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Research Article

Health Detection System for Sports Dancers during Training Based on an Image Processing Technology

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Dance sport is a competition of athletes for qualities such as speed, strength, endurance, flexibility, and coordination, requiring a high level of overall physical fitness. As China's sports fever continues to heat up, especially among students, the active nature of young people can lead to overenthusiasm for sports, dance, and other sports, which can lead to various physical discomforts during sports. Especially in the current sports habits of students, there is a great hidden danger of sports injuries. It is mainly due to excessive exercise, irregular exercise methods, and incomplete sports protective equipment. On this basis, this study proposes a model to further assess the health status of individuals and groups from the rate of energy consumption during exercise by building a real-time motion detection system. The development of sports health assessment systems, including the application of imaging techniques, is also analyzed. The experimental results in this article show that when the error threshold is set to 10%, the accuracy of the model is 85%, and the obtained results are ideal.

1. Introduction

With the development of sports infrastructure and sports careers, the performance of athletes in sports dance depends, to a large extent, on their physical fitness level. Sport dance is also called international standard ballroom dance is the one of the sports events. Only athletes with good physical fitness can complete combinations with high technical specifications and standards and achieve excellent results. To scientifically select, train, and manage sports dancers and to minimize the differences with outstanding sports dancers from other countries, this study takes the physical fitness characteristics of outstanding school sports dancers as the research object and constructs a real-time sports test system. And through the data, it evaluates the health of individuals and groups, and it assesses the state of athletes.

To further improve the overall competitive level of athletes and become the world's leading sports dance country, special attention must be paid to the physical fitness of the county's dancers to excel in technical and artistic performance. Therefore, the fitness level is one of the most important considerations when selecting athletes for technical and skill training and scientific selection. The importance of physical fitness should be emphasized, but there is still a lack of academic research on the physical fitness of sports dancers in China. Exploring the physical health characteristics of sports dance athletes will help to improve the coaches and athletes in sports dance programs. Cognition and understanding of the connotations of physical fitness are also important. In this way, sports dancers can improve their physical fitness with quality and efficiency and then lay a solid foundation for improving their competitive ability and level of competition.

This article proposes a Markov model-based exercise fitness assessment model based on exercise data collected from a real-time exercise data monitoring system, suitable for both individuals who exercise and groups that exercise. Markov model is a statistical model that is widely used in speech recognition, automatic tagging of parts of speech, phonetic words, transformations, probabilistic grammars, and other application areas of natural language processing. Based on the Markov model, a health assessment model for the energy consumption rate of individual exercisers is proposed, and the health assessment model is combined with the exercise data collected by the system to analyze the individual exercise limit time. This model eliminates individual differences in fitness within the group and provides a fairer and more reasonable assessment of the health status of the exercise group compared to the results of traditional averaging methods of assessment.

2. Related Work

Sports injuries are a major problem for athletes. As participation in sports activities expands, the associated injuries can have a national impact. Therefore, sports injury prevention is a major concern in the sports and medical communities. Two-dimensional image signals are now available for human gesture recognition. Huang and Liu added a corrective exercise training component to functional motion detection techniques and used an open limb detection artificial intelligence model as a basis for diagnosis (combined with clinical knowledge of rehabilitation interventions from physical therapists). They proposed a two-dimensional imaging system for detecting physical health conditions [1]. Cao et al. proposed an object-oriented technology-based design model for human motor rehabilitation. Combining the object-oriented technology with the visual fuzzy perception of human motor rehabilitation training, the adaptive kinematic model can be used in motor rehabilitation design to improve the control convergence and overall stability of human motor rehabilitation process [2]. Based on the importance of physiological status data to support athletes' training and competition, Xiong et al. designed and implemented a physiological planning system that allows coaches to interact with athletes at the interface level and present the results to the coach. The system simultaneously acquires and analyzes an athlete's ECG, EMG, and 3D acceleration and presents the results back to the coach, solving the problem of not being able to acquire and analyze the athlete's physical data in real time [3]. El-Refaay et al. assessed the effect of Web-based health education on adolescent weight and nutrition knowledge design and found that mean weight in this study decreased from 77.69 (14.1) before the intervention to 68.84 (13.3) three months after the intervention and 72.12 (12.32) six months after the intervention. There was a statistically significant difference in the level of nutritional knowledge before and after the intervention ($p \le 0.001$) [4]. These studies have promoted the development of sports health testing, but most of them are monitoring the injury after the occurrence of sports injury rather than predicting the injury before the injury, but the research in this article can still provide specific reference and help.

To understand the characteristics of the physical quality of outstanding sports dancers, and to improve the level of competitive ability and competition performance in the future, the following collections are made on the establishment of the relevant athletes' health detection system.

In particular, Wu investigates the application of a classifier model based on behavior recognition in personal health care. First, to obtain a curve model for identifying classifier models, human behavior recognition technology by mobile devices is modeled. Then, the functions of the human behavior recognition technology were studied and designed accordingly. Finally, the overall design of the application related to the smartphone system platform was completed [5]. Ahmadi et al. proposed a system combining discrete wavelet transform and random forest classifier for automatic classification of a large number of learning activities. The classifier successfully classified various activities with an accuracy of 98% [6]. Dai and Lu investigated an improved bioimage tracking algorithm under color feedback for cervical spine health of athletes. The aim is to propose a new algorithm to improve the accuracy of detection and tracking [7]. Jiang addresses the shortcomings and deficiencies of conventional object inspection as well as target detection algorithms in different scenarios and proposes a target detection and tracking algorithm according to the current status and technology level of domestic and foreign object inspection and tracking research. Then the target classification results are obtained by the SVM classifier. The research results show that there is a definite effect of recognizing and could apply to the sportsmen's training [8]. The relevant research results of the above scholars provide a theoretical reference for the future scientific selection of athletes and coaches to formulate scientific training plans, reasonable training content, and methods. However, most of them are based on exercise monitoring and analysis, and there is a lack of detailed descriptions in the health evaluation part.

3. Sports Dance Movement Detection Method

3.1. Dance Sports. Different scholars have different concepts and definitions of sports dance. However, most scholars believe that sports dance is a sports performance project integrating art, sports, and music, so it is highly decorative and competitive. Sports dance has won people's love and respect because of the above characteristics, and the number of participants has been increasing [9, 10]. Sport dance is divided into two groups of 10 dances. Among them, the modern dance group includes waltz, Vienna waltz, tango, Fox Trotter, and Fast Trotter; Latin dance groups include rumba, chacha, samba, cowboy, and bullfight. Each dance type has its own dance music, steps, and styles, which are organized according to the music and movement requirements of different dance styles and one's own complete set of actions.

Since physical fitness is an external manifestation of physical ability, athletes are likely to develop a range of physical skills in the basic practice of physical exercise and skill learning. The improvement of one's physical fitness is evidenced by the significant performance of physical fitness [11]. In addition, without the basic conditions of good physical fitness, it is impossible to master a certain sport proficiently, improve sports performance, and attempt more professional sports training [12, 13].

3.2. Development of Sports Health Detection System. In traditional athlete-assisted training, biomedical methods are often used to monitor changes in the physiological data of the body during exercise and realize real-time monitoring of exercise data [14, 15]. Although this method can more accurately measure the physiological indicators of human movement, it is difficult to apply to the scene of real-time monitoring of youth sports due to the difficulty of measurement and operation [16].

With the development of imaging and video technology, video surveillance methods are beginning to be used for sports monitoring. By capturing the movement process through the camera, the movement process can be reconstructed truly and comprehensively, and the real-time monitoring of the movement can be realized. It can adjust the responsive exercise plan or treatment plan according to the state of exercise. All video images need to be processed. To eliminate noise, they need to be smoothed. Now, several image smoothing methods are briefly introduced. Image smoothing methods are divided into two categories: spatial domain methods and frequency domain methods, mainly including domain averaging methods and low-pass filtering methods [17, 18].

Neighborhood averaging method is an algorithm for image local space processing. The pixel points in the neighborhood are averaged to remove the abrupt pixels, to filter out certain noise. The advantage is that the algorithm is simple and the calculation speed is fast. The idea is to use the gray value of the image point (x, y) and its neighboring pixels. The gray value of the point (x, y) is replaced by the mean value of the intensity, which results in a "smoothing" effect on points with sudden changes in brightness. Assuming that the image $D(a, b)$ is an $N \times N$ array, the gray level of each pixel is determined by the average value of the gray level of multiple pixels in a predetermined neighborhood contained in (a, b). The smoothed image $P(a, b)$ is expressed as:

$$P(a, b) = \frac{1}{W} \sum_{(x,y)\in E} D(x, y). \tag{1}$$

Among them, $a, b = 0, 1, 2, \cdots, i-1$, E is the neighborhood pixel set of the center of the coordinate point but does not include the coordinate, point W is the total number of coordinate points in E, and the convolution is expressed as:

$$P(a, b) = \sum_{(x,y)} \sum_{\in E} D(x, y) m(a - x + 1, b - y + 1). \tag{2}$$

In the formula, m denotes the $L \times L$ impulse response array, also known as the convolution template [19].

3.2.1. Low Pass Filtering. Low-pass filtering is a filtering method. The rule is that low-frequency signals can pass normally but exceed the set threshold. The high-frequency signals of the value are blocked and attenuated. As far as the image is concerned, the frequency components of its edge and nuisance noise are in the higher part of the spatial frequency domain. The slow-changing part of the signal belongs to the low-frequency part in the frequency domain, while the fast-changing part of the signal is the high-frequency part in the frequency domain. Therefore, the noise can be removed by low-pass filtering. Because of the filtering method of low-pass filtering, the rule is that low-frequency signals can pass normally, while high-frequency signals that exceed the set threshold are blocked and weakened. As long as the unit impulse response matrix in the spatial domain is properly designed, the filtering in the frequency domain can be easily realized, thereby realizing the filtering effect of noise [20, 21].

$$P(a, b) = \sum_{(x,y)} \sum_{\in E} D(x, y) M(a - x + 1, b - y + 1). \tag{3}$$

In the formula, M represents an $L \times L$ impulse response array, also known as a low-pass convolution template. The low-pass convolution templates commonly used for noise smoothing include:

$$Td1 = \frac{1}{9} \begin{bmatrix} 1, 1, 1 \\ 1, 1, 1 \\ 1, 1, 1 \end{bmatrix}, \tag{4}$$

$$Td2 = \frac{1}{10} \begin{bmatrix} 1, 1, 1 \\ 1, 2, 1 \\ 1, 1, 1 \end{bmatrix}, \tag{5}$$

$$Td3 = \frac{1}{16} \begin{bmatrix} 1, 2, 1 \\ 2, 4, 2 \\ 1, 2, 1 \end{bmatrix}. \tag{6}$$

The detection system based on an image processing technology can observe the movement situation in real time, but it is difficult to obtain the data generated by the movement of human beings, so it is not suitable as a real-time monitoring system for movement data.

The rapid development of wireless communication technology, micro-electromechanical systems, and intelligent mobile terminals has made the communication and interconnection between devices more convenient and the computing power of devices more powerful, thus creating conditions for sensors to be used in motion monitoring [22]. The athletes wear smart mobile devices to process the collected data through the mobile terminal. Then use the wireless communication network to send the data to the overall system, and finally realize the real-time detection of motion.

4. Motion Detection System Experiment Training

This article quantifies physical fitness data for sports dancers. In this article, the quantitative indicators of the motion detection system are established to better evaluate their health standards from the aspects of body shape, physical function, and physical quality.

4.1. System Functional Requirements. To meet the overall system requirements set, the functional requirements of the

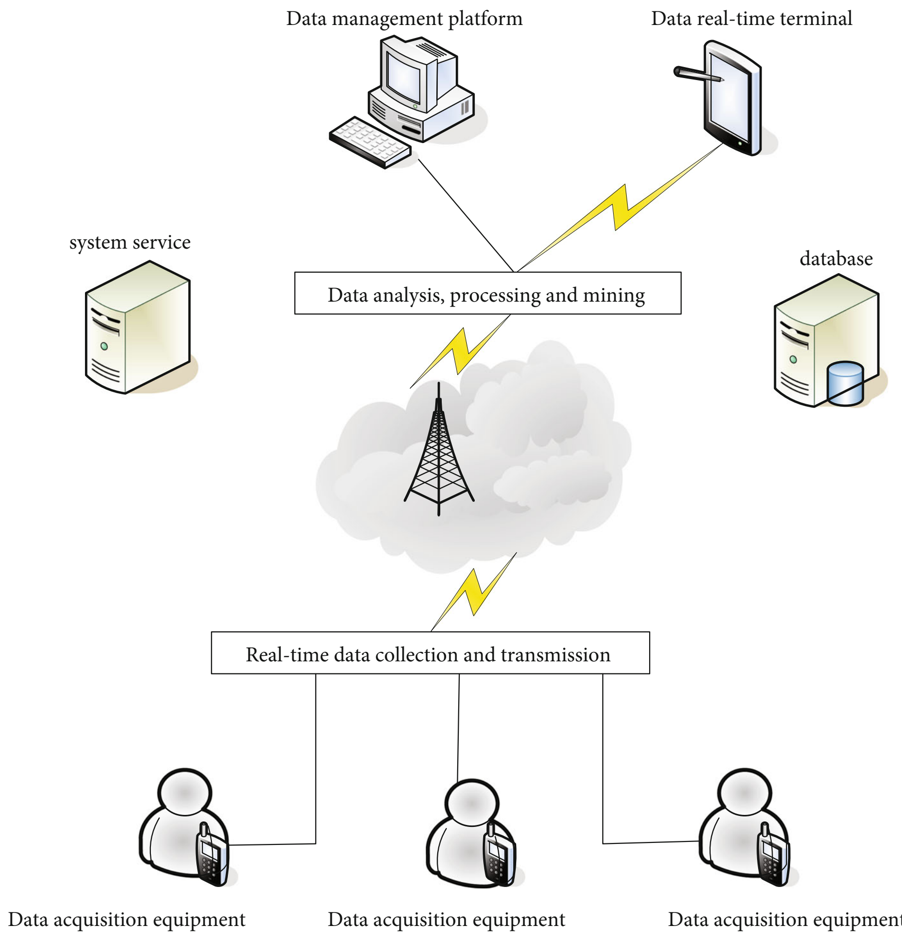

FIGURE 1: Real-time monitoring system architecture.

real-time motion data monitoring system are described as follows:

(1) The data collection device uses the three-dimensional acceleration sensor to collect and store the acceleration data of the athlete in the three-dimensional space during the exercise in real time and obtain the number of steps of the athlete.

(2) The data collection device can be tied or unbundled with the designated exerciser to identify the designated exerciser in the exercise state.

(3) The data base station covers a standard 400-meter sports field and can simultaneously receive data from more than 200 data acquisition devices.

(4) The sports data display terminal can select the sports group to be monitored (by class, by project, etc.), check the attendance of group members, and control the start and end time of real-time monitoring. In the process of real-time monitoring, not only the sports status of group members can be viewed, but also individual and group members, as well as the change trend of the group's real-time sports data.

(5) When a certain action is not standardized, or the danger exceeds the set alarm threshold, the system will issue an alarm. Warning thresholds can be set to determine whether a warning should be issued to the exerciser himself or to the monitor based on changes in exercise data monitored in real time

(6) The system management platform can manage past exercise data and make comparisons in various aspects, such as observing the exercise effect of exercisers and discovering exercise rules.

4.2. Design of the Overall Architecture of the System. Because it involves motion feature, information processing, communication technology, computer technology, and many other aspects, designing a reasonable architecture model can more effectively meet the application requirements of the system. Therefore, it is essential to study and design the system architecture. According to the previous requirement analysis, the overall architecture of the real-time motion data monitoring system can be divided into four major categories, as shown in Figure 1.

As shown in Figure 1, the basic architecture of the monitoring system is mainly composed of data management

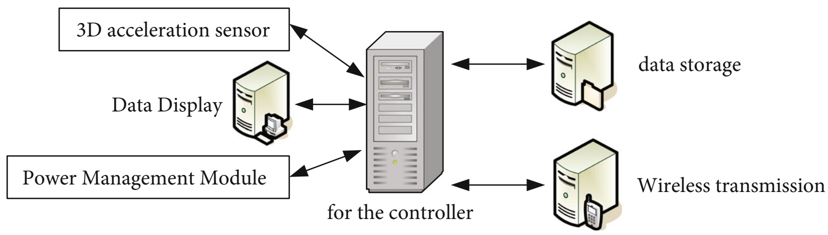

Figure 2: Composition of the data acquisition device.

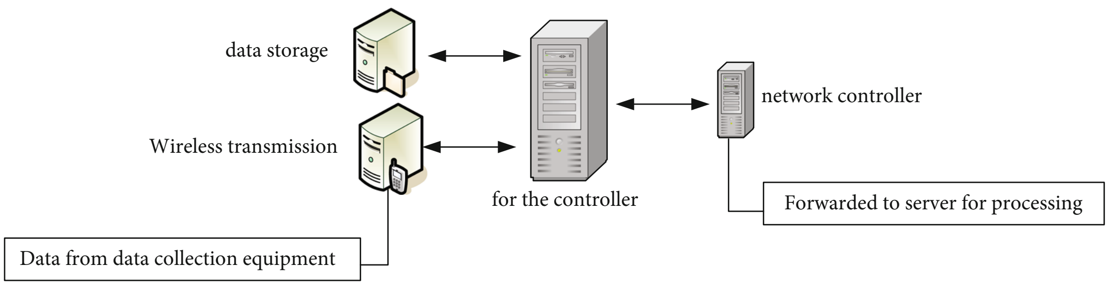

Figure 3: Composition of a database station.

Table 1: Comparison of wireless communication technologies.

	Wi-Fi	Bluetooth	ZigBee	RFID	NFC
Transfer speed	11–50 Mbps	1 Mbps	100 kbps	1 kbps	424 kbps
Communication distance	20–200 m	20–100 m	2–20 m	1–10 m	0–20 m
Frequency band	2.4 GHz	2.4 GHz	2.4 GHz	1–100 GHz	13.56 GHz
Power consumption	10–50 mA	20 mA	5 mA	10 mA	10 mA
Main application	PC, PDA	Car, multimedia	Wireless sensor	Barcode	Near field communication

platform, data real-time terminal, database, real-time data acquisition and transmission module, and system service module.

4.3. Design of System Components. The data collection device is worn on the body when the athlete participates in the exercise and is used to monitor the data in real time, such as the number of steps and energy consumption generated by the human body during exercise. This can better capture the movement state of the athlete and the change data of the body during exercise in real time. According to the analysis and design requirements of the system, the composition of the data acquisition device is shown in Figure 2.

A data base station is a device located in a motion monitoring area that receives and transmits motion data from data collection equipment. Therefore, to meet the functional requirements of the system, the data base station is equipped with a high-power radio antenna to increase the radio signal strength of the monitoring area, expand the coverage, and is equipped with a high-performance microprocessor. Supports receiving and processing a large amount of motion data and transmitting it to the server for subsequent processing. The configuration of the data base station is shown in Figure 3.

Since the data acquisition equipment in this system is worn by athletes and distributed throughout the exercise area. For wearing comfort and convenience, the communication between the data acquisition device and the data base station is carried out by a wireless method. The advantages of wireless communication is not only low power consumption and low cost but also its flexibility without the constraints of cables, which is very suitable for sports data collection. The short-range wireless communication techniques commonly used in research applications are listed in Table 1.

As the system needs to be able to monitor the actions of multiple groups and users at the same time, radio communication technology needs to be able to meet the simultaneous connection requirements of more devices, therefore, considering communication distance, connection limitations, cost, and scalability. The system uses a wireless communication technology called Wi-Fi for data acquisition equipment and data base stations. The automatic bandwidth adjustment of Wi-Fi communication technology can effectively ensure the stability and reliability of the network. Its main features are high speed and high reliability. But the problems of low security and small coverage are the main shortcomings of Wi-Fi.

As the core of the system, the server side of the motion data monitoring system is responsible for controlling and connecting other submodules of the system to complete all functions of the system together. Due to the powerful processing and computing power on the server side, most of

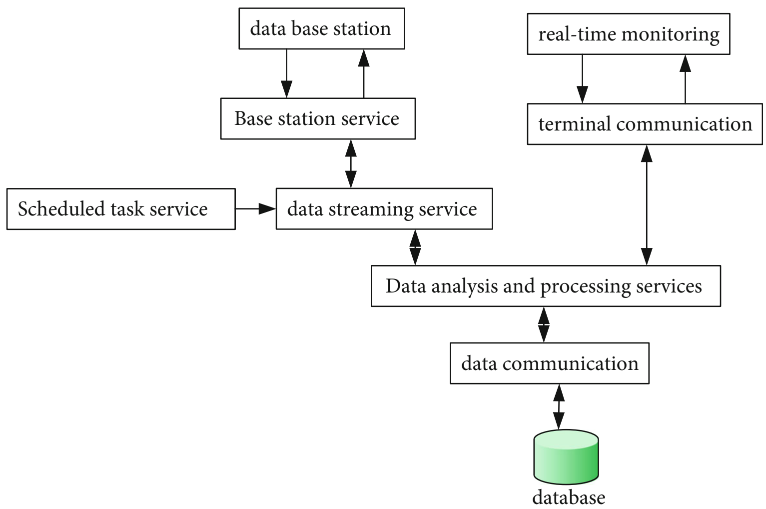

Figure 4: Schematic diagram of the structure of the motion monitoring system.

Table 2: Physical fitness test indicators of sports dancers.

First-level indicator	Secondary indicators	Three-level indicator
Speed quality	Action speed	10 s high leg raises, jumping
Strength quality	Explosive force	Vertical jump
	Strength endurance	1 min sit-ups
Endurance quality	Anaerobic endurance	400 m
	Aerobic endurance	20-MST
Flexibility	Flexible	Sitting forward bend
Agility and coordination	Agility and coordination	10 s standing up
Balance quality	Balance	Basel

the data processing happens on the server side. The situation on the server side is shown in Figure 4.

(1) Real-time monitoring terminal communication service module. Communicate with the real-time monitoring terminal, receive the instructions requested by the real-time monitoring terminal, and return relevant data (such as student sports information, real-time sports during training, and announcement information) to the terminal. The message request is received and sent to the data stream service terminal, and the hardware base station communication is responsible for forwarding the data to the service terminal.

(2) Schedule task service module. It is responsible for providing support for customized scheduled tasks, triggering processing events for scheduled tasks, and triggering and processing related tasks for data analysis and processing services.

(3) The data stream service module receives the data from the base station server, collects the data according to different requests, and forwards it to the corresponding data analysis and processing module for processing. For example, collecting heart rate information and calorie consumption of the exercisers.

(4) Data analysis and processing service module. Receive the data transmitted from the data stream server and analyze and process the received data according to different instruction operation requirements.

(5) Data base station service module. Communicate with the data base station and process the requests received from the data base station to receive from the data collector, survey data collector, and push messages to the data collector.

(6) The database communication service module provides an interface between the server system and the database system for storing and loading data and supports transaction-level processing and parallel processing.

5. Health Evaluation Training

5.1. Indicators of Sports Health Evaluation. To evaluate the sports health of athletes, it is first necessary to select an effective evaluation index. The assessment indicators defined by the health standards take into account body shape, physical function, and physical fitness. The physical fitness test indicators selected through expert questions are shown in Table 2.

After comprehensive consideration of body shape, physical function, and physical quality, for the lack of corresponding text descriptions for the contents of Table 2 The quality of speed, strength, stamina, flexibility, agility and coordination, and balance of an athlete's movement establishes the first-level indicators.

5.2. Health Evaluation Model Based on Sports Dance Motion Detection. Studies have shown that the energy consumption of the human body during exercise reflects changes in physical health. The energy consumption of exercise can be roughly divided into three categories according to exercise intensity: non-compliance, compliance, and excess, have minor, moderate, and detrimental effects on human health, respectively, and exercise energy expenditure reflects the total amount of exercise an individual performs at different fitness levels. Therefore, it can be said that energy consumption during exercise is used as an indicator of exercise health assessment.

Regarding the health assessment of exercise individuals, due to the different physical foundations of each person, the amount of exercise energy consumption during the same exercise process is also different. For sports individuals with different individual characteristics, it is necessary to give individualized health assessment results. During the exercise process, the exercise energy consumption of the athlete increases gradually, then becomes relatively stable, and finally decreases gradually and manifests as physical fatigue. For this reason, this study adopts the exercise energy consumption rate Dv of the exercise individual as the index for the health evaluation of the exercise individual. Specifically expressed as:

$$Dv = \frac{K}{St}(v = 1, 2, 3..). \tag{7}$$

Among them, K represents the consumption of exercise energy, St represents the time of exercise, and v is the time.

The method of using the Markov model is to infer the transfer rate of various people based on historical data, then count the distribution of various people at the beginning, and finally establish a Markov model for predictive analysis. To predict the limit consumption rate of a moving individual based on the Markov model, it can be calculated by calculating the exercise consumption checked in real time, and an energy consumption sequence $S_1, S_2 \cdots, S_i$ can be obtained, and the Markov process of this sequence is as follows;

First, divide the state space. Find the maximum value of $S_{\max}$ and the minimum value of $S_{\min}$, divide the state space Q, and the span of each interval is:

$$\Delta S = \frac{(S_{\max} - S_{\min})}{S}. \tag{8}$$

The state component of the energy consumption series is then divided.

$$[S_{\min}, S_{\min} + \Delta S], \ldots, [S_{\min} + (S-1) \cdot \Delta S, S_{\max}]. \tag{9}$$

Calculate the transition probability matrix, analyze the transition state of the energy consumption rate for each consecutive 30 s (such as the state transition from 30 s to the 60 s), and calculate the transition probability matrix J_z of the energy consumption rate.

Find the steady-state vector and take the energy consumption transition state of the ith 30 s as the initial state, expressed as K_n, then the following inequality is established.

$$K_{n+1} = K_n \cdot J_z, K_{n+2} = K_{n+1} \cdot J_z, \ldots. \tag{10}$$

According to the stability of the Markov chain, there is finally a state vector:

$$K = (K_1, K_2, \ldots, K_n). \tag{11}$$

It satisfies:

$$K = K \cdot J_z. \tag{12}$$

Then the vector K is called the stationary vector of the Markov chain.

Calculate the limit energy consumption rate of the exercise individual, according to the principle of maximization, take the maximum value of $(H_i, i \in [1, n])$ in each state interval as the quantitative index of the interval. It is possible to further calculate the limit energy consumption rate R of the exercise individual;

$$R = \sum_{1}^{n} H_i \cdot K_i. \tag{13}$$

By using the above calculated marginal energy consumption rate R as the fitness evaluation model of the exercise individual, the energy consumption rate ΔS of the exercise individual can be compared with the marginal energy consumption rate R. To determine whether the current exercise state of the individual is within the range of human health, to achieve the effect of performing exercise health assessment on the exercise individual.

5.3. Individual Evaluation Test Results. The sports data real-time monitoring system can collect the sports energy consumption data of all athletes in real time. Fitness assessment of athletes based on their energy expenditure data during continuous real-time exercise. To facilitate the analysis and calculation, the energy consumption rate is set every 30 seconds. Table 3 shows the energy expenditure rate of an athlete exercising continuously for 10 minutes.

According to the formula, the above energy consumption rate is divided into four state spaces, and two adjacent 30-second energy consumption rate transition statistics can be obtained through the above state space division, as shown in Table 4.

Figure 5 shows that from 450 seconds, the energy expenditure rate of the exercisers began to fall below the marginal energy expenditure rate of 5.6 kcal/30 seconds and continued to decline over time, indicating that physical fitness began to decline. In such cases, athletes should be advised

Table 3: Energy expenditure rates of sports dance athletes exercising for 10 minutes continuously.

Time (s)	Energy consumption rate (%)	Time (s)	Energy consumption rate (%)	Time (s)	Energy consumption rate (%)
30	3.6	270	5.8	480	4
60	4	300	6.8	510	3.8
90	3.9	330	6.3	540	4
120	4.1	360	7.2	570	3.1
180	5.1	390	6.9	600	2.7
210	5.7	420	5.9		
240	4.3	450	4.5		

Table 4: Transfer of exercise energy consumption.

Number of transfers		After transfer				
		State 1	State 2	State 3	State 4	Total
Before transfer	State 1	1	1	0	0	2
	State 2	0	5	2	0	8
	State 3	1	2	2	1	5
	State 4	0	0	1	3	4

to gradually reduce the intensity of exercise or stop exercising for rest to ensure healthy exercise and reduce risk.

5.4. Individual Evaluation Analysis Structure. To evaluate the accuracy of the conclusions of the fitness assessment model for exercise individuals, we selected 20 exercisers, all of whom participated in a 2 km run. The calculation method of the actual exercise time R is as follows: when the athlete feels that his/her physical energy is exhausted during the exercise, he/she stops exercising. The exercise data are evaluated with the exercise individual health assessment model proposed in this paper, and the recommended exercise time R_0 is obtained. In this way, the error C between the recommended exercise time and the actual exercise time R can be calculated.

$$C = \frac{|R_0 - R|}{R}. \tag{14}$$

At this time, if the error threshold is controlled within C_{RS}, it indicates that the evaluation result is correct. This paper evaluates the accuracy of the health evaluation model based on the overall correct rate of 20 sports dancers.

Through the test result data in Table 5, the error occurred in each exercise individual in the exercise individual health assessment model is calculated, and the error is plotted, and the obtained result is shown in Figure 6.

As can be seen from Figure 6, the error between the time to stop exercising and the actual time to stop exercising using our exercise personal fitness assessment model is within 20% for all 20 participants. Even taking into account the influence of human subjective factors, the error of the model prediction results is within a reasonable range. In addition, when the error threshold is set to 10%, the accuracy of the model is 85%, and the obtained results are ideal. This is due to setting the error threshold to 10%, which is just around the average error.

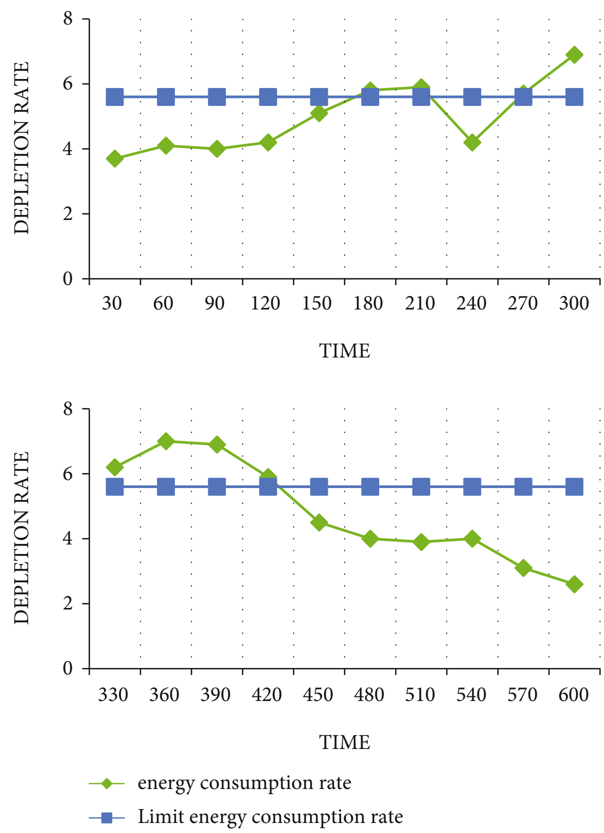

Figure 5: Changes in the rate of energy expenditure of the exerciser.

5.5. Group Evaluation Results. For the exercise health assessment of the exercise group, based on the analysis in the previous section, a group health assessment model based on the progress of exercise energy consumption transfer was used to obtain the degree of improvement in exercise effect between exercise groups within the same period.

Here, the average weekly exercise energy consumption of each individual exerciser is calculated according to the

Table 5: Actual exercise time and recommended exercise time for athletes.

Numbering	Actual exercise time	Recommended exercise time	Numbering	Actual exercise time	Recommended exercise time
1	621	600	11	692	720
2	672	630	12	642	600
3	702	660	13	686	570
4	647	600	14	622	600
5	729	690	15	667	690
6	607	570	16	717	660
7	730	630	17	620	570
8	598	630	18	628	690
9	582	600	19	637	630
10	657	630	20	671	600

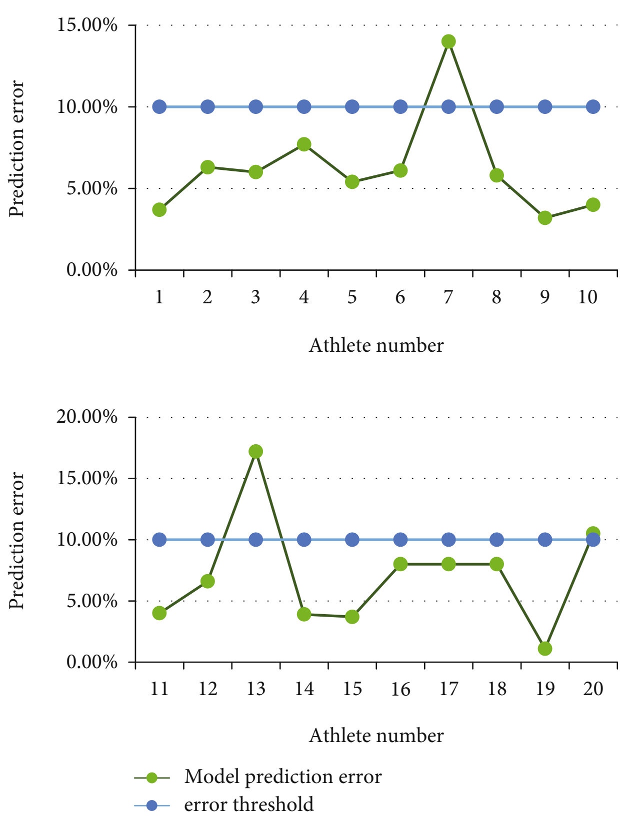

Figure 6: Prediction error of the health assessment model.

energy consumption data generated by the real-time exercise of the A and B classes for two consecutive weeks. Figures 7 and 8 show the weekly average exercise energy consumption (unit: kcal) of all athletes in classes A and B during real-time exercise for two consecutive weeks.

Table 6 shows the average exercise energy expenditure statistics for all category A individuals in the adjacent two weeks.

Similarly, the statistics of the average exercise energy consumption of all people in class B in the adjacent two weeks can be obtained, as shown in Table 7.

From the trends in energy expenditure shifts in Tables 6 and 7, the following calculation matrix can be used to calculate the probability of change in average exercise energy expenditure over two weeks for all individuals in both classes.

$$G_a = \begin{bmatrix} 0.25, 0.75, 0, 0 \\ 0, 0.67, 0.33, 0 \\ 0.33, 0.67, 0, 0 \\ 0, 0, 0, 1 \end{bmatrix}, \tag{15}$$

$$G_b = \begin{bmatrix} 0.33, 0.67, 0, 0 \\ 0.5, 0.5, 0, 0 \\ 0, 0.33, 0, 0.67 \\ 0, 0, 0, 1 \end{bmatrix}. \tag{16}$$

According to the calculation formula of the transfer process, the process is obtained:

$$J_a = 0.75 \times (2-1)^3 + 0.33 \times (3-2)^3 + 0.33 \times (1-3)^3 + 0.67 \times (2-3)^3 + 0.5 \times (3-4)^3 = -2.7, \tag{17}$$

$$J_b = 0.67 \times (2-1)^3 + 0.67 \times (3-4)^3 + 0.5 \times (1-2)^3 + 0.67 \times (2-1)^3 + 0.5 \times (2-3)^3 = 0.5. \tag{18}$$

As can be seen from the calculation results above, the transition progress of class A was −2.7, indicating that the physical activity of class A in the second week has regressed compared to the first week. While the transition progress of class B was 0.5, indicating that the physical activity of class B increased in the second week compared to the first week. It can be concluded that in these two consecutive weeks, the exercise effect of class B is better than that of class A.

To test the validity of the proposed exercise population health assessment model, we next compare it with the traditional mean comparison method to derive an assessment of the model's validity. The advantage of the mean analysis process is that all descriptive statistics are based on the value

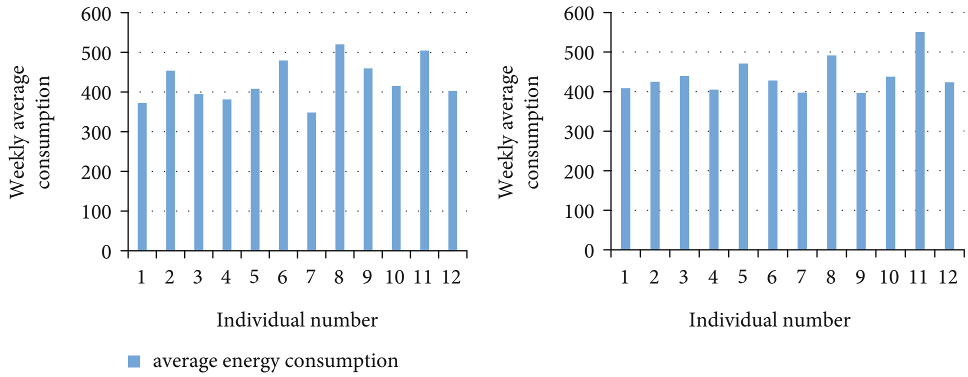

Figure 7: Average energy consumption of class A over two weeks.

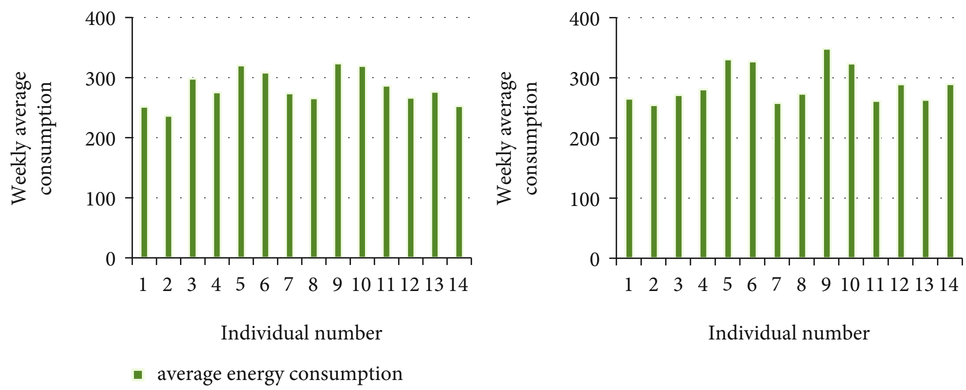

Figure 8: Average energy consumption of class B over two weeks.

Table 6: Transfer of average exercise energy expenditure for everyone in class A in the adjacent two weeks.

Number of transfers		Week 2 State 1	State 2	State 3	State 4	Total
Week 1	State 1	1	3	0	0	4
	State 2	0	2	1	0	3
	State 3	1	2	0	0	3
	State 4	0	0	1	1	2

Table 7: Transfer of average exercise energy expenditure for all people in class B in the adjacent two weeks.

Number of transfers		Week 2 State 1	State 2	State 3	State 4	Total
Week 1	State 1	1	2	0	0	4
	State 2	3	3	1	0	6
	State 3	1	2	0	2	3
	State 4	0	0	0	2	2

of the dependent variable. Group calculations without having to run the file splitting process first, as other programs do. The comparison results of the two health assessment models are shown in Table 8.

According to the calculations in Table 8, the traditional average evaluation method show that the average exercise energy expenditure of class A was 11.5 which has greater improvement than the consumption of class B was 6.2. Therefore, using the traditional average evaluation method to assess the improvement of athletic performance in the two weeks between classes A and B, it was determined that the athletic performance of class A was better than the athletic performance of class B in the adjacent two weeks. In the evaluation model of this article, the athletic ability of class A dropped to −2.7, whereas the athletic ability of class B increased to +0.5. In other words, in this adjacent two-week athletic performance, class B performed better than that of class A. This model is based on a uniformly delimited state interval and considers the instantaneous progress of movement of all individuals in the group, not the absolute value of the movement performance, but only the relative value. This model of exercise group health assessment only focuses on the progress of the group itself, eliminates

Table 8: Results of the traditional average of the two classes A and B and the group health evaluation model.

	Traditional mean evaluation method			Sports group health evaluation model
	Mean exercise energy expenditure in the first week	Transfer progress	Two-week progress	Transfer progress
Class A	428.2	439.6	11.5	−2.7
Class B	282.3	288.5	6.2	0.5

differences between groups, and provides a fair assessment of exercise effects.

6. Conclusions

This article first analyzes the requirements of the real-time motion data monitoring system, designs the overall architecture of the system according to the system requirements, and briefly introduces the functions of each part of the system architecture. The exercise data collected by the real-time exercise data monitoring system is used to assess the health of exercise individuals and groups. Markov models are used to analyze the motion process. Then it introduces the principle of choosing the health evaluation index system and determines the health evaluation index of individuals and groups. Finally, through the analysis and comparison of specific cases, a health assessment model for the different needs of sports individuals and sports groups is proposed and tested. By proposing a health assessment model for the exercise population based on the increment of exercise energy consumption, the exercise effect of the exercise population is improved, the influence of the individual physical differences of the exercise population on the exercise evaluation results is eliminated, and a fair evaluation is realized. This article reflects on the process of the experiment and found that if more groups are set in the experimental test, presetting more influencing factors for comparison may result in more accurate results, but due to time constraints, this article does not conduct relevant tests and hopes to provide references for future research.

Data Availability

The data underlying the results presented in the study are available within the manuscript.

Conflicts of Interest

The author declare that they have no conflicts of interest.

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