

Retraction

Retracted: Optimization of IoT-Based Motion Intelligence Monitoring System

Complexity

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] J. Qiao, Z. Zhang, and E. Chen, "Optimization of IoT-Based Motion Intelligence Monitoring System," *Complexity*, vol. 2021, Article ID 9938479, 10 pages, 2021.

Research Article

Optimization of IoT-Based Motion Intelligence Monitoring System

Jian Qiao,¹ Zhendong Zhang ,² and Enqing Chen ³

¹Department of Arts and Sports, Henan College of Transportation, Zhengzhou 450000, China

²School of Physical Education (Main Campus), Zhengzhou University, Zhengzhou 450001, China

³School of Information Engineering, Zhengzhou University, Zhengzhou 450001, China

Correspondence should be addressed to Zhendong Zhang; zzd0506@zzu.edu.cn

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We design and implement an intelligent IoT-based motion monitoring system to realize the monitoring of three important parameters, namely, the type of movement, the number of movements, and the period of movement in physical activities, and optimize the system to support the simultaneous use by multiple users. Considering the motion monitoring scenario for smart fit, the framework of an IoT-based motion monitoring system is proposed. The framework contains components such as active acquisition nodes, wireless access points, data processing servers, and terminals. In terms of algorithm optimization, research related to active pattern recognition and periodic calculation methods is conducted. For active pattern recognition, two types of classification algorithms with different complexity are proposed based on Support Vector Machine (SVM) and deep neural networks, respectively, to adapt to scenarios with different computational capabilities. For period calculation, a method based on over-zero detection and wavelet transform is proposed to count the number of actions and calculate the period of each action. In 100 times action cycle calculation experiments, the count statistic calculation method achieves 100% calculation accuracy and the active cycle calculation results are close to the real value, which proves the effectiveness of the cycle calculation method. The system provides a multiuser-oriented communication method and realizes accurate and reliable human movement monitoring, which has a wide application prospect in the fields of physical education and rehabilitation training.

1. Introduction

The Internet of Things is an important part of the new generation of information technology and an important development stage of the information age. In a broad sense, the Internet of Things is the Internet where things are connected; in a narrow sense, the nucleus and foundation of the Internet of Things is still the Internet, which is a network extended and expanded on the basis of the Internet, and its user side has the tendency to extend and expand to any item and the trend of information exchange and communication between items, which is also the interest of things [1]. IoT is widely used in the integration of the network through intelligent sensing, identification technology, and communication sensing technology such as pervasive computing and is therefore called the third wave of development of the

world information industry after computers and the Internet. With the development of IoT technology, standardized sensors and components are increasingly adaptive, more and more control system integration functions are transferred to product manufacturing, the degree of equipment standardization and system self-adaptation is greatly enhanced, and the integration of professional systems is greatly enhanced. The era of cloud platform network management and operation is bound to come. The workload and difficulty of system integration and on-site debugging of intelligent buildings are becoming less and less and will become an incidental project of construction enterprises [2].

Health is a topic of great concern to people today, and maintaining good health is a common hope. Good health not only helps us to maintain a positive and optimistic mood

and attitude toward life but also helps to improve our sense of well-being and self-confidence, and furthermore, having a strong and healthy body brings fundamental protection to study and work. However, illness, injury, and unhealthy lifestyles continue to pose challenges to maintaining physical health, and one of the most significant adverse effects is on physical mobility [3]. Limitations in physical activity due to injury or disease can affect people's ability to care for themselves and reduce their quality of life. In addition, lack of exercise can result in weakness and obesity. For a motion monitoring system, the most important function is to be able to identify the type of movement and to be able to count the number and period of movements, as all three are important movement indicators. In addition, a reliable sensor node design and a communication method that support multiple users can also improve the ease of use and reliability of the system [4].

This paper designs an end-to-end limb movement monitoring platform, which uses a wearable bracelet for movement data collection, and uses Wi-H supporting multiple users to transfer the data to the cloud, where the data can be analyzed in the cloud server for movement pattern recognition, movement count, and movement cycle calculation. The platform not only allows the simultaneous use of multiple users for limb movement monitoring but also provides a more comprehensive and accurate analysis and description of the movements. The proposed monitoring algorithms for limb movements include an action recognition algorithm and periodic calculation method. For action recognition, action pattern recognition is implemented using deep neural networks and support vector machines (SVM) on a small data set, and the performance of different models is compared. In terms of period calculation, wavelet transform and over-zero monitoring-based limb action period calculation are studied to achieve high-precision active count statistics and active period calculation.

2. Related Works

At present, most of the smart fall monitoring devices at home and abroad are communicated through Bluetooth, WiFi, or GPRS, and each device is a relatively single function, relatively large, and inconvenient to wear. Power consumption is also large, and the scope of use is not very wide. People often hope that a variety of functions can be integrated into a smart wearable device, such as making a wristband, having personnel positioning, heart rate monitoring, and life environment monitoring. For example, a wristband should have functions such as personnel positioning, heart rate monitoring, life environment monitoring, fall monitoring, and automatic trigger notification to emergency contacts [5]. Abdel-Basset et al. proposed a sensor network for remote home health monitoring based on the Internet of Things [6]. Farné et al., based on understanding and research on the commonly used physiological data of the human body, proposed two systems of remote home health monitoring based on ZigBee and remote home health monitoring based on Bluetooth and through comparison [7]. Saravanan et al. chose the Bluetooth-based remote home health monitoring system and conducted a feasibility study on it [8]. Robinson

et al. designed a system of medical health monitoring based on the cloud computing platform, which firstly obtains the physiological information of heart patients accurately through the hardware platform and then realizes the remote diagnosis of doctors through the cooperation of cloud computing platform, while keeping in touch with the patient's family in a timely manner [9]. Considering that it is used in a mobile environment and the basic requirements of wearable devices are ultralow power consumption, ultrasmall size, stand-alone usability, and ultralow cost, it requires us to find a new technology to make up for the shortcomings of existing technologies.

In foreign countries, more and more people use remote monitoring to take care of athletes' health. Experiments have also proved that remote monitoring is indeed a very effective means of accompanying, which greatly reduces the admission rate. The IoT module follows stringent quality standards. It provides a suitable solution for the difficulties encountered in the deployment of IoT LPWAN application scenarios, which is very suitable for application scenarios with low power consumption and wide coverage requirements. It can be widely used. It is applied to many highly targeted vertical applications of the Internet of Things, such as independent wearable smart devices. In the future, telemedicine and health monitoring can rely on the advantages of the physiological collection sensor device and wireless connection technology provided by the Internet of Things to be well developed.

The IoT technology-based sport intelligence monitoring device integrates a variety of sensors to monitor whether the user has an accident and the user's heart rate, the environmental parameters, etc., and transmits the data collected by the sensing layer sensor devices back to the One NET IoT open platform through the NB module, and the system will automatically trigger the platform end trigger after detecting the abnormal phenomenon, which will promptly notify the preset [10]. The system will automatically trigger the trigger at the platform after detecting anomalies, and the trigger will promptly notify the predefined emergency contact. The device is highly practical and can enable users to be detected in time after abnormal movement so that they can be rescued as soon as possible and reduce the rate of casualties caused by accidents [11]. In addition, the wide coverage, low power consumption, low cost, and high stability of IoT technology can maximize the data transmission efficiency of these wearable devices, and the environment is not limited to indoor but extends to the whole city and is more suitable for various outdoor environments and special people, so that the smart wearable sport intelligent monitoring devices with communication functions are easier to use, are more universal, and have a broader market application prospect and have certain scientific research significance. It has some scientific research significance [12].

3. Optimization of Intelligent Monitoring System for Sports with IoT Technology

3.1. IoT Motion Intelligent Detection Scheme Designs. This system uses smart wear as a carrier, putting the sensing

device and hardware equipment on the body of the measured user, in order to achieve real-time monitoring of indicators affecting the health of the elderly, including blood pressure, blood oxygen, and heart rate. An important indicator of this system is the BDS positioning information. For some Alzheimer's disease patients, there is a real-time grasp of the positioning information of the disease. For some Alzheimer's disease patients, it is indispensable to have real-time positioning information of the patient. As a smart wearable device, the terminal device needs to be small in size, safe, and reliable and have high accuracy, low power consumption, wide communication coverage, and low cost. According to the demand analysis, this system should also meet the following characteristics [13]:

- (1) *Reliability*. For the data related to human body health, the reliability of the data is a very important indicator; therefore, the selection of the sensor and the design of the acquisition circuit in the hardware terminal need to be carried out under the premise of satisfying the accuracy of the data, and the processing of the raw data collected needs to be solved by the optimization algorithm [14].
- (2) *Real-Time*. This system contains a very important monitoring indicator, which is BDS positioning, for location monitoring; in order to achieve the guardian at any time to know the location of the monitored information, whether out of the present range, the real-time requirements of the system are very high.
- (3) *Low Power Consumption*. Low power consumption is the basic requirement of a smart wearable device; too high power consumption will greatly affect the user experience. The product itself in the promise of having the function of BDS positioning and low power consumption is a great challenge.
- (4) *Low Cost*. With the development of the chip market, the price of the chip is also getting higher and higher; in the development of the program to select the device, there should be a comprehensive consideration of its function and price, if the product cost is too high so as to increase the difficulty of popularization [15]. It is not a good product.

This system is an interactive system integrating sensor technology, Internet of Things technology, and Internet technology and is based on hardware a collection platform, a smartphone platform, a cloud platform, and a PC end website platform. The system consists of a terminal equipment platform, cloud service platform, and remote monitoring platform, where the terminal equipment platform is divided into data collection and processing module and data transmission module, and the remote monitoring platform contains management PC terminal and user cell phone client, and its system control scheme is shown in Figure 1.

The terminal device platform of intelligent controller collects the information of blood pressure, blood oxygen, heart rate, position, and movement status of elderly users by corresponding sensors, and the master controller in it processes the collected data and then sends the processed

data to the cloud service platform through a wireless network. Then, the platform transmits the data to the mobile client and PC side of the guardian through the network, and the cloud platform in this scheme can be directly used as a PC terminal, or the data can be transferred to a third-party PC terminal website and can store a large amount of data and also play the role of a database in the whole system [16]. The guardian can access the cell phone client and PC website at any time to view the test data and movement track of the elderly, which not only can monitor the physical condition of the elderly for a long time but also send an alert to the guardian when there is an abnormal situation so that the unexpected situation can be dealt with in time.

3.2. Movement Intelligent Monitoring System Optimization.

Deep coverage capability, low power consumption, and massive connectivity are its unique advantages, and it is mainly applicable to applications of IoT such as sensing, monitoring, and metering. Smart meter reading, vehicle tracking, smart parking, logistics monitoring, smart agriculture, forestry, animal husbandry, and fishery, as well as smart home, smart wear, and smart community, are all areas where it can be applied. Because the needs of low power consumption, wide coverage, and low cost are very clear in these fields, however, these challenges are exactly what the 2G/3G/4G and other related wireless technologies that are widely commercialized now cannot meet.

In this paper, a combined network model based on a 1D convolutional neural network and a long and short-term memory network is developed, which combines the features of both and can be well used to process the time series signal output from the pose sensors and requires less data volume. The one-dimensional convolutional neural network has the advantage of requiring a low number of training samples. The network has a one-dimensional convolutional kernel, and its convolutional operation can scan every local part of the time-series signal and mine its local features. By combining convolutional kernels with different window lengths, the extraction of features at different scales of the signal can be achieved. Such a feature also makes the 1D convolutional neural network have better results on small data sets compared with other networks. In addition, due to the presence of pooling layers, 1D convolutional neural networks can also achieve downsampling of the signal, which shortens the length of the signal to speed up the training process and shorten the time required to train the network. However, 1D convolutional neural networks are not sensitive to the temporal order, so they cannot mine the information related to the temporal order in the signal [17]. On the other hand, the long short-term memory network is a temporal recurrent neural network, which was originally designed to process time series. The unique gate structure inside the long short-term memory network allows it to selectively retain or forget previous information and has a better memory for events with longer intervals in the time series. However, long short-term memory networks require a large amount of data for training. Therefore, by combining a 1D convolutional neural network with a long short-term

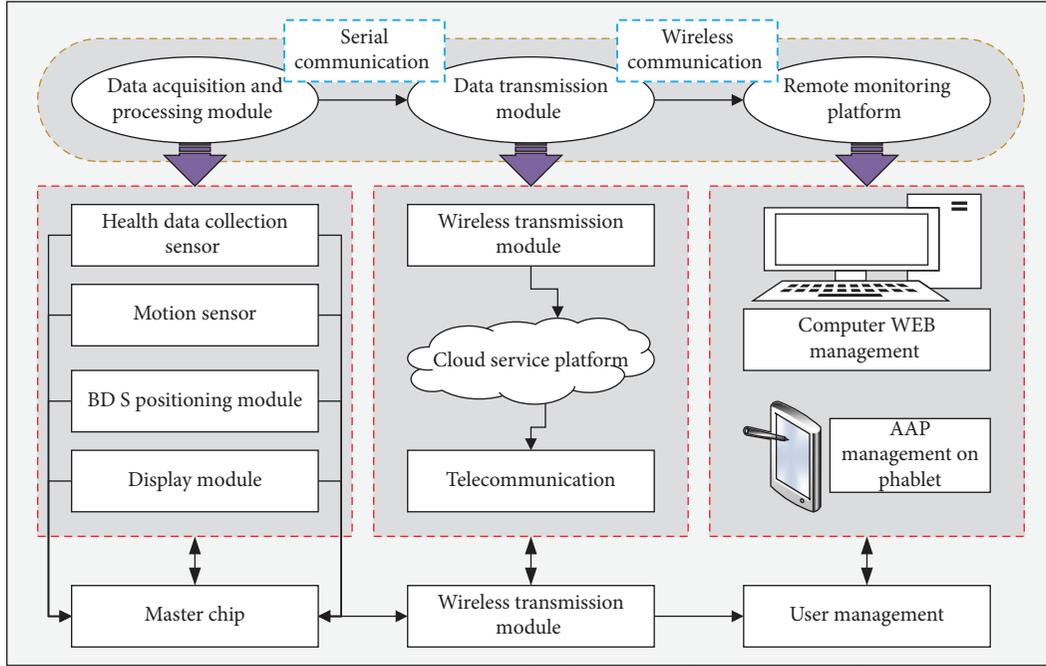


FIGURE 1: General scheme diagram.

memory network can fully utilize the advantages of both, which can mine the temporal information in the data without the need of a large number of training samples and thus well achieve the recognition of actions.

In selecting the sensitive axes, three angular (Eulerian) axes are excluded and only one of the remaining six axes is selected and analyzed. The specific selection method of the sensitive axes is as follows:

$$M = [M_1, M_2, M_3, M_4, M_5, M_6]^T, \quad (1)$$

$$H_i^2 = \frac{1}{n} \left| \sum_{i=1}^m \sum_{j=1}^n \left(M_{ij} - \frac{M_i}{M_j} \right)^2 \right|.$$

This paper combines the respective characteristics of over-zero detection and wavelet transform to propose a motion counting and period calculation method, which can eliminate the interference caused by limb jitter or other noise and can be used to count the number of reciprocal limb movements and calculate the period of each movement [18].

$$B = \int_{\varphi}^{\mu(\varphi)^2} d\varphi + \int_o^{\mu(o)^2} do. \quad (2)$$

For the key axis signal that has been selected, its continuous wavelet transform is

$$F(m, n) \leq f(\varphi(m, n)) \geq \frac{b^{1/3}}{a^{1/2}} \int f(x) \frac{\mu(x-b)^2}{a} dx. \quad (3)$$

After doing wavelet transform on the key axis signal, the wavelet coefficient matrix $A_{m \times n}$ can be obtained, where n denotes the number of layers of wavelet transform and m denotes the number of sampling points, i.e., the length of the signal.

$$A = \begin{bmatrix} b_{11}^3 & b_{12}^3 & b_{1m}^3 \\ b_{21}^3 & b_{22}^3 & b_{2m}^3 \\ b_{31}^3 & b_{32}^3 & b_{3m}^3 \end{bmatrix}^T * \begin{bmatrix} c_{11}^3 & c_{12}^3 & c_{1n}^3 \\ c_{21}^3 & c_{22}^3 & c_{2n}^3 \\ c_{31}^3 & c_{32}^3 & c_{3n}^3 \end{bmatrix}^T. \quad (4)$$

Each wavelet scale in the wavelet transform corresponds to a frequency vector F , which is determined by both the number of layers and the scale of the specific wavelet transform [9]. Since the period is the reciprocal of the frequency, the vector G , which reflects the period of the action at each sampling moment, can be expressed as

$$G = \left[\frac{1}{F_{ai}}, \frac{1}{F_{bi}}, \frac{1}{F_{ci}} \right], \quad i \in [1, m]. \quad (5)$$

3.3. Motion Intelligent Detection System Design Implementation. The pulsed sensor kit based on the photo volumetric method of measuring heart rate pulse used in the design of the system hardware includes a 24" color-coded cable with a male connector that allows easy embedding of the sensor into the project. When the sensor's light source shines on the body, most of the light is absorbed or reflected by our organs and tissues, but if they are thin enough, some light will pass through our tissues. When blood is pumped into the body, it is squeezed into the capillary tissue and the volume of these tissues increases slightly. Then, between the periodically changing heartbeat and pulse beat, the peripheral arterial blood volume of the body also changes periodically [19]. The change in blood volume affects the light transmission rate, and although this fluctuation is very small, we can sense it through electronic devices, and this is how the heart rate sensor based on the

optical volume method is accomplished to measure the heart rate. In the optical heart rate pulse sensor, light is shot into the fingertip, wrist arterial blood vessels, or earlobe, and the light will reflect back to be received by the integrated light receiver on the sensor and convert the light signal into an electrical signal and then amplify the output. At this time, to obtain the electrical signal cycle output from the photoelectric pulse sensor, you can get the heartbeat pulse reading of the device user. The sensor includes high-quality kit accessories, designed for plug-and-play, with the advantages of small size, practicality, ease to wear, and high reliability, and it is also unbendable in wearable devices and applicable to any MCU with ADC. In addition, the chip can be powered on or off through software control of the module, and its standby current is almost close to zero, which can meet the demand of the power supply to maintain the power state at all times. In addition, the sensor has an integrated glass cover and a low-noise electronic circuit with ambient light suppression, which can effectively exclude external or internal visible light interference factors and have optimal reliability.

The system hardware platform mainly consists of STM32 microcontroller as the microcontroller, integrated NB-IoT communication module, three-axis sensor ADXL345, temperature and humidity sensor, heart rate sensor, GPS module, and other terminal sensing pieces of equipment. A three-axis acceleration sensor is used to monitor whether the fall phenomenon occurs, temperature and humidity sensor will collect the environmental temperature and humidity data reported, heart rate sensor is responsible for collecting the wearer's heart rate information, GPS positioning module is responsible for reporting the device location information after the system detects a fall. The GPS positioning module is responsible for reporting the location of the device after the system detects a fall, and the illumination sensor is used as an auxiliary environmental monitoring sensor together with the temperature and humidity sensor to monitor the suitability of the elderly living environment. The touch sensor is used to light up the device to meet the wearer's lighting needs during nighttime activities. The information of all the parameters sensed by all the sensors will eventually be uploaded to the application side of the elderly fall monitoring created by the One NET IoT open platform, so as to realize the query, management, and display functions of the device information on the platform side.

The system divides the current motion state into 3 states: stationary, daily activity, and fall, and its functional implementation process is as follows: the hardware acquisition system collects the relevant data of human body state through the motion sensor MPU6050 and sends the motion state in the form of identification code to One NET cloud platform after the algorithm operation by the underlying master chip, and then the Android application reads the motion state identification code in the platform data through HTTP request. The Android application then reads the motion status identification code in the platform data through HTTP request and analyzes the current motion status of the human body through the identification

code in reverse, the human motion status identification code is shown in Table 1, and Android then displays the status through the text form. At the same time, if the human body's motion status is in the fall, the Android application will ring the bell and pop up the warning box to remind, and in this state, you can check it. If the human body is in the daily activity state, no warning message will appear, and the same can be clicked to view the current positioning, but when the human body is in the stationary state, the BDS is in the hibernation state and the system is also in the PSM mode with lower power consumption, so the current positioning point cannot be viewed at this time, and no track record will be generated.

The application mainly contains four functions: user personal information view, physiological parameters display, exercise status display, and exercise track drawing line. The display interface of physiological parameters contains all the collection history data of blood pressure, blood oxygen, heart rate, and a note reminder for the data; the display interface of current exercise status contains the view of current exercise status, static, daily activity, or fall, and contains all the fall records; the exercise trajectory line contains the interface of selecting the viewing time period and the display interface of the trajectory line of the time period.

4. Results and Analysis

4.1. System Performance Analyses. In the process of physiological parameter testing, in addition to using the data acquisition system of this system for data acquisition, the Philips pulse oximeter DB15 and the home wristband electronic blood pressure meter were selected to collect blood pressure, blood oxygen, and heart rate of volunteers for comparison, and the absolute error method was used to analyze the measurement error of this system. In the experimental process, for 8 volunteers, each group of volunteers collected 20 sets of data per device; in total, each group of devices contains 80 sets of data, one set of blood oxygen, and heart rate test comparison data as shown in Figure 2. According to the data in the figure, the relative error value of blood oxygen is not more than 1.25%, and the relative error value of heart rate is not more than 2.14%, through the calculation of all data. The relative error of blood oxygen is no more than 1.38%, and the relative error of heart rate is no more than 2.49%, which is small and meets the expectation of this system design.

One set of blood pressure test comparison data is shown in Figure 3, the data in the figure shows that the relative error of blood pressure value is not more than 5.23%, and the relative error of low pressure value is not more than 5.31%. Through the statistics of all the collected data, the relative error of high pressure value is not more than 5.43%, and the relative error of low pressure value is not more than 5.76%, because the blood pressure collection of this system chooses the way of continuous blood pressure measurement, and its accuracy is slightly lower than that of systolic. Therefore, the reliability of blood pressure monitoring can be considered high.

TABLE 1: Human motion status identifiers.

Binary identification code	Hexadecimal identification code	Meaning
0 × 001	0 × a	Stationary state
0 × 010	0 × b	Daily activity status
0 × 011	0 × c	Fall state

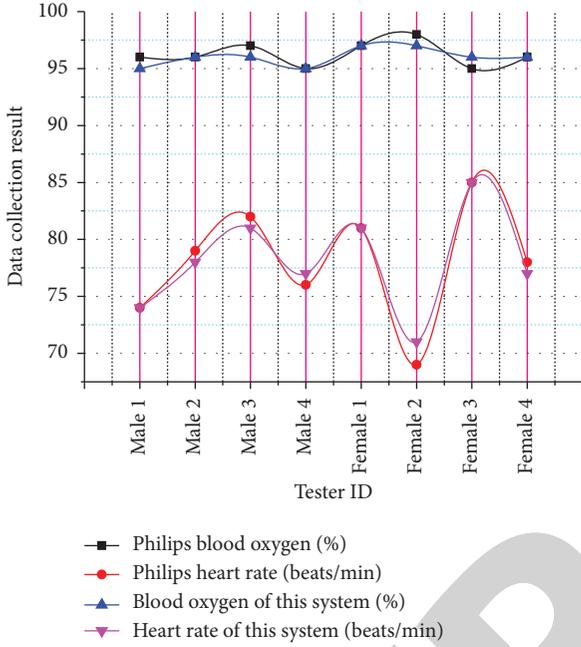


FIGURE 2: Comparison of blood oxygen and heart rate collection data.

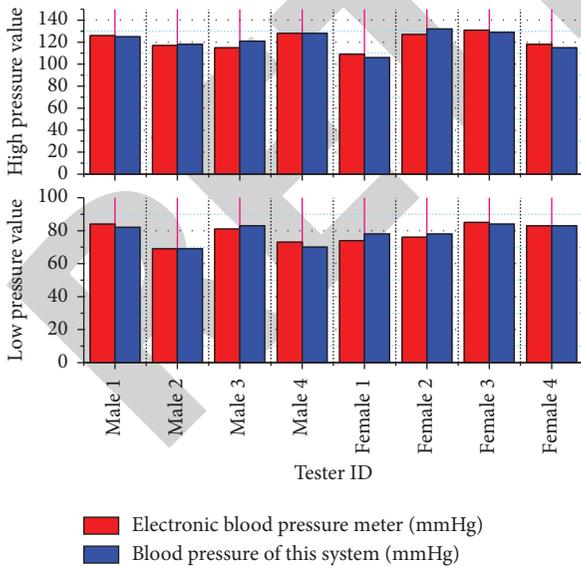


FIGURE 3: Comparison of blood pressure collection data.

4.2. *System Accuracy Analyses.* After debugging the communication flow of the terminal device based on the M5310 communication module, the terminal module and the platform side fall monitoring application are working in a

normal state, and then, we need to focus on debugging the heart rate pulse sensor, three-axis acceleration sensor, and GPS module, respectively, to ensure that each module is working in normal state and can complete their respective information acquisition tasks under the control of MCU and platform. The first step is to debug the photoelectric heart rate sensor. The optical pulse heart rate sensor is essentially an optical densitometer, which is a well-known medical device for noninvasive heart rate monitoring. Figure 4 records manually counted heart rate values of the same subject in ten separate measurements per minute and the heart rate values tested by the device, and comparison reveals that the device testing error is below 2.98%.

During the test, the acceleration value of each axis of the three-axis accelerometer and the change curve of the acceleration vector sum received from the One NET platform are shown in Figure 5, and the buzzer and platform break trigger are triggered when the vector change exceeds the set threshold value. The upper two graphs of Figure 5 are the X-axis value curve of the three-axis accelerometer and the Y-axis value curve of the three-axis accelerometer. The bottom two graphs of Figure 5 are the Z-axis value curve of the three-axis accelerometer and the three-axis acceleration vector sum curve. Here, the detection threshold and time parameters of the relevant interrupt can also be set flexibly according to the needs.

Comparing the sum of square deviations of the curves obtained by modeling temperature and humidity with three models, it can be concluded that the optimal model for temperature and humidity is the gem model. Figure 6 shows the maximum value of the absolute value of the deviation at each time point in the temperature optimal model and the maximum value of the absolute value of the deviation at each time point in the optimal model. This is very useful in setting the threshold for abnormal motion alarms in future studies.

4.3. *Motion Detection Analyses.* In this paper, seven types of body movements were selected for identification, as shown in Figure 7. These movements include four types of dumbbell movements and three types of leg exercise movements, namely, dumbbell curl, dumbbell side planks, dumbbell shoulder press, dumbbell flying bird, seated calf raise, standing calf raise, and heel lift. These seven types of movements are common physical exercise movements, with a strong representative. Among them, the similarity between some movements is high, such as seated calf lift and standing calf lift, which is challenging for the classifier and can fully verify the classification ability of different models.

In the action recognition experiments, two types of data preprocessing in deep neural networks were first compared. For deep neural networks, one way of preprocessing is to join the nine axes first and last. The other way is to make it less dimensional using linear discriminant analysis. The results of experiments comparing the two and processing methods are shown in Table 2, which shows that linear discriminant analysis is less accurate when used for action recognition. The reason is that although linear discriminant analysis can effectively reduce the dimensionality of the data

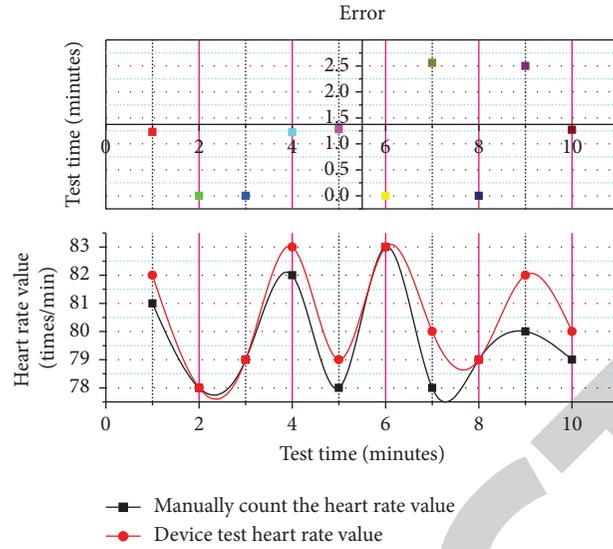


FIGURE 4: Device heart rate test results.

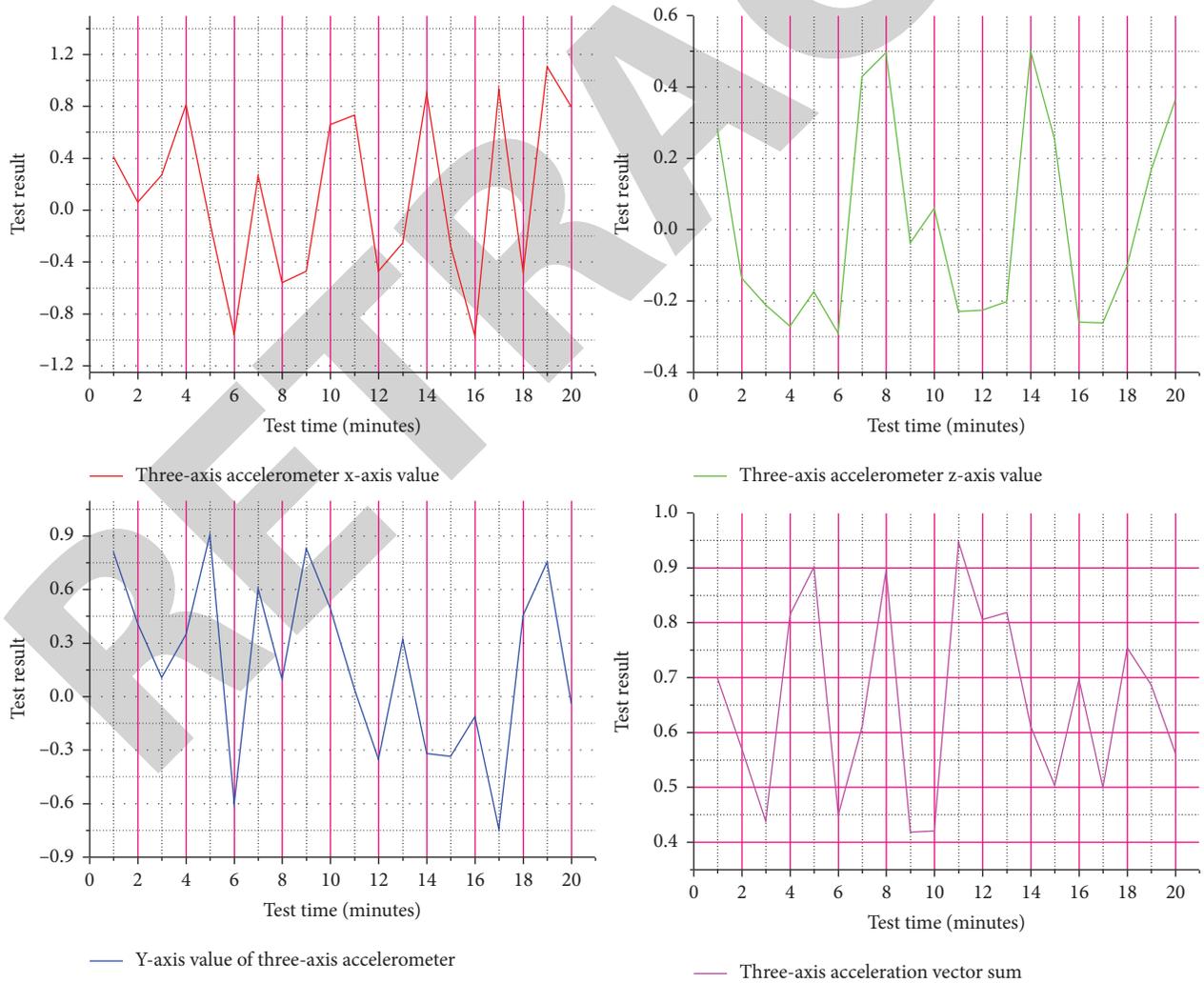


FIGURE 5: Curves of the triangle accelerometer measurements received at the platform side.

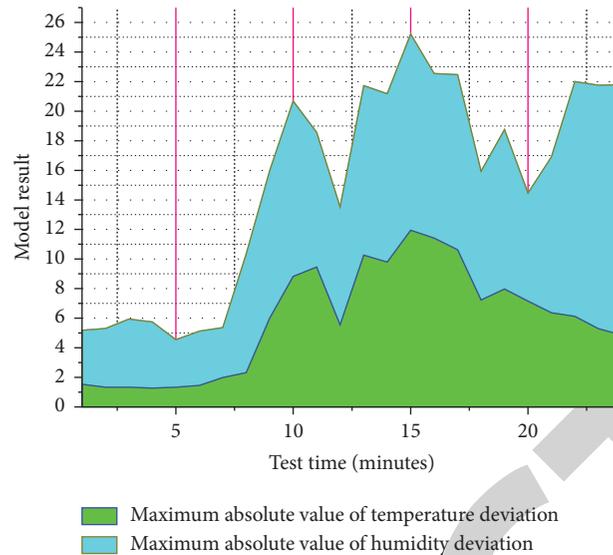


FIGURE 6: Maximum values of absolute temperature and humidity deviations.

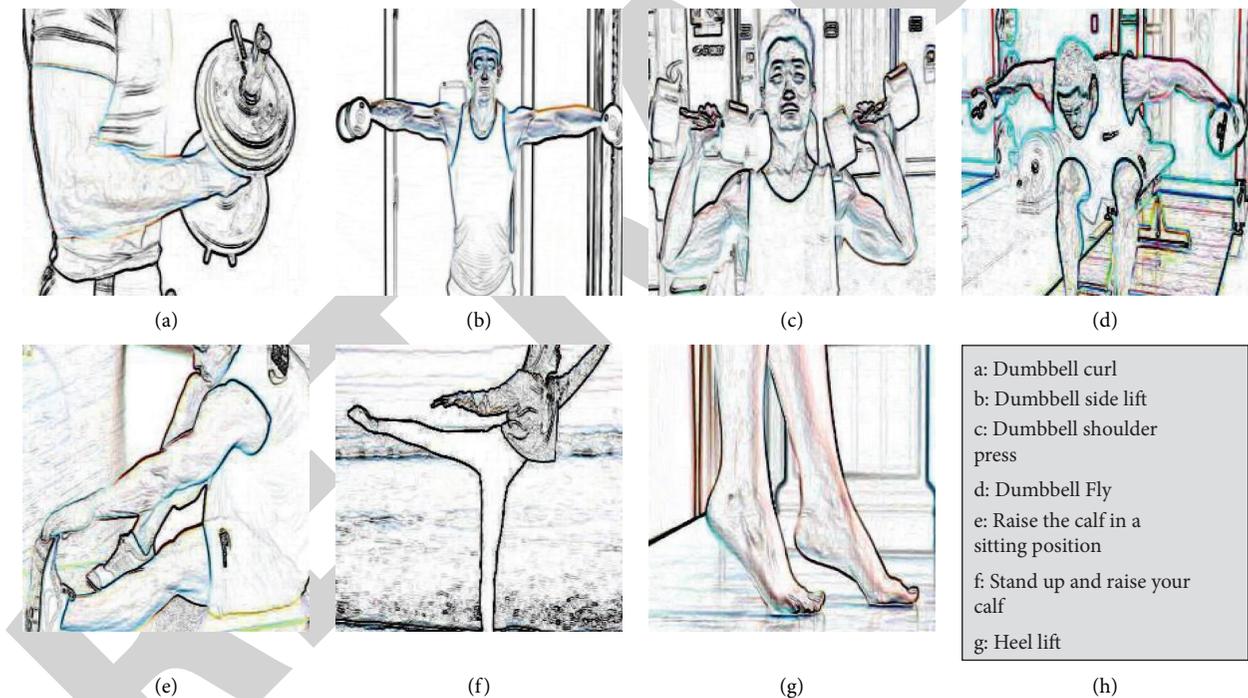


FIGURE 7: Seven types of body movements not intended. (a) Dumbbell curl. (b) Dumbbell side lift. (c) Dumbbell shoulder press. (d) Dumbbell fly. (e) Raise the calf in a sitting position. (f) Stand up and raise your calf. (g) Heel lift.

and convert the original nine-axis data to one-dimensional while keeping the data length unchanged, a large amount of information is inevitably lost in the process, resulting in poor results when the reduced-dimensional data is used for classification. Therefore, this paper finally chooses the first-tail splicing method as the data preprocessing method of the deep neural network, which retains all the information of the original data and does not disrupt the temporal relationship in the data and finally achieves a good recognition accuracy.

Next, the experiment was performed with 50 repetitions of the dumbbell bend movement as an example, the number of times was counted, the period was calculated based on its sensitive axis data, and finally, the measured values were compared with the actual values and analyzed. The exact cycle calculation and actual values of the 100 movements in this experiment are shown in Figure 8. The dashed line marked with a square is the measured value using the cycle calculation method, and the solid line marked with a triangle

TABLE 2: Accuracy of different preprocessing methods.

Data preprocessing method of deep neural network	Number of experiments	Action recognition accuracy rate (%)
LDA dimensionality reduction	200	87.59
Data end to end	200	97.46

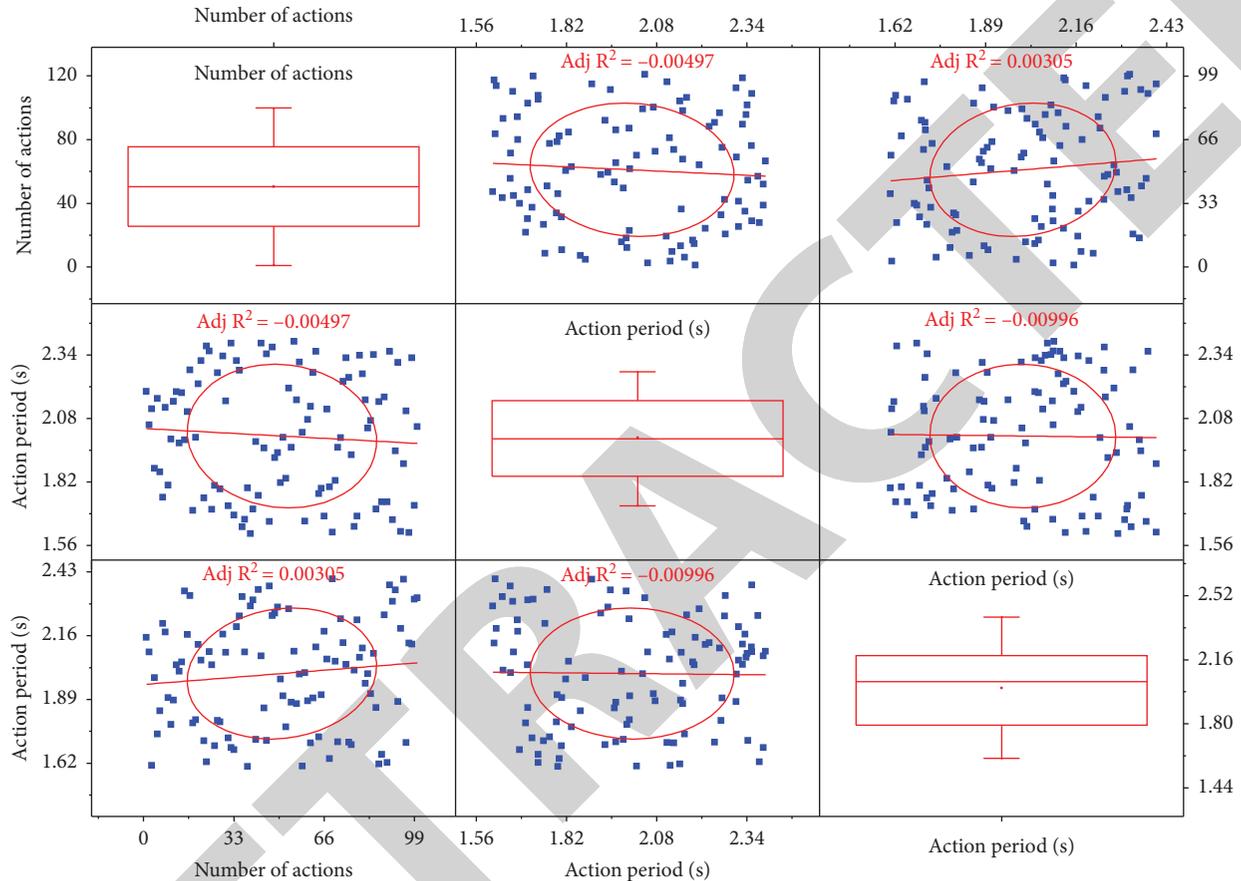


FIGURE 8: Motion count and cycle calculation results.

is the actual value recorded using a stopwatch, with the vertical axis being the cycle time in seconds and the horizontal axis being the number of movements.

The data obtained by the intelligent sport monitoring system are analyzed, and the data analysis is mainly carried out in three aspects. The control analysis of the collection time interval proves the accuracy of the distance control of the collection point of this system. The daily trend analysis proves the effectiveness of the information collected in this system. The comparison between the tracking collection mode and the fixed-point information, from every hour to every day and 15 days of individual-level analysis, proves that the tracking collection mode is better than the fixed-point data collection mode in monitoring sports information. In addition, three models are used to model and analyze the changes in temperature, humidity, and light, to find the relatively optimal model, and count the maximum deviations of each time period, so as to realize the intelligent motion detection abnormal alarm for the next step.

5. Conclusion

This paper implements a hardware and software platform for a multiuser motion monitoring system. The hardware part is a wearable sensor node based on the posture acquisition module, ESP8266 communication module, and power supply module, while the software includes two main parts, the host computer for serial communication debugging and the service system software integrating data transmission, start/stop detection, action recognition, and cycle calculation. The system software and hardware work well in practice and have an important application value. The motion recognition algorithm and cycle calculation method are also studied and verified by experiments. The action recognition algorithm includes SVM and a deep neural network composed of IDCNN and LSTM. The period calculation method is mainly based on over-zero detection and wavelet implementation. After experimental validation, the deep neural network and SVM have good recognition

results, both achieving more than 97.51% accuracy, while the cycle calculation method achieves accurate counting for 50 repetitions of the experiment, and the cycle calculation results maintain a small error. The experimental results show that the active monitoring system achieves a high level in both action recognition and period calculation. The number of training data sources was small due to the experimental conditions; in addition, computers in the local area network were used in the experiment instead of the cloud server. In the follow-up study, the number of subjects can be increased and a remote server can be used to run the data processing system software.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known conflicts of interest or personal relationships that could have appeared to influence the work reported in this paper.

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