = S \cdot a + V_{offset} \tag{1}$$

where S represents the sensor sensitivity parameter, a is the acceleration value to be measured and V_{offset} is the zero bias voltage component.

The gyroscope measures the angular velocity parameter through the principle of Coriolis effect, when the sensor rotates around a specific axis the internal vibration mass block is subjected to Coriolis force to produce displacement in the direction perpendicular to the vibration direction and the rotation axis, the displacement is proportional to the angular velocity, which is mathematically described as:

$$F_c = 2mv \times \Omega \tag{2}$$

where F_c denotes the Coriolis force, m is the mass of the mass block, v is the vibrational velocity vector, and Ω is the angular velocity vector.

Magnetometers use the magnitude of the Earth's magnetic field in 3 orthogonal axes to measure the absolute azimuth of the sensor, and work on the basis of the Hall or magnetoresistive effect, where a current is generated in a magnetic field proportional to the magnetic field. Biosensors can be better used to test physiological indicators of athletes, heart rate sensors use the optical volume change tracing method, photoelectric heart rate sensors use a certain wavelength of light passing through the skin tissue, and by measuring the change in the degree of regular absorption of light by hemoglobin in the blood to find out the value of the heart rate, and the principle of which satisfies the Beer-Lambert law:

$$I = I_0 e^{-\alpha cl} \tag{3}$$

where I is the transmitted light intensity, I_0 is the incident light intensity, α is the molar absorption coefficient, c is the hemoglobin concentration, and l is the optical range length.

Pulse oximetry utilizes the different absorption rates of oxyhemoglobin and deoxyhemoglobin in the red and near-infrared regions, and the value of SpO_2 is obtained by detecting the ratio of the light absorption at two different wavelengths and performing a calculation.

$$SpO_2 = \frac{HbO_2}{HbO_2 + Hb} \times 100\% \tag{4}$$

Myoelectric signal sensor is based on the electrodes pasted on the body surface to detect the bioelectric current generated by human muscle activity, and the current size will change with the change of muscle excitability, so that it can quantitatively analyze the muscle fatigue degree of the sports personnel; Sweat conductivity sensor is to reflect the athlete's psychological and tension status by measuring the change of conductivity value of the surface of the body, and it mainly utilizes the change of sweat volume Sweat conductivity sensor is to reflect the mental and tension condition of the athlete by measuring the change of the conductivity value of the body surface, mainly utilizing the change of sweat to realize the measurement function.

The environmental sensor network provides comprehensive data support for the monitoring of training field conditions, in which the temperature sensor for temperature measurement is mainly composed of thermistors or thermocouples, and the resistance value of the thermistor and the temperature satisfy the Steinhardt-Hart equation:

$$\frac{1}{T} = A + B\ln(R) + C(\ln(R))^3 \tag{5}$$

where T is the absolute temperature, R is the resistance value, and A, B and C are the material characteristic constants.

Humidity sensor based on capacitive or resistive principle of work, capacitive humidity sensor capacitance value and relative humidity is a linear relationship:

$$C = C_0(1 + \alpha \cdot RH) \tag{6}$$

where C_0 is the capacitance value in dry state, α is the humidity coefficient, and RH is the relative humidity value.

The light intensity sensor adopts silicon photodiode or photoresistor, and its output current is proportional to the incident light intensity $I_{ph} = S \cdot \Phi$, S is the spectral responsivity, and Φ is the incident light flux. The air quality sensor evaluates the training environment by detecting the concentration of pollutants, such as fine particulate matter 2.5, respirable particulate matter 10, carbon dioxide, carbon monoxide and so on. Air quality conditions.

2.2 Methods for analyzing motion data

2.2.1 Digital filtering techniques

Motion data analysis technology is an important bridge between sensor-acquired data and training instruction recommendations, in which a variety of algorithms need to be used for in-depth analysis of the data; data cleaning technology is a technical means to remove the interference factors in the sensor-acquired data, to correct the bias and to unify the data units. As the data measured by the sensor is mixed with high-frequency random noise and baseline drift values or some outliers and other issues, in the frequency domain space or time domain space of these data for the process of precision processing is called digital filtering, Butterworth low-pass filter transfer function is:

$$H(s) = \frac{1}{1 + \left(\frac{s}{\omega_c} \right)^{2n}} \tag{7}$$

where ω_c represents the cutoff frequency parameter and n denotes the filter order. It maintains the maximum flat response property in the passband range, a property that gives it a significant advantage in maintaining the waveform integrity of motion signals.

The Kalman filtering algorithm constructs the optimal estimation framework of the dynamic system based on the state space model by predicting the steps:

$$\hat{x}_{k|k-1} = F_k \hat{x}_{k-1|k-1} + B_k u_k \tag{8}$$

and update steps recursively computed to achieve state estimation:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \left(z_k - H_k \hat{x}_{k|k-1} \right) \tag{9}$$

where F_k is the state transfer matrix, B_k is the control input matrix, H_k is the observation matrix, and K_k is the Kalman gain, which together form the mathematical basis of the algorithm.

The outliers are identified using a statistical determination method based on the 3σ criterion, and the data points are labeled as outliers when they satisfy the condition $|x_i - \mu| > 3\sigma$ (μ is the sample mean and σ is the standard deviation). The data interpolation technique is based on the linear interpolation formula:

$$y = y_1 + \frac{x - x_1}{x_2 - x_1}\left(y_2 - y_1\right) \tag{10}$$

Alternatively, a segmented polynomial with trisample interpolation is used to fill in the gaps in the sensor's data, and for synchronization between multiple sensors, a time-stamped alignment and resampling approach is used to solve the problem due to the unequal sampling rates of the sensors, where an interpolation or extraction method is used to align the data at the same point in time.

2.2.2 Feature extraction techniques

Feature extraction methods are used to extract and characterize important motion features from motion data that have been preprocessed, and time domain features are used to portray the overall nature of the signal from a number of aspects, with the mean value calculated as:

$$\overline{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{11}$$

Frequency domain feature extraction is built on the basis of Fourier transform theory, and the discrete Fourier transform realizes the conversion of the time domain signal to the frequency domain space.

$$X(k) = \sum_{n=0}^{N-1} x(n)e^{-j2\pi kn/N} \tag{12}$$

The power spectral density function $P(f) = |X(f)|^2$ reveals the distribution law of the signal energy in the frequency dimension, the main frequency component is determined by searching for the peak of the power spectrum, and the frequency center of gravity is calculated to provide information about the centralized trend of the spectral energy distribution.

$$f_c = \frac{\sum_{k=1}^{N/2} f_k \cdot P(f_k)}{\sum_{k=1}^{N/2} P(f_k)} \tag{13}$$

The joint time-frequency domain analysis introduces the wavelet transform technique to deal with non-stationary signals, continuous wavelet transform:

$$W(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right)dt \tag{14}$$

Multiresolution analysis is realized by coordinated cooperation of the wavelet function $\psi(t)$, the scale parameter a, and the time-shift parameter b, the Morlet wavelet:

$$\psi(t) = \frac{1}{\pi^{1/4}} e^{j\omega_0 t} e^{-t^2/2} \tag{15}$$

With its excellent localization characteristics in the time-frequency domain it becomes an ideal choice for analyzing non-stationary motion signals. The kinematic characterization covers the statistical properties and variation patterns of parameters such as displacement, velocity, acceleration, etc. Velocity information is deduced from acceleration data by numerical integration and differential operations, trapezoidal integration method:

$$v(t) = v_0 + \int_0^t a(\tau) d\tau \approx v_0 + \sum_{i=1}^{n} \frac{a_i + a_{i-1}}{2} \Delta t \tag{16}$$

and displacement calculations:

$$s(t) = s_0 + \int_0^t v(\tau) d\tau \tag{17}$$

Forming the mathematical basis for the derivation of kinematic parameters, physiological feature extraction involves multiple dimensions such as heart rate variability analysis, EMG signal processing and fatigue state assessment.

The time-domain metrics of heart rate variability include the standard deviation of adjacent interbeat intervals:

$$SDNN = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (RR_i - \overline{RR})^2} \tag{18}$$

and the root mean square of the difference between adjacent interbeat intervals:

$$RMSSD = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (RR_{i+1} - RR_i)^2} \tag{19}$$

Frequency domain metrics are obtained by power spectral analysis of key parameters such as low frequency power, high frequency power and their ratios, and EMG signal feature extraction including root mean square values:

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^{N} x_i^2} \tag{20}$$

Average power frequency:

$$MPF = \frac{\sum_{i=1}^{M} f_i \cdot P_i}{\sum_{i=1}^{M} P_i} \tag{21}$$

These indicators are sensitive to the process of dynamic changes in the degree of muscle activation and fatigue state.

2.2.3 Data mining algorithms

Data mining algorithms are the core part of intelligent analysis techniques for sports data, machine learning methods are used to discover implicit relationships between data by learning from training samples and to build data models with predictive functions, SVM algorithms are used to classify data on high-dimensional spaces by solving the optimal separating hyperplane, and the objective equation:

$$\min_{w,b,\xi} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i \tag{22}$$

Solving for optimal parameters under constraints:

$$y_i(w^T\phi(x_i)+b) \geq 1-\xi_i \tag{23}$$

The kernel function implements a nonlinear mapping of low-dimensional features to a high-dimensional space:

$$K(x_i, x_j) = \phi(x_i)^T\phi(x_j) \tag{24}$$

Linear nuclei:

$$K(x_i, x_j) = x_i^T x_j \tag{25}$$

Polynomial kernels:

$$K(x_i, x_j) = (x_i^T x_j + c)^d \tag{26}$$

Radial basis function kernel:

$$K(x_i, x_j) = \exp\left(-\gamma\left\|x_i - x_j\right\|^2\right) \tag{27}$$

Provide flexible options for different application scenarios.

Cluster analysis is used to mine the implicit pattern structure in motion data, and the K-means algorithm achieves automatic grouping of data by minimizing the sum of squares within classes:

$$J = \sum_{i=1}^{k}\sum_{x\in C_i}\|x-\mu_i\|^2 \tag{28}$$

where μ_i is the i th clustering center.

Hierarchical clustering performs merging or splitting operations step by step by calculating the inter-sample distance matrix, Density clustering algorithms are capable of recognizing arbitrarily shaped clustering structures, Association rule mining reveals potential correlations between motion parameters, Support degree:

$$\sup port\left(A \Rightarrow B\right) = \frac{|A\cup B|}{|D|} \tag{29}$$

Confidence:

$$confidence\left(A \Rightarrow B\right) = \frac{|A\cup B|}{|A|} \tag{30}$$

$$lift(A \Rightarrow B) = \frac{confidence(A \Rightarrow B)}{\sup port(B)} \tag{31}$$

It constitutes a quantitative assessment system of associated strength.

In practice, appropriate analysis techniques should be used in conjunction with specific athletic programs and research purposes, such as race walking, sprinting and other sports biomechanical analysis and technical diagnosis, soccer, basketball and other tactical behavior analysis and collective cooperation analysis, long-distance running and other training intensity monitoring and functional evaluation, gymnastics and other action completion analysis and mastery analysis, the above analysis methods are integrated to form a complete sports data analysis system, thus providing comprehensive guidance and reference for scientific training. A complete sports data analysis system is formed by combining the above analysis methods, thus providing comprehensive guidance and reference information for scientific training.

2.3 Adaptive environment optimization design

Adaptive environmental control system is a multilevel feedback control system: the information collection part is the environment perception; the information processing part is the decision-making judgment; and finally the execution part is the control. In the temperature setting should be combined with the body's own thermal regulation ability to consider, without increasing too much physiological heat consumption under the premise (18 ~ 24 ℃) to ensure that the body's motor muscles can achieve a high rate of contraction and will not be adversely affected by the temperature is too low. Humidity in the air affects the speed of sweating and heat dissipation, humidity at 40% ~ 60% helps sweating and heat dissipation without dry mouth.

Brightness meets the needs of visual function and the human body's biological clock, with an illuminance value of 300 to 500 lux; CO_2 content of less than 1,000 ppm protects the indoor personnel's demand for O_2, and PM2.5 of less than 35 μg/m³ reduces the load on the lungs.

The coupling relationship between environmental parameters is quantified by the heat index formula:

$$\begin{aligned} HI = c_1 + c_2 T + c_3 RH + c_4 T \cdot RH + c_5 T^2 + c_6 RH^2 \\ + c_7 T^2 \cdot RH + c_8 T \cdot RH^2 + c_9 T^2 \cdot RH^2 \end{aligned} \tag{32}$$

where T denotes temperature, RH denotes relative humidity, and c_1 to c_9 are empirical coefficients, which comprehensively reflect the degree of influence of temperature and humidity combination on human comfort.

This paper adopts a hybrid intelligent algorithm based on particle swarm algorithm and fuzzy control method to optimize the environmental parameters. In this type of algorithm, the particle swarm algorithm mainly completes the global search work, and its basic idea is to imitate the behavioral characteristics of birds foraging in groups, while the fuzzy control method is a control algorithm designed using fuzzy theory. Where the particle is a feasible solution i.e. a set of environmental parameter values, the movement of the particle in the search space is represented as:

$$v_{i,d}^{t+1} = w \cdot v_{i,d}^{t} + c_1 \cdot r_1 \cdot \left(p_{i,d}^{t} - x_{i,d}^{t} \right) + c_2 \cdot r_2 \cdot \left(g_d^{t} - x_{i,d}^{t} \right) \tag{33}$$

$$x_{i,d}^{t+1} = x_{i,d}^{t} + v_{i,d}^{t+1} \tag{34}$$

where w is the inertia weight, c_1 and c_2 are the acceleration coefficients, r_1 and r_2 are the random numbers, $p_{i,d}^t$ is the particle's historical optimal position, and g_d^t is the global optimal position.

Adaptation function:

$$F = \alpha_1 \cdot f_{comfort} + \alpha_2 \cdot f_{energy} + \alpha_3 \cdot f_{stability} \tag{35}$$

Considering the three objectives of athlete comfort, energy efficiency and environmental stability, the comfort function $f_{comfort}$ is constructed based on the human thermal comfort model, the energy consumption function f_{energy} evaluates the power consumption characteristics of the equipment, and the stability function $f_{stability}$ measures the degree of fluctuation of the parameters.

3 Experiments and analysis of results

3.1 Experimental design

In order to verify the validity of the method based on the sensor-collected information to realize the dynamic regulation of personalized sports field, the controlled group experimental design method was used for analysis in this study. The basic information of the subjects in the two groups is shown in Table 1. 60 athletes from a provincial team were selected as subjects in this study, with ages ranging from 18 to 25 years old, with an average of 21.3±2.1 years old. The subjects had been training for more than 5 years and had high specialized sports performance (national level 2 and above). The age of the athletes was from 18 to 25 years old; among them, 36 were male athletes and 24 were female athletes; the sports involved were four categories: track and field, swimming, ball games and gymnastics. Athletes were enrolled in the trial after passing a physical examination, excluding athletes with cardiovascular disease, respiratory disease and other chronic diseases that might interfere with the trial, and obtaining consent from the subjects and permission from the ethics committee. A computer-generated random number table was applied to divide the 60 athletes into an experimental group and a control group of 30 athletes each. There were no significant differences ($p>0.05$) between the two groups in terms of age, gender, years of training, specialization distribution and basic physical fitness indexes, which ensured a balanced and comparable grouping.

Table 1: Statistical Table of Basic Information of Experimental Subjects

Grouping	N	Age (years)	Training years (years)	Male/female ratio	Specialized distribution
Experimental Group	30	21.2±2.0	7.8±1.5	18/12	Track and field 8, Swimming 7, ball games 9, Gymnastics 6
Control group	30	21.4±2.2	7.6±1.7	18/12	Track and field 8, Swimming 8, ball games 8, Gymnastics 6
Total	60	21.3±2.1	7.7±1.6	36/24	Track and field 16, swimming 15, ball games 17, Gymnastics 12

In this study, two gymnasiums of the same type were selected for comparative tests, each with a floor area of about 800m², a net height of about 4.5m, and exactly the same internal facilities and sports equipment, the only difference being that one of them adopts an intelligent regulation system based on sensing technology to regulate the environment. The sensors are laid out in a grid, with one environmental parameter collector set up in every certain area (area not larger than 100m²), and the distance between two neighboring environmental parameter collectors is not larger than 10 m. Constant Temperature: the room temperature is controlled by the inverter air-conditioner and underfloor heater, with a control error of ±0.3℃, and a regulation time of 2~4min; Constant Humidity: a closed-loop adjustment is made by the use of a humidifier and dehumidifier, with a control error of ±1.5%, and a regulation time of ±4min. 1.5%, the adjustment time is 3 to 6min; illumination: LED intelligent lighting to control indoor illumination, the illumination value can be adjusted between 200 to 800lux, the color temperature can be adjusted between 3000K to 6500K; clean air: by the fresh air machine, air purifier, CO_2 detection device composition. Ensure that the indoor air quality is continuously good. The control group training hall adopts the traditional environmental control method, i.e., the indoor temperature is constant at 22℃, the relative humidity is 50%, and the light level is maintained at 400lux. The facilities, equipment and management of the two training halls are the same, and only the environmental control is different, which ensures the uniformity and singularity of the experimental conditions.

The comparison of training load changes during the experiment is shown in Figure 1. The experimental process strictly followed the norms of scientific research, and the whole experimental period was set as 8 weeks, which was divided into three phases, namely, baseline testing period (1 week), acclimatization period (1 week), and official experimental period (6 weeks). In the baseline testing period, we assessed all athletes' physiological indexes, fitness levels and specialized skills, and established individual basic data files.

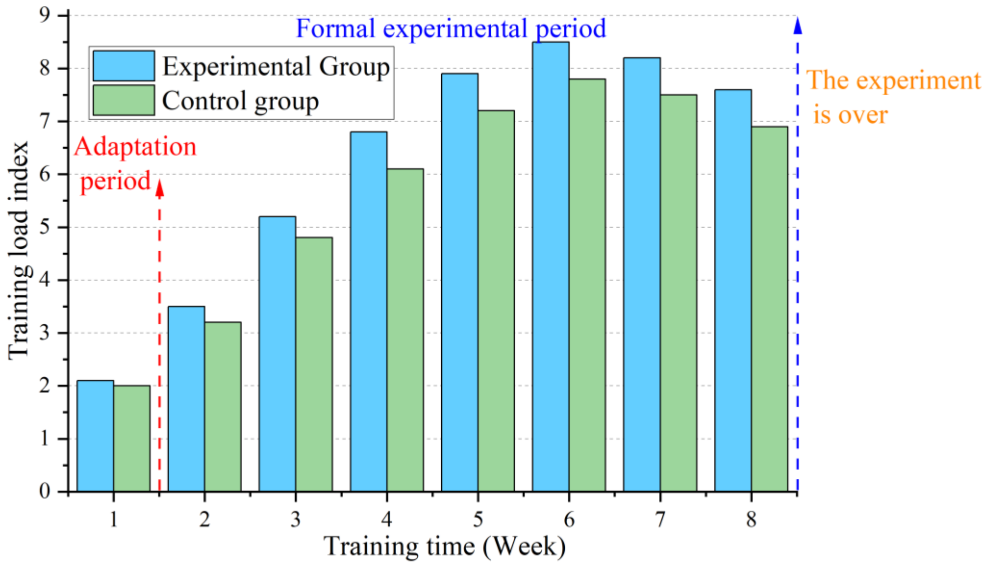

Figure 1: Comparison of training load changes during the experiment

The acclimatization period is mainly to familiarize the subjects with the laboratory environment and process, so as to avoid the effect of the experiment due to the change of environmental factors. After entering the formal experimental stage, the corresponding training as well as data collection were carried out according to the experimentally designed program. The same periodical training program was used in the training, six days a week, one day off, three hours of training per day, skill training from 9:00 a.m. to 11:30 a.m., and physical training from 3:00 p.m. to 4:00 p.m. According to the different programs, different training contents were developed, but the intensity of the training and the amount of training as well as the training methods were the same between the two groups.

The test method was designed as a multi-level and high-frequency data collection program, and the physical indicators covered heart rate, blood pressure, body temperature, oxygen saturation, lactate level, etc. The portable multi-parameter monitor was used to detect the values of the indicators in the quiet state every 15 min; the smart bracelet was worn to dynamically detect the heart rate and body temperature during the exercise period. The kinetic indexes were obtained with the help of inertial sensors and video analysis software, the sampling rate of the collector was 200Hz, and the shooting rate of the camera was 120fps.

Environmental factors: environmental factors were collected every 60 seconds, mainly including temperature, humidity, illuminance, airflow rate, CO_2 concentration and PM2.5 concentration; subjective feeling scale: mainly including subjective effort scale, heat sensation scale, and fatigue self-assessment scale, etc., which were filled out at the end of each training session. Specialized skill tests were conducted in the form of biweekly quizzes, and physical fitness tests were conducted once a week, and strength, speed, endurance, flexibility and coordination were assessed. Strict quality control measures, regular maintenance and repair of instruments, unified training of data entry personnel, audit and confirmation of data entry, timely review of questionable data, and video monitoring of the entire test process ensure the design of the test program and the authenticity of the test data.

3.2 Data analysis and results

In this paper, multilevel modeling combined with descriptive statistics, hypothesis testing and multiple regression analysis is used to ensure the validity and accuracy of the results obtained. After first organizing the collected data from the large sample and removing invalid data, the valid data obtained through this process is 52,680, with a missing data rate of only 2.7%. The data quality is good and can be used for the next study.

The statistical results of various physiological indexes of the athletes in the two groups are shown in Table 2, and in-depth analysis reveals that there are significant differences between the experimental group and the control group. In particular, the average heart rate of the athletes in the experimental group was 142.6±18.4 beats/min during the 8-week experimental period, which was significantly lower than that of the control group, which was 156.8±22.1 beats/min ($p<0.001$), suggesting that the adaptive environment optimization system was able to reduce the cardiovascular loads of the athletes effectively. In the analysis of heart rate variability, which is an important physiological index, the root mean square continuous difference of the experimental group was 45.2±8.7 milliseconds, while that of the control group was only 38.9±7.3 milliseconds, and the difference was statistically significant between the two groups ($p<0.01$), which reflected that the athletes in the experimental group had a better ability to regulate their autonomic nerves.

Table 2: Statistics of Experimental Data

Measurement index	Experimental Group (Mean+SD)	Control group (Mean+SD)	Difference (%)	P value	Effect size
Average heart rate (beats per min)	142.6±18.4	156.8±22.1	-9.1	<0.001	0.68
Root mean square continuous difference (ms)	45.2±8.7	38.9±7.3	+16.2	<0.01	0.78
Recovery time of body temperature (min)	23.4±4.2	31.7±6.8	-26.21	<0.001	1.42
Peak lactic acid (mmol/L)	8.9±1.6	10.4±2.1	-4.4	<0.01	0.81
Subjective comfort score	6.8±0.9	4.2±1.3	+61.9	<0.001	2.31
Specialized skills improvement (%)	12.7±3.2	6.4±2.8	+98.4	<0.001	2.12
Improvement in physical fitness index (%)	15.3±4.1	8.7±3.5	+75.9	<0.001	1.73
Training satisfaction score	8.4±1.1	6.1±1.6	+37.7	<0.001	1.68
Fatigue recovery index	7.9±1.4	5.6±1.8	+41.1	<0.001	1.43

The results of thermoregulatory capacity assessment further supported our research hypothesis. The average time for the experimental group athletes to return to the baseline level after training was 23.4±4.2 minutes, which was 26.2% shorter than that of the control group (31.7±6.8 minutes), and this significant shortening of the recovery time indicated that the optimized environment could promote the body's thermal homeostatic regulation mechanism. The results of blood lactate concentration measurement, as a key index reflecting anaerobic metabolic capacity, showed that under the same training intensity conditions, the peak lactate concentration of the experimental group was 8.9±1.6 mmol/L, compared with 10.4±2.1 mmol/L in the control group, and the lactate clearance rate of the experimental group was increased by 18.7%, an improvement which directly reflects the positive impact of the optimized environment on metabolic efficiency. Although the blood oxygen saturation monitoring data showed no significant difference between the two groups, both maintained at a normal level of 97% or above, it is worth noting that the fluctuation of blood oxygen saturation was smaller in the experimental group, with a standard deviation of 0.8%, compared with 1.3% in the control group, and this improved stability reflects the positive regulatory effect of environmental optimization on the respiratory system function.

4 Conclusion

This paper designs and develops the intelligent auxiliary sports system based on the sensor to collect information for automated environmental regulation can provide athletes with scientific and effective training services, and to a certain extent, it can improve the physical quality level of athletes and improve the performance of special sports. After the auxiliary training of the system, the test group athletes' physical function indexes and the performance of physical quality test items are improved, and there is an obvious advantage over the control group athletes; at the same time, there is a certain improvement in physiological function, the average heart rate decreased by nearly 10%, and the degree of fatigue is also reduced, which helps the athletes to better recover their physical strength, so that they can achieve a better training state. According to the data obtained from multi-source heterogeneous information sensing to assess the physical condition of the athletes, and using artificial intelligence methods to process and formulate regulation strategies, to achieve effective and accurate regulation of indoor temperature, relative humidity and illumination (temperature control error ± 0.4 ℃, humidity control error ± 1.8%) and sports state judgment (accuracy of 92.76%) and automatic regulation management (reliability of 99.2%). The intelligent regulation method integrating sensing, analyzing and decision-making proposed in this paper can be used as a feasible way to guide exercise training. It has good value for popularization and application.

About the Author

Qiubin Chen, female, Physical Education Institute of Jimei University, Xiamen, Fujian, China, Associate Professor.

References

[1] Vera-Rivera, J. L., Ortega-Parra, A. J., & Ramírez-Ortiz, Y. A. (2019, November). Impact of technology on the evolution of sports training. In Journal of Physics: Conference Series (Vol. 1386, No. 1, p. 012144). IOP Publishing.

[2] Ma, B., Nie, S., Ji, M., & Song, J. (2020). Research and Analysis of Sports Training Real-Time Monitoring System Based on Mobile Artificial Intelligence Terminal. Wireless Communications and Mobile Computing, 2020(1), 8879616.

[3] Dong, X. (2021). Physical training information system of college sports based on big data mobile terminal. Mobile Information Systems, 2021(1), 4109794.

[4] Mali, N. P., & Dey, S. K. (2020). Modern technology and sports performance: An overview. International Journal of Physiology, 5(1), 212-216.

[5] Wang, X. Q., & Yin, J. (2019). Application of machine learning in safety evaluation of athletes training based on physiological index monitoring. Safety Science, 120, 833-837.

[6] Enoiu, R. S., Găinariu, I., & Mîndrescu, V. (2023). Implementing Modern Technology for Vital Sign Monitoring to Enhance Athletic Training and Sports Performance. Sustainability, 15(3), 2520.

[7] Ding, W. (2023). Role of sensors based on machine learning health monitoring in athletes' wearable heart rate monitoring. Human-centric Computing and Information Sciences, 13.

[8] Maranesi, E., Morettini, M., Agostinelli, A., Giuliani, C., Di Nardo, F., & Burattini, L. (2016). Health monitoring in sport through wearable sensors: A novel approach based on heart-rate variability. In Mobile Networks for Biometric Data Analysis (pp. 235-246). Cham: Springer International Publishing.

[9] Seshadri, D. R., Li, R. T., Voos, J. E., Rowbottom, J. R., Alfes, C. M., Zorman, C. A., & Drummond, C. K. (2019). Wearable sensors for monitoring the physiological and biochemical profile of the athlete. NPJ digital medicine, 2(1), 72.

[10] Fu, Y., & Liu, J. (2015). System design for wearable blood oxygen saturation and pulse

measurement device. Procedia manufacturing, 3, 1187-1194.

[11] Martín-Escudero, P., Cabanas, A. M., Fuentes-Ferrer, M., & Galindo-Canales, M. (2021). Oxygen saturation behavior by pulse oximetry in female athletes: breaking myths. Biosensors, 11(10), 391.

[12] Zeng, Q. (2025). Al-driven fitness solutions: Utilizing biosensors for personalized training plans and optimal athletic results. Molecular & Cellular Biomechanics, 22(3).

[13] Ding, Z. (2025). Personalized Optimization of Sports Training Plans Based on Big Data and Intelligent Computing. Scalable Computing: Practice and Experience, 26(3), 1395-1402.

[14] Hao, P., & Qian, K. (2024). The Integration of Personalized Training Program Design and Information Technology for Athletes. Scalable Computing: Practice and Experience, 25(5), 4351-4359.

[15] Abbas, B. K., & Jasim, I. A. (2018). The models of used virtual reality technology in sports. International Journal of Computer Science and Mobile Computing, 7(9), 76-85.

[16] Kong, F., & Wang, Y. (2019). Design of computer interactive system for sports training based on artificial intelligence and improved support vector. Journal of Intelligent & Fuzzy Systems, 37(5), 6165-6175.

[17] Rajšp, A., & Fister Jr, I. (2020). A systematic literature review of intelligent data analysis methods for smart sport training. Applied Sciences, 10(9), 3013.