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THE APPLICATION SYSTEM OF INTELLIGENT WEARABLE DEVICES IN PHYSICAL EDUCATION

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Abstract. To address the challenge of real-time data collection and analysis in human motion data mining, the author proposes a system that integrates intelligent wearable devices into physical education. Initially, motion data is gathered through these smart devices, then transformed into binary format. This data undergoes cleaning and supplementation processes before being clustered. The Firefly Algorithm is employed to enhance the K-means clustering technique, which is then applied to the processed data. Experimental results indicate that this refined approach achieves an average recall rate of 97.12% and an average data mining accuracy of 98.42%, thus offering a valuable foundation for the real-time monitoring and assessment of students' physiological metrics. This algorithm can be applied in student physical condition assessment, sports injury and fatigue monitoring, sports posture and movement assessment, personalized training and rehabilitation program development, scientific decision-making and management, and other aspects.

Key words: Smart wearable devices, Human movement, Data mining, Data cleaning, K-means clustering algorithm, data acquisition

1. Introduction. With the rapid development of technology, smart wearable devices have become an indispensable part of people's lives [1]. These devices provide new possibilities for health management and lifestyle improvement by monitoring users' physiological and behavioral data [2]. Especially among the student population, smart wearable devices have received widespread attention due to their interactivity and fun. Student life is a critical stage for physical and psychological development, and exercise not only contributes to physical health, but also has a positive impact on social skills and mental health [3]. Therefore, studying the application of smart wearable devices in student sports is of great significance for promoting students' comprehensive development [4]. There are various types of smart wearable devices, including smartwatches, fitness trackers, exercise monitoring belts, etc. These devices enable the continuous tracking of different physiological metrics, including heart rate, step count, caloric burn, and sleep quality. In recent years, with the advancement of technology, the functions of smart wearable devices have become increasingly powerful, and the user interface has become more user-friendly, resulting in a rapidly growing market trend [5].

Intelligent wearable sports equipment can not only obtain exercise data during the exercise process for fitness tracking and data recording, real-time monitoring of physical indicators, but also help users with exercise analysis and provide targeted fitness, dietary advice, and scientific training plans [6]. Based on the fact that most students only engage in sports activities unilaterally without forming a complete exercise prescription based on their own physical data indicators. In this context, the development and demand for intelligent sports wearables for students have also attracted people's attention. Smart wearable devices have great development prospects and innovation space; Sports smart wearables bring us convenient functions and real-time monitoring of physical health in sports, while advocating for more college students to develop healthy lifestyles and good sports habits. In this context, studying the application system of smart wearable devices in physical education has important theoretical and practical significance. Through research, we can explore how to better integrate these advanced devices with the modern physical education teaching system, solve the pain points in current physical education teaching, and promote the comprehensive development of students' physical literacy [7].

2. Literature Review. In recent years, physical education has developed rapidly, and sports training is the key to improving physical education performance. Therefore, it is of great significance to obtain real-time

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data on sports training in order to provide scientific basis for formulating targeted technical and physical training plans, thereby improving students' physical performance and enhancing the guidance and training level of sports training. Therefore, the optimization of real-time data collection methods for sports training has become a hot topic of concern for researchers. In previous studies, a large number of researchers have provided various data mining algorithms, but there are still some shortcomings in the mining of human motion data. Jiang et al. developed an innovative real-time 3D interactive system that leverages smart clothing. This system employs compact sensor modules to gather human motion data and incorporates a dual-stream fusion network with pulse neural units for motion classification and recognition, facilitating seamless real-time interaction between users and the sensors [8]. Dong et al. developed a system for analyzing and evaluating physical education steps using deep learning techniques. The system employs smart wearable devices to continuously track students' exercise steps and heart rate during class, creating a dataset of physical education activities. They utilized a transformer-based deep model to analyze temporal step sequences, enabling the assessment of motion effects [9]. Ma, Z. et al. introduced an affordable solution designed to assist teenagers in practicing basketball dribbling independently. This solution incorporates a smart wearable headband along with a dribbling aid called DribbleAid. The system monitors typical posture problems during dribbling sessions and delivers targeted feedback to help users overcome common challenges [10].

To address these challenges, the author presents a human motion data mining algorithm leveraging intelligent wearable devices. Initially, these devices gather motion data, which is then refined through data cleaning and clustering processes. To enhance clustering accuracy, the algorithm employs the Firefly Algorithm to optimize the K-means clustering approach. The experimental results show that the algorithm designed by the author can quickly and accurately mine human motion data, provide decision-making information for sports training, and promote the development of sports training technology.

3. Method.

3.1. Human motion data mining algorithm . In response to the problem that current human motion data mining algorithms cannot collect and analyze real-time data, resulting in low accuracy and long time for human motion data mining, the author proposes a human motion data mining algorithm based on intelligent wearable devices [11]. Specifically, by analyzing and mining the collected data, the following objectives can be achieved:

1. Assessing students' physical condition and exercise performance: By analyzing data such as heart rate, steps, speed, muscle activity, etc., students' physical condition and exercise performance can be evaluated to determine training intensity and frequency, and improve training effectiveness [12].
2. Monitoring and warning of sports injuries and fatigue: By analyzing data on students' muscle activity and energy expenditure, sports injuries and fatigue can be monitored and warned to avoid overtraining and sports injuries.
3. Optimizing training and competition strategies: By analyzing students' posture, gait, movements, and other data, training and competition strategies can be optimized to improve students' competitive level and performance.
4. Personalized training and rehabilitation programs: By analyzing students' physical condition and exercise performance, personalized training and rehabilitation programs can be developed for different students to meet their needs and requirements.
5. Scientific decision-making and management: By mining and analyzing a large amount of sports data, it can provide coaches, doctors, and managers with scientific decision-making and management basis to improve the quality and effectiveness of training and competition.

From this, it can be seen that the purpose of human motion data mining based on smart wearable devices is to improve students' competitive level and physical health status, optimize training and competition strategies, achieve personalized training and rehabilitation plans, and provide a basis for scientific decision-making and management [13,14].

3.2. Data collection of smart wearable devices. In the process of traditional sports data analysis research, the inability to obtain accurate real-time data results in low reliability of the analysis results. In this study, smart wearable devices were used as collection devices for human motion data, which can obtain

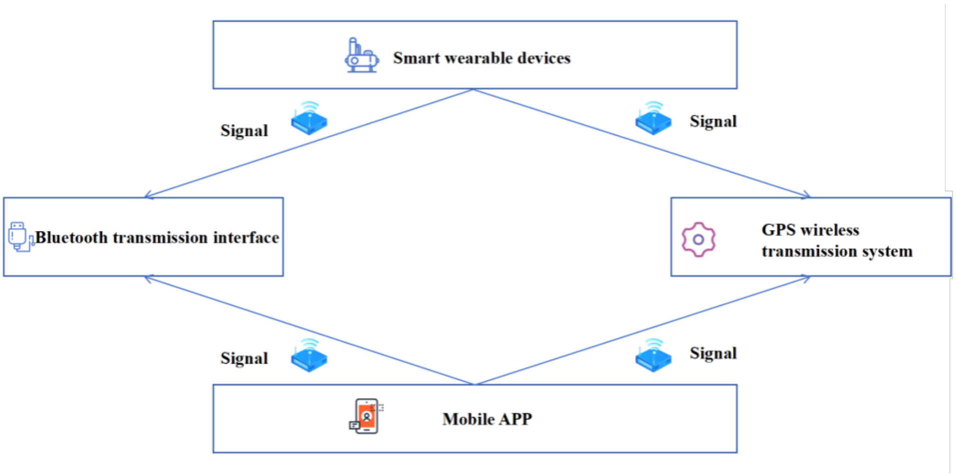

Fig. 3.1: Architecture of Intelligent Wearable Devices

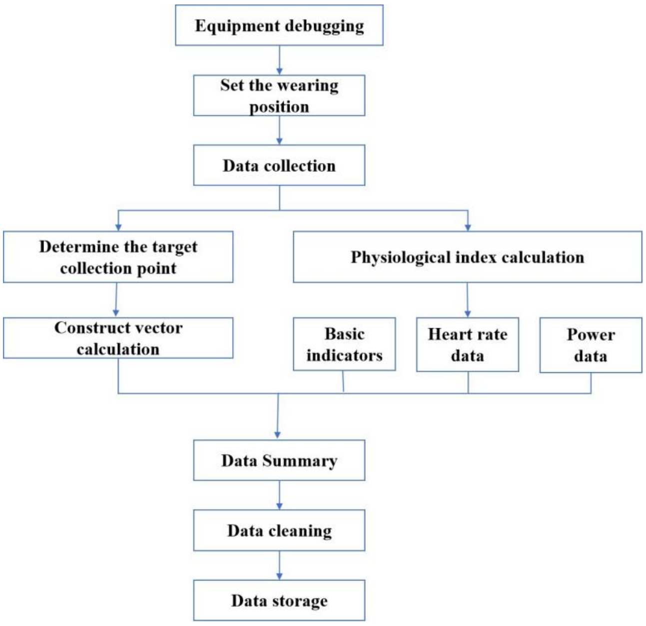

Fig. 3.2: Data Collection Process

real-time motion data of students [15]. The architecture of smart wearable devices is shown in Figure 3.1.

As shown in Figure 3.1, the architecture of smart wearable devices consists of smart wearable devices, Bluetooth transmission ports, GPS wireless transmission systems, and mobile apps. Install smart wearable devices into the elastic sportswear worn by students to collect human motion signals, and transmit the signals to the mobile app through Bluetooth transmission ports and GPS wireless transmission systems to ensure the quality and efficiency of data collection. The process of collecting human motion data for smart wearable devices is shown in Figure 3.2.

As an intelligent motion monitoring device, smart wearable devices can obtain various physiological indicators of students during their exercise process, providing a data foundation for subsequent data mining. During the data collection process on this device, corresponding settings need to be made [16]. Assuming that the smart wearable device is worn on the limbs of the human body and used as a data collection point, this point can be represented as $q(x, y, z)$. During the data collection process, it is necessary to import its constructed vector into the data collection results, which can be represented as:

$$\begin{cases} \overline{o_1} = q_1 - q_0 \\ \overline{o_2} = q_2 - q_1 \\ \overline{o_3} = q - q_3 \\ \overline{o} = q - q_4 \end{cases} \tag{3.1}$$

In the formula, q_0, q_1, q_2, q_3 and q_4 represent the wearing points of smart wearable devices, and $\overline{o}, \overline{o_1}, \overline{o_2}, \overline{o_3}$ represents different construction vectors.

Using this formula, basic physiological indicators during human movement can be collected. Some physiological indicators cannot be reflected in the form of data and need to be converted into data information in order to complete subsequent analysis work. Therefore, the following indicators were selected for conversion processing in the study:

1) Real time heart rate.

$$g = \frac{\alpha}{r_1 - r_2} = \frac{(e_1 - e_2)}{2} \tag{3.2}$$

In the formula, r_1 and r_2 represent the heartbeat data of the previous time node and the current period, α represents the standard coefficient for heart rate calculation, and e_1 and e_2 represent the blood pressure data of the previous time node and the current period, respectively [17].

2) Total power of exercise. Assuming that the real-time physiological index data fitting function $f(a)$ of students is continuous within a certain constant interval, the total exercise power of students can be obtained based on this fitting function. The specific calculation result can be expressed as

$$\int_j^i f(a) = f(j) - f(i) \tag{3.3}$$

In the formula, $f(i)$ represents the fitting function calculation result of interval endpoint 1, and $f(j)$ represents the fitting function calculation result of interval endpoint 2.

According to the above formula, after sorting and analyzing these two physiological indicators, they will be imported into the same database as the results collected by smart wearable devices, providing a foundation for subsequent human motion data mining [18].

3.3. Organizing and Analyzing Human Movement Data. Due to the diverse categories and different dimensions of the raw data collected by smart wearable devices, in order to better complete the data mining process, it is necessary to preprocess the collected data and integrate it into binary data format. Assuming the collected raw data is $E = (1, 2, 3, \cdots, n)$, the binary digit β_v of physiological indicator data can be represented as

$$\beta_v = (\beta_{v1}, \beta_{v2}, \cdots, \beta_{vn}) \tag{3.4}$$

In the formula, n represents the number of physiological indicators. After completing this part of the processing, set H as the candidate dataset for mining data 3, and calculate the basic support for each physiological indicator. This includes:

$$sup(H) = \sum_{i=1}^{n} N_i \tag{3.5}$$

In the formula, the calculation formula for the support coefficient N_i is as follows:

$$N_i = \begin{cases} 1, \beta_v \cap H = H \\ 0, \beta_v \cap H \neq H \end{cases} \tag{3.6}$$

According to the above formula, integrate the data into binary data format and import it into the database. The raw data collected by smart wearable devices may contain abnormal data, which needs to be cleaned and subjected to secondary analysis. Assuming the data is complete, then $\beta_v = 1$; If the data is abnormal, then $\beta_v = 0$. After discovering abnormal data, use interpolation method to supplement the data. After completing the analysis of all data in the database, conduct human motion data mining.

3.4. Human motion data mining. On the basis of the previous text, the author cited the K-means clustering analysis method in data mining technology to mine and process the data, and constructed a human motion data mining algorithm [19]. Assuming that this part of the data can be divided into k subclasses, and multiple iterative calculations are required during the subclass partitioning process, the variation between each subclass can be expressed as

$$U = \sum_{i=1}^{n} \sum_{w \in L,i} dist(w, l_i)^2 \tag{3.7}$$

In the formula, U represents the deterioration of data category, l_i represents the data cluster code, w represents the centroid of each data cluster, and (w, l_i) represents the Euclidean distance between the observed data and the centroid of the data cluster. Based on this formula, construct a human motion data mining algorithm. Enhance and refine sports data according to its specific features. Given the substantial volume of collected human motion data, extended computation times during processing are an unavoidable challenge. Therefore, in this study, the cocoon firefly algorithm was used to optimize it. Assuming that the core information of each raw data is C, there exists:

$$C_i = f(A_i) \tag{3.8}$$

In the formula, A_i represents the basic information value, and $f(A_i)$ represents the objective function of sports information data mining. According to this formula, the attractiveness between the original data can be determined as follows:

$$\mu = \mu_0 * exp(-vp_{ij}) \tag{3.9}$$

In the formula, μ_0 represents the initial attraction between data, p_{ij} represents the Euclidean distance between two raw data, and v represents the absorption coefficient of attraction between different data [20]. When the basic information of two data sets is different, the clustering mining process of the data can be represented as

$$g_{i+1} = g_i + \mu(g_j - f_i) + \eta(rand - \frac{1}{2}) \tag{3.10}$$

In the formula, g_i and g_j represent the spatial positions of two sports data, μ represents the attractiveness of the data, η represents a random constant, and rand represents any integer from 0 to the maximum random number. Combine formula 3.10 with formula 3.7 to complete the data mining process. Thus, the design of a human motion data mining algorithm based on smart wearable devices has been completed.

3.5. Experimental verification.

3.5.1. Dataset. The author chose the Actions dataset and the measured dataset as the data sources. The Actions dataset contains 7 types of sports data, including diving, skiing, snowboarding, platform diving, racewalking, artistic gymnastics, and trampoline, with 10000 pieces of data. The measured dataset is a spatiotemporal data detection dataset, which comes from human motion measurement data of 30 volunteers. The data can be divided into 6 categories of human movements, totaling 5000 pieces of data. Merge the data from the two datasets into the test data and randomly divide them into 10 groups, each containing data from both datasets. The division results are shown in Table 3.1.

Select test groups XC1-XC5 as the training group and XC6XC10 as the testing group. Apply the proposed algorithm to analyze the data through mining techniques to assess the effectiveness of the algorithm in practice. The types of human motion data collected by smart wearable devices include the following aspects:

Table 3.1: Example Test Data Group

Group number	Data volume	Group number	Data volume
XC1	1500	XC6	1500
XC2	1500	XC7	1500
XC3	1500	XC8	1500
XC4	1500	XC9	1500
XC5	1500	XC10	1500

(1) Heart rate: By measuring electrocardiogram (ECG) signals, students' heart rate data can be obtained to evaluate their exercise status and physical health. The data size is 15.61GB.
(2) Step count and step frequency: Through sensors such as accelerometers and gyroscopes, students' step count and step frequency data can be obtained to evaluate their gait and walking posture, with a data volume of 10.36GB.
(3) Distance and speed: Through sensors such as GPS and accelerometers, students' distance and speed can be obtained to evaluate their exercise intensity and speed, with a data volume of 7.89GB.
(4) Posture and motion trajectory: Through sensors such as gyroscopes and accelerometers, students' posture and motion trajectory data can be obtained to evaluate whether their posture and actions are correct. The data size is 8.96GB.
(5) Muscle activity and energy consumption: Through technologies such as electromyography (EMG) sensors, students' muscle activity and energy consumption data can be obtained to evaluate their muscle state and exercise intensity, with a data volume of 5.96GB.
(6) Blood oxygen and blood pressure: Through technologies such as blood oxygen and blood pressure sensors, students' blood oxygen and blood pressure data can be obtained to evaluate their physical condition and exercise load, with a data volume of 11.34GB.

3.5.2. Experimental indicators. The experiment selected algorithms such as big data analysis based motion wearable smart devices (Algorithm 1), data mining algorithm based motion wearable smart devices (Algorithm 2), information entropy based optimization algorithm (Algorithm 3), improved mean and LSTM based algorithm (Algorithm 4), and full entropy based anomaly data mining algorithm (Algorithm 5) to conduct data mining analysis with the proposed methods. Assess the strengths and weaknesses of different algorithms based on predefined evaluation criteria to confirm that the proposed algorithm meets the design specifications. The evaluation metrics include three main categories: recall rate, accuracy rate, and precision of human motion data collection. By analyzing these indicators in combination, determine the computational performance of the proposed algorithm.

The recall rate calculation formula for human motion data mining:

$$D_1 = \frac{S_0}{S_{all}} \times 100\% \tag{3.11}$$

In the formula, S_{all} represents the data that should be recalled, and S_0 represents the actual recall data.

Formula for calculating the accuracy of human motion data mining:

$$D_2 = \frac{S_1}{S_0} \times 100\% \tag{3.12}$$

In the formula, S1 represents the data that has been correctly mined and processed in the recall data.

Formula for calculating the accuracy of human motion data collection:

$$D_3 = \frac{S_1}{S_{all}} \times 100\% \tag{3.13}$$

Table 4.1: Comparison Results of Data Recall Rates

Group number	Proposed algorithm	Algorithm 1	Algorithm 2	Algorithm 3	Algorithm 4	Algorithm 5
XC6	98.874	96.85	95.06	96.14	96.52	95.74
XC7	95.46	95.03	96.03	96.24	96.58	96.01
XC8	96.89	96.03	95.70	96.36	95.10	96.07
XC9	97.26	95.48	96.63	96.56	95.02	96.03
XC10	97.78	95.04	96.80	96.37	96.73	96.23
average value	97.20	95.67	96.05	96.33	96.09	96.02

Table 4.2: Comparison Results of Data Accuracy

Group number	Proposed algorithm	Algorithm 1	Algorithm 2	Algorithm 3	Algorithm 4	Algorithm 5
XC6	98.12	95.89	95.88	94.18	94.01	95.01
XC7	98.68	94.88	95.64	95.36	94.33	95.22
XC8	98.02	94.07	94.67	94.55	95.13	94.16
XC9	98.16	94.46	94.34	95.57	95.44	94.55
XC10	98.64	94.31	95.44	95.16	94.71	94.49
average value	98.31	94.71	95.29	95.05	94.72	94.65

Table 4.3: Comparison Results of Data Collection Accuracy

Group number	Proposed algorithm	Algorithm 1	Algorithm 2	Algorithm 3	Algorithm 4	Algorithm 5
XC6	98.49	94.61	93.02	94.06	94.05	93.14
XC7	98.00	94.05	93.55	93.04	94.17	93.03
XC8	97.87	94.04	93.06	93.16	93.81	94.91
XC9	97.57	94.88	95.21	94.17	93.75	94.08
XC10	98.04	95.03	94.43	93.24	93.76	94.25
average value	98.05	94.45	93.83	93.51	94.00	93.82

4. Results and Discussion. Table 4.1 compares the recall rates of various algorithms for human motion data mining. Analysis of the data reveals that the recall rate of the proposed algorithm is comparable to those of the other five algorithms, with any differences being no greater than 4.0%. Through analysis, it can be seen that the average recall rate of the algorithm proposed by the author is 97.31%, which is 1.53%, 1.15%, 0.87%, 1.21%, and 1.18% higher than Algorithm 1, Algorithm 2, Algorithm 3, Algorithm 4, and Algorithm 5, respectively. The algorithm proposed in the experiment has a relatively high recall rate, overall stability, and relatively stable data analysis and processing capabilities, demonstrating a certain degree of feasibility.

From the analysis of the data in Table 4.2, it can be seen that there are differences in the accuracy of data mining between the algorithm proposed by the author and the other five algorithms. Among them, the average data mining accuracy of the algorithm proposed by the author is 98.31%, which is 3.5%, 3.01%, 3.25%, 3.48%, and 3.55% higher than algorithms 1, 2, 3, 4, and 5, respectively. The proposed algorithm demonstrates notably superior accuracy in data mining compared to other methods, highlighting its strong capabilities in data analysis. While the other five algorithms meet the accuracy standards for human motion data, their overall performance in this aspect is relatively lower, suggesting a need for further optimization.

The analysis presented in Table 4.3 reveals that the proposed algorithm significantly outperforms the other five algorithms in terms of human motion data collection accuracy. Specifically, the proposed algorithm achieves an average accuracy of 98.04%, which surpasses the accuracy of algorithms 1, 2, 3, 4, and 5 by 3.3%, 4.01%, 4.22%, 4.04%, and 4.01%, respectively. This demonstrates that the proposed algorithm excels in accurately collecting human motion data compared to the alternatives.

5. Conclusion. In this paper, we put forward a study on the application of intelligent wearing equipment in physical education. In response to the problems that arise in the current sports data analysis research process, smart wearable devices are applied to obtain raw data and a new data mining algorithm is set up. The results of the example show that the proposed method is of great practical value. This algorithm can be applied in student physical condition assessment, sports injury and fatigue monitoring, sports posture and action assessment, personalized training and rehabilitation program development, scientific decision-making and management, etc., to improve students' physical health status, optimize training and competition strategies, implement personalized training and rehabilitation programs, and provide a basis for scientific decision-making and management. Although the research has achieved certain results, this design only focuses on optimizing real-time data collection problems and has not improved other issues in the data mining process. In future research, it is necessary to optimize other aspects of sports data analysis to ensure that the application effect of this algorithm meets the requirements of data analysis.

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