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Research Article

Analysis of Digital Long Jump Take-off Wearable Sensor Monitoring System

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The wearable sensor monitoring system builds a long jump take-off recognition network model based on different digital feature extraction methods (one-dimensional digital feature extraction method, two-dimensional digital feature extraction method, and feature extraction method combining one-dimensional digitization and recursion). Experimental verification and analysis are performed on the processed sample data, and the identification effects, advantages, and disadvantages of the four methods are obtained. First, the sensor behavior movement collection software is designed based on the Android system, and the collection time and frequency are specified at the same time. In addition, for the problem of multisensor behavior recognition, an effective result fusion method is proposed. In a multisensor behavior recognition system, constructing a parallel processing architecture is conducive to improving the rate of behavior recognition. To maintain or increase the rate of behavior recognition, the result fusion method plays a vital role. Finally, this paper analyzes the process of multitask behavior recognition and constructs a residual model that can effectively integrate multitask results and fully mine data information. The experimental results show that, for the monitoring of exercise volume, we use step count statistics to extract feature values that can distinguish activity types based on human motion characteristics. This paper proposes a sample autonomous learning method to find the optimal sample training set and avoid occurrence of overfitting problems. In the recognition of 11 types of long jump take-offs, the average accuracy rate reached 98.7%. The average replacement method is used to count the number of steps, which provides a data reference for the user's daily exercise volume.

1. Introduction

With the continuous progress of microelectronics and sensor technology and the continuous development of deep learning theory, long jump take-off recognition based on wearable devices has become an emerging research direction. This research can better reflect the nature of human motion, compared with computer vision. In terms of long jump take-off recognition, long jump take-off recognition based on wearable devices is not restricted by specific scenarios and time, has low energy consumption and low cost, and is more suitable for popularization [1]. Long jump take-off is a way of expression that people react by perceiving the surrounding environment. From a macroperspective, it includes the posture and movement process of the head, limbs, and torso. As far as pattern recognition is concerned, long jump take-off recognition refers to the analysis and recognition of the behavior patterns and action types of the observed person, and the use of natural language to describe them [2–4]. In recent years, human behavior recognition based on wearable devices has made great progress, but still faces many urgent problems to be solved, such as how to extract features with strong characterization ability and how to design an end-to-end long jump takeoff analysis system. Applying behavior recognition technology to sports competitions can help athletes analyze angles, speeds, etc., so as to better understand their own sports characteristics and improve the professional skills of professional athletes

[5]. By collecting the behavior data of athletes participating in the competition, doing postmatch analysis and guidance, and finding out their own shortcomings, it will help to improve the performance of the game and contribute to the national sports industry [6–8].

In addition, wearable motion recognition has received extensive attention from researchers in a series of fields such as game control, video surveillance, indoor positioning and navigation, virtual reality, fatigue driving detection, motion tracking, personal feature recognition, and urbanization computing. In practical applications, because the acquisition of target video information requires the support of video capture devices, such devices usually have a fixed location, high power consumption, and large size. Therefore, this type of method is suitable for fixed scenes. Behavior recognition is more suitable, not suitable for long-term, continuous long jump take-off records [9–11]. Marcu [12] proposed a local sparse classification method and a distributed sparse method for behavior recognition. 13,000 training samples were selected from the data, and the recognition rate reached 93% in the best case. Parrilla [13] combines sparse expression and compressed sensing theory and regards energy efficiency as an important measure. 1300 action sequences are selected as training samples, and individual independent verification methods are also used. Using random projection method to compress the data, the recognition rate can reach 89% when the data is not compressed. When the data compression ratio is 0.1, using Bernoulli and Gaussian random matrix to compress the data, the recognition rate can still reach 85% or more. Ye [14] combines feature extraction and recognition algorithm improvement. First, the GA algorithm is used to extract features of data, and then the RVM algorithm is used to recognize behavior. The final recognition rate can reach 99%. Its recognition rate is higher than that of the other two algorithms. However, the verification method it uses is 3-fold crossvalidation, which is not an individual-independent verification method. In addition, the amount of data it uses is significantly larger than the previous two articles. With the advancement of research, energy consumption is taken into consideration as a research focus. Koldenhoven [15] uses 19 sensors to extend the working time of the entire network by dynamically adjusting the working conditions of the sensors. Pan [16] focused on feature extraction and selection, customized a series of physical features, combined with traditional features to form a data set, and extracted features through ReliefoF, SFC, and SFS algorithms, and the results showed that the defined features have a significant effect on behavior recognition. At the same time, a multilayer recognition structure is introduced, and a crossover method is used for verification. When the multilayer recognition structure is used to distinguish 9 kinds of daily behaviors, a recognition rate of 93% can be obtained. At the same time, a self-defined feature with special physical meaning is used to verify the effectiveness of the proposed feature by using a variety of classification algorithms in the public data mining tool [17–19].

Aiming at the time-frequency domain feature problem that the features based on sensor behavior recognition mostly use digital signal processing, the paper proposes a correlation feature. In a multisensor system, according to the characteristics of long jump take-off, there is correlation between the data of different position sensor nodes. The correlation feature is a combination of different position sensor information, which can better reflect the characteristics of human movement. This feature can effectively mine the potential information in the existing data and improve the behavior recognition rate. Researchers based on sensor behavior recognition mainly solve the problem of system energy consumption from two aspects [20–22]. First, by improving the system recognition architecture, reducing the energy consumption in the entire behavior recognition process, and in terms of commercial applications, improving the information transmission method to meet the demand for low power consumption. Second, we reduce the amount of transmitted data through data dimensionality reduction to achieve the purpose of energy saving, including data compression and feature extraction. On the basis of theoretical research, a long jump take-off monitoring system based on wearable devices was designed and implemented, and the method proposed in this paper was verified in real time. The system first collects the activity data of the experimenters in the daily environment and uploads the data to the cloud platform, and then the back-end server analyzes the data, recognizes human movements, and alarms when the human body has a long jump event. The platform is real-time, and it accurately realizes the monitoring of human behavior. Finally, this paper selects two public sensor behavior recognition databases to conduct a large number of simulation verification experiments. A large number of experimental results show that the method proposed in the paper can effectively improve the performance of behavior recognition [23–25].

2. Construction of a Wearable Sensor Monitoring Model for Long Jump Take-off Based on Digital Technology

2.1. Level Distribution of Digital Technology. Digital technology transforms the original data layer by layer to realize the transformation of the data from the original data space to the new feature space, thereby automatically learning the hierarchical features of the data. These feature representations can be used to complete tasks such as classification, regression, and feature visualization. Compared with shallow learning, deep learning can learn more abstract concepts and fit more complex functions. Moreover, deep learning can use fewer parameters to build complex models. For example, a function can be expressed concisely with a k-layer structure, while an exponential number of parameters are required to express the function with a k-1 layer structure. Figure 1 is the hierarchical topology of digital technology.

The quality of service (QOS) issues considered based on wearable sensor behavior recognition research mainly include recognition rate, energy consumption, and recognition rate. The recognition rate largely depends on the behavior recognition method used and the extracted features. The energy consumption is mainly considered from the aspects

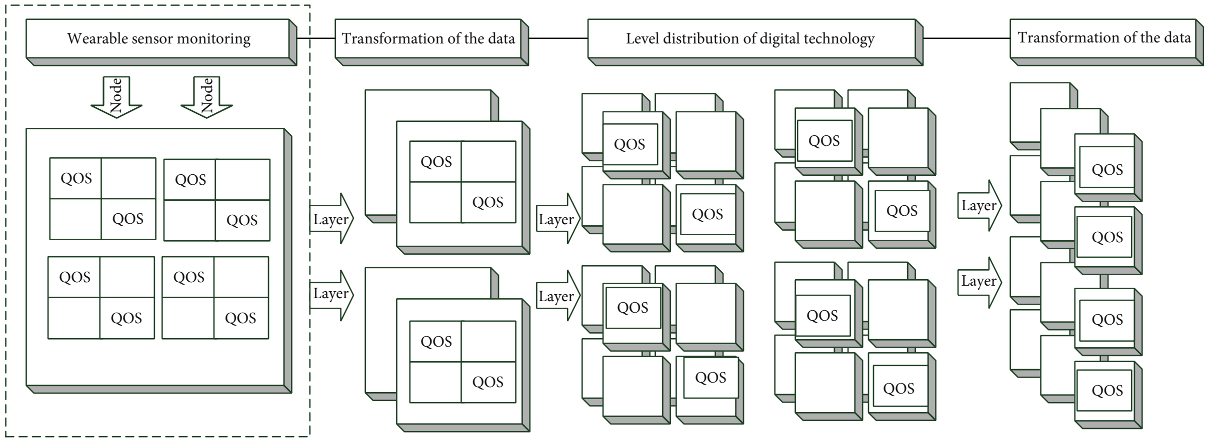

Figure 1: Hierarchical topology of digital technology.

of data compression and energy-saving architecture. The recognition rate depends on the adopted recognition algorithm, data scale, and processing model. The parallel processing strategy is an effective way to solve the recognition rate. The universal public database is a prerequisite for establishing a unified evaluation standard.

$$P\{X \mid x, m\} = A_N^m \left(\frac{2}{L+d}\right)^m \left(1 - \frac{2}{L+d}\right)^{N-m}. \quad (1)$$

Normally, a sensor node includes four different units: sensor, processor, wireless communication, and energy supply. The main types of sensors used for long jump take-off recognition based on wearable sensing include accelerometers, gyroscopes, magnetometers, pressure sensors, and heartbeat detection sensors. The output of the lower layer unit is used as the input of the higher layer unit, and the data characteristics are described hierarchically through multiple transformation stages to obtain the data essential representation.

$$\left(\frac{z+\lambda}{a_1}\right)^2 - \left(\frac{x+y}{a_2}\right)^2 = 1, \quad (2)$$

$$t' = [r \times \cos\theta, r \times \sin\theta, r \times \tan\theta_1 - t]. \quad (3)$$

Its essence is to obtain the motion signal generated by physical activity through the body sensor network (BSN) composed of multiple sensor nodes that are bundled or worn on the body, and transmit the signal to the background through the access point, and then the back-end center preprocesses the data, extracts features, and selects them. Finally, it classifies and recognizes behaviors based on the selected features. Considering the actual situation, in the process of building a behavior recognition system based on wearable sensors, a large number of complex calculations cannot be placed in the sensor node for calculation, and a large amount of data cannot be cached at the same time.

$$c = \Pr(c|o) \times \Pr(o) \times \mathrm{IoU} = \Pr(c) \times \mathrm{Iou}, \quad (4)$$

$$S = \frac{E(m=1)}{L} = \frac{N}{L} \times \left(1 - \frac{2}{L+d}\right)^{N-m}. \quad (5)$$

Assuming that the size of the original sample set is N, then the size of the training sample set formed by replacement sampling is also N. This sampling method allows the formation of repeated samples in the training sample set. When sampling samples with replacement, after sample sampling is completed, the probability that a certain sample is not selected is $1 - N$. When N tends to infinity, the value of this probability is about 0.368; so, every 37% of the samples were not selected in the subsampling. The feature subspace idea is mainly applied to the node division of decision tree. In the random forest, when dividing the nodes of each decision tree, it is also necessary to select the optimal dividing point, and the set of selected dividing points is randomly generated.

$$l = \alpha \times \sum_{i=0}^{S^2} \sum_{j=0}^{B} \left[(x_i - \bar{x})^2 + (y_i - \bar{y})^2 + \left(x_j - \bar{x}\right)^2 + \left(y_j - \bar{y}\right)^2 \right]. \quad (6)$$

The basic principle is to sort the sampled sequence from small to large in a digital sequence or digital image and then use the midpoint of each point value in the neighborhood to replace the value of a certain point, so that the nearby values are closer to the real value of to eliminate isolated noise points. Deep learning can express more complex functions with fewer parameters, has better generalization ability, and is suitable for processing more complex tasks. Deep learning, with its powerful feature representation ability and function modeling ability, has well alleviated the problems of insufficient generalization ability and dimensionality disaster of traditional shallow machine learning algorithms.

2.2. Decomposition of Long Jump Take-off Action. The long jump take-off recognition system is a classification and discrimination system based on input information. From the perspective of system input and output model, the input of the system is one or more kinds of sensor data related to long jump take-off. The data is usually a time series obtained by sampling at a certain frequency; the output of the system

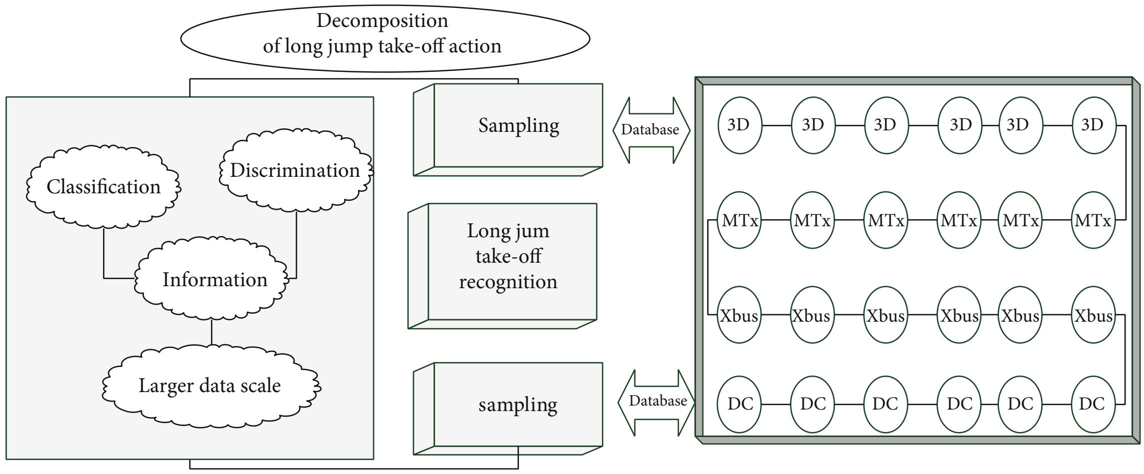

Figure 2: Schematic diagram of decomposition of long jump take-off action.

is for the current or past period of time. The DSAD database has a larger data scale than the WARD database. Its sampling frequency is 25 Hz, and it contains 19 daily behaviors of 8 volunteers (4 males, 4 females, aged between 20 and 30). Each volunteer was collected for 5 minutes for each action. Using 5 s as the normalized sampling time, the data within each sampling period was divided into 60 action sequences, and the total action sequence was $8 \times 19 \times 60 = 9120$. DSAD data set acquisition uses the inertial motion capture device of Xsens. Multiple motion capture systems (MTx) are connected in series through one or more Xbus. MTx corresponds to the sensor node, which can provide unbiased 3D positioning and kinematics data. The same as the WARD database is that the data set is also obtained through five sensor nodes fixed on the body. Figure 2 is an exploded schematic diagram of the long jump take-off action. Behavior actions can be represented by data acquired by sensor nodes tied to the body. A subset of sensor data represents a behavior action, and then L sensor node data constitute an action space.

The original gyroscope and accelerometer data are windowed to form a number of overlapping data vectors. After the dimensional sensor vector is aliased, the Fourier transform is performed to obtain the frequency domain representation, and then the DCNN directly conducts supervised learning training on the frequency domain data. After training, the DCNN actually constitutes a feature extractor suitable for wearable device data. For the subsequent test, only the 6-dimensional sensor vector needs to be windowed as described above. The Fourier transform deterministic transform can extract the features of DCNN and perform behavior recognition. Deep belief network (DBN) is a generative model, which can learn multilayer data compression representation of sensor data and can learn unlabeled high-dimensional data. In the box chart, if the box representing an activity exceeds the threshold, it means that the human body has a long jump. Otherwise, the activity is a daily behavioral activity. Limiting filtering method is to determine the maximum allowable difference between two samplings (assumed to be threshold) based on the characteristics or experience of past data. If the difference between the current sampling value and the previous sampling value is greater than the threshold, the value is regarded as noise, and the last sampled value is used instead of the current sampled value. If the difference between the current sampled value and the last sampled value is less than the threshold, the current sampled value is valid data. This filtering method is very effective for impulse interference caused by accidental factors, but it cannot suppress periodic noise and has poor smoothness. For example, the advantage of using this method is that we can learn features from unlabeled sensor data, learn all invariants for irrelevant changes, and use nonlinear dimensionality reduction for high-dimensional sensor data.

2.3. Wearable Sensor Data Collection. With the advancement of big data technology and deep learning, deep learning can abstract hierarchical features from massive training data. Such feature learning methods directly rely on data and can extract the most valuable features from the original data at the best cost. Compared with perceptrons, digital networks with added hidden layers can build more complex mathematical models and can transform data more flexibly to obtain richer expression capabilities. In view of the high degree of competition in the local area caused by concurrent data transmission requests to multiple nodes, a reservation scheduling algorithm is designed to reasonably allocate the data transmission time of each competing node on the transmission path. The network updates the network parameters through the backpropagation algorithm, and the residual value is transferred layer by layer from the output layer to the input layer, and the error sensitivity (residual value) on each neuron is calculated, so as to obtain the cost objective function relative to each weight. The gradient of (network parameters) realizes the update of network parameters. However, the increase in the number of layers of the digital network also brings some new problems. The solution of the nonconvex objective loss function is easy to fall into the local optimum, and the global optimum cannot be obtained through the backpropagation algorithm. At the same time, gradient dispersion is likely to occur during the back propagation of the residual value. For a digital network with more layers, the residual value will continue to decrease as the number of back propagation layers increases, resulting in a network close to the input layer. The parameters cannot be effectively trained. Figure 3 is the distribution of the proportion of sensor data features.

There are mainly two methods for data dimensionality reduction: feature extraction and data compression. In the actual application of machine learning or pattern recognition, there are a large number of original acquired features, irrelevant/redundant features and dependence between features that are inevitable, resulting in feature analysis, model training time is too long, and dimensional disasters. Feature issues will also complicate the system model and reduce the ability to promote the system. On the one hand, feature extraction can remove irrelevant features and redundant features, reduce the number of features, improve model accuracy, and reduce the time required for model calculation. Among them, the encoder inputs the sensor data into the hidden layer through transformation, and then the decoder reshapes the output to the input value to minimize the error rate. This method can have a significant filtering effect on signal interference caused by accidental factors. The collected signal must change relatively slowly, such as temperature and liquid level, which is not suitable for signals that change rapidly. The deep autoencoder is an unsupervised feature learning algorithm. The purpose is to find the correlation between features, extract low-dimensional features, and then use the error back propagation algorithm to reconstruct the sensor sample data. The sparse representation model captures the structure of the data and determines the correlation between different input vectors. In recent years, some scholars have proposed the use of sparse coding methods to learn the characteristics of sensor data for long jump take-off recognition. These methods use mobile phones and wearable devices to provide a feature dimension reduction strategy for the long jump take-off recognition system to reduce computational complexity and time.

2.4. Monitoring Model Factor Replacement. The shallow learning algorithm of the monitoring model usually contains one or two layers of nonlinear transformations and performs well on limited simple problems. However, shallow learning has the shortcomings of insufficient representation and modeling capabilities and cannot be effectively processed when faced with complex application scenarios such as speech processing and visual images. By adding network layers, the network can obtain stronger modeling capabilities and feature representation capabilities. However, digital network models with too many network layers have problems such as difficulty in training and easy overfitting. By looking for a set of basis vectors, in the subspace formed by the basis vectors, samples of the same class have the smallest intraclass divergence, while samples of different classes have the largest interclass divergence. PCA mainly calculates a number of orthogonal basis vectors to achieve the original space reconstruction, so that the error between the new space and the original space approaches the minimum; so, the optimal subspace obtained is only under the premise of the minimum linear reconstruction error.

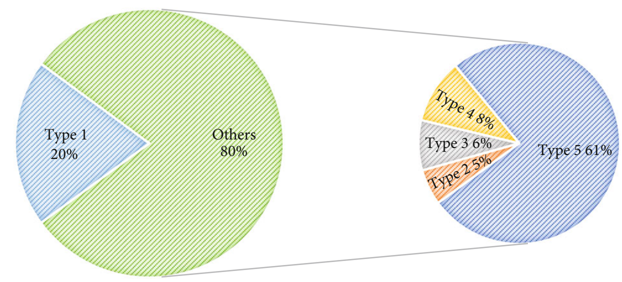

Figure 3: Distribution of the proportion of sensor data features.

Figure 4 is the residual vector of the sensor residual value. The network model adopts a new inception architecture, which effectively reduces the number of network parameters while improving network performance. At the same time, the number of layers of the network is increased to 22. According to the concept of residual network, the jump connection between networks is realized. The combination of traditional algorithms and digital neural networks is also the focus of current research. For example, the combination of recursive digital networks and digital networks can be used to generate image summaries. For example, the WARD data set recognizes actions with behavior category number 7, and the results show that the residuals of the behavior categories corresponding to tasks 1 to 5 are relatively small.

3. Results and Analysis

3.1. Digital Data Preprocessing. In this article, we set the sampling frequency of the acceleration sensor to 62 Hz. Considering the flexibility of the behavior recognition and condition monitoring system, we choose an Android phone as the transfer station for raw data. There are 5 columns of data in total: the first column represents the tester's number, the first column. It represents the behavior category number performed by the tester, the fourth and fifth columns represent the start row and end row of the sensor data corresponding to each behavior action, such as first line represents the first experiment conducted by the first tester, and the fifth type of action corresponds to the 250th to 1232th lines in the data sample file. These noises are not only unfavorable for feature extraction but also have a great impact on the accuracy of recognition. In the data preprocessing stage, we must first filter the original signal to eliminate some interference noise. Usually, we can filter out the noise by designing a digital filter or an analog filter. However, the use of digital filtering does not require the use of hardware equipment, which is stable and reliable. High performance: so we use digital filtering methods.

Figure 5 shows the time-domain characteristic deviation of sensor data. The time-domain characteristics of the data also become statistical characteristics, which are calculated by the method of probability statistics. The mean and root mean square are used to reflect the central tendency of the data, standard deviation, variance, quarterback spacing, and kurtosis that are used to reflect the fluctuation or dispersion of the data, and the skewness reflects the degree of

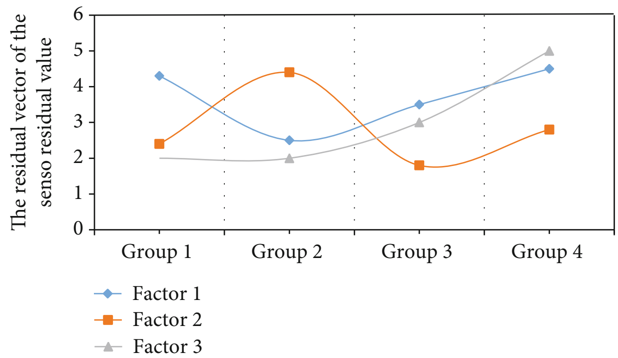

FIGURE 4: The residual vector of the sensor residual value.

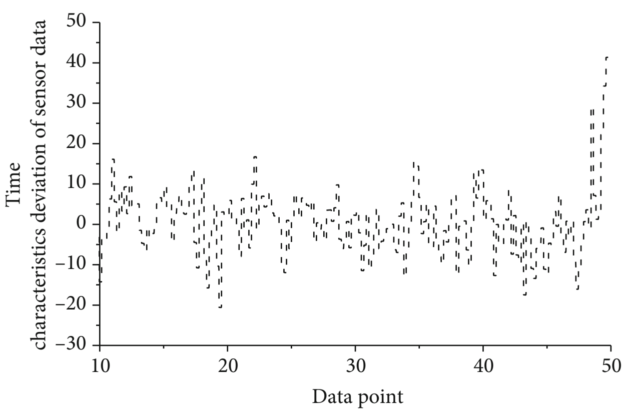

FIGURE 5: Time domain characteristic deviation of sensor data.

symmetry of the data. To read the data of the wireless communication unit, the receiving FIFO in the NRF24L01 communication module is mainly read through SPI. In order to ensure that the data is received in time, the wireless communication module uses interrupts to trigger the MCU to receive the data. It can be seen that the position of the leg sensor node has been adjusted upward relative to the WARD data set to avoid the problem of poor discrimination of upper body movements. Moreover, the sensor nodes of the DSAD data set contain richer sensor information (each sensor node is embedded with a three-axis accelerometer, a three-axis gyroscope, and a three-axis magnetometer). Therefore, 5 sensor nodes at a time obtain a $5 \times 3 \times 3 = 45-$dimensional time series data, where 5 represents 5 sensor nodes, the first 3 represents 3 different sensor types of each sensor node, and the second 3 represents the three sampled values of each sensor type. The sampling time of each action sequence is 5 s; that is, an action sequence is a $125 \times 45-$dimensional motion vector.

3.2. Wearable Sensor Monitoring Simulation. The given medfilt function in Matlab can implement this algorithm. The default neighborhood window size of the function is 3, which is set to 5 in this article, which can appropriately make the signal smoother. Then, we randomly select a piece of experimental data from the experimenters and analyze the changes in sensor data before and after filtering. After median filtering, the influence of signal peaks is removed, making the periodic characteristics of the signal more obvious. In order to eliminate the interference caused by irrelevant actions in the collection process, this paper will use the median filter algorithm to filter the original three-axis acceleration data collected by the sensor to eliminate the interference of noise. The sampling module of the model is used to filter and sample the historical order information and the current state information in the cloud computing service platform system database to generate basic historical order data. When the sample set is divided, there must be a fixed standard to measure the quality of the sample set. For an attribute, if its attribute value is continuous, we usually choose the average of two adjacent values as the dividing point. Assuming that a certain attribute in the sample set has m consecutive attribute values, the attribute values are sorted in ascending order to generate an ordered sequence of attribute values. Commonly used digital filtering methods include arithmetic average filtering, weighted arithmetic average filtering, moving average filtering, median filtering, and inertial filtering. The digital filtering method used in this article is median filtering.

Figure 6 is the filter identification weight coefficient of sensor data. The data lines, respectively, represent the ability to recognize each behavior from the data of sensors 1 to 5 in two different databases. It can be clearly seen that different sensors have different distinguishing capabilities for the same behavior, and the same sensor has different distinguishing capabilities for different behaviors. Therefore, the paper adds a weight coefficient to the residuals of each task, highlighting the importance of each task. Many researchers tend to use empirical values to replace the weight coefficients of each residual, and through repeated experiments, select appropriate values, but this method has certain limitations, empirical values are prone to overfitting, and scalability is poor.

Figure 7 is a wearable sensor monitoring unit. In this article, we only extract the amplitude of the signal. In the previous section, we mentioned that the length of the segmented data is 64, and the result of FFT is symmetrical. Since the FFT transformed data has multiple low-frequency components, we follow the amplitude after sorting the low-frequency components by the magnitude of the value, and only M-dimensional data is advanced. The main basis for determining M is the ratio of the energy of the low-frequency components of the first M dimensions to the total energy of the signal. The article is the ratio of the energy of the first N-dimensional low-frequency components to the total energy after FFT transformation of the data segment. It can be seen from the figure that the energy of the first 16-dimensional low-frequency components has reached more than 90% of the total energy; so, when we extract features in the frequency domain, we only extract the amplitude of the first 16-dimensional low-frequency components.

3.3. Analysis of Experimental Results. When the human body moves, the motion conversion amplitude corresponding to different activities is different. The recognition of human motion state requires a strong real-time performance. When

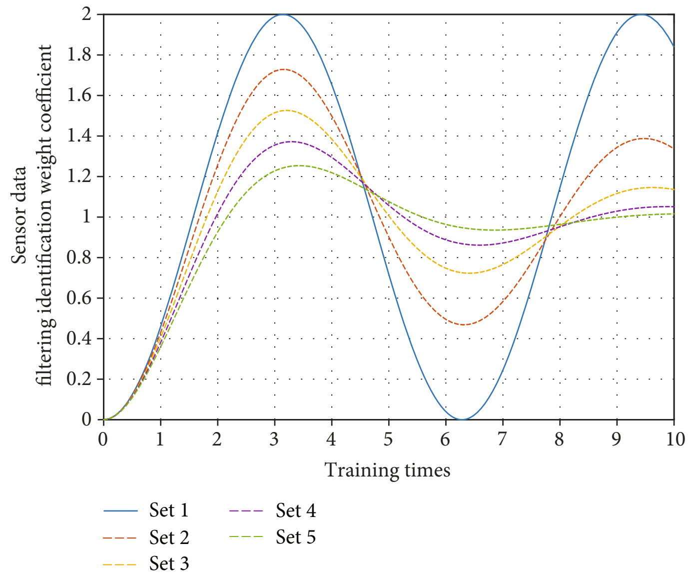

Figure 6: Filtering and identifying weight coefficients of sensor data.

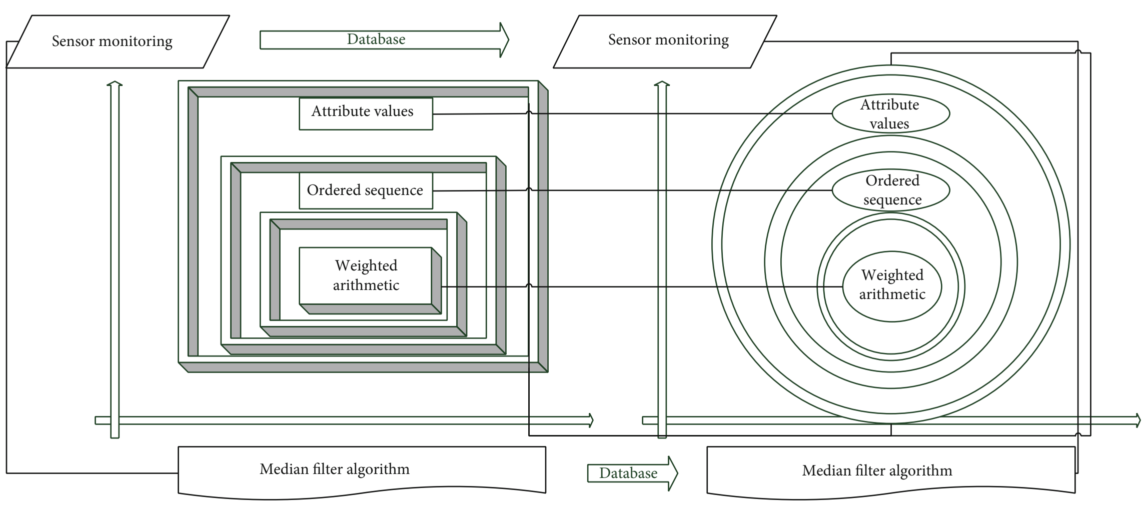

Figure 7: Wearable sensor monitoring unit.

extracting feature points, the real-time requirement is very important. Therefore, this chapter will synthesize the extreme value of the acceleration point, that is, the peak and valley value as the research object. In the actual data processing process, when a new sampled value is received, it is compared with the previous sampled value. If the waveform change turns in, then point is the extreme point. Since the sensor data collected by mobile devices are continuous time segments, feature extraction and classification cannot be performed directly; so, longer time series data must be segmented. This chapter uses a fixed sliding window to segment the data, where the time window size is set to 2.56 s; that is, $T = 2.56$, adjacent windows cover 50%, each window contains 128 sampling points, and the acceleration used the sensor contains numbers in three directions: X-axis, Y-axis, and Z-axis. The experiment uses a complete data set including long jump and daily behavior activities. These data sets are composed of long jump take-off data collected using self-developed embedded devices. The data can be easily copied for data analysis. The data set contains 19 types of daily behavior activities and 15 types of long jump activities.

Since the digital network is a continuous value, when the output value of the node in the output layer is greater than or equal to 0.5, we set it to 1, and when the output is less than 0.5, we set it to 0; so, there will be undefined output results. This part is the part that the digital network classifier we built cannot correctly classify. We define this part as unknown. Figure 8 shows the accuracy of sensor network coding classification. In the end, the digital network classifier with 11 nodes in the hidden layer has a recognition rate of more than 90% for walking, going upstairs, stationary, and a recognition rate of more than 80% for going down. The recognition rate for jumping and running is at around 75%. After the original sensor data is denoised and data segmented, the data samples need to be labeled. For

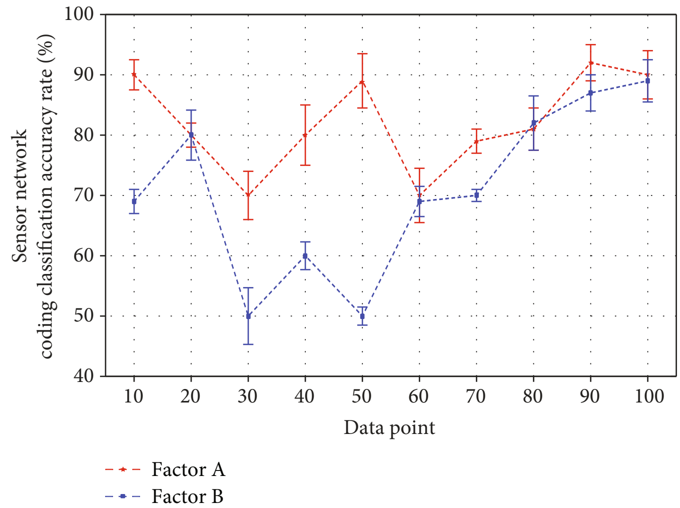

Figure 8: The accuracy of sensor network coding classification.

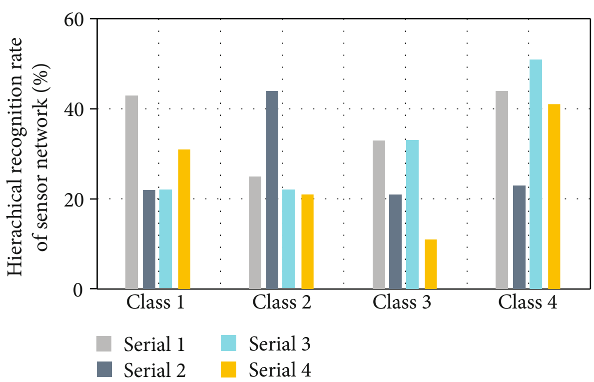

Figure 9: Hierarchical recognition rate of sensor network.

the long jump takeoff recognition studied in this article, pot performs sample labeling on the sample. One-hot encoding is also called a one-bit effective code. The method is to use N-bit status registers to encode N states. Each state has its own independent register bit, and at any time, only one of them is valid. The error control algorithm aims to control packet loss caused by exceeding the maximum number of retransmissions. These include packet loss caused by multiple collisions and packet loss caused by channel errors. For each feature, if it has m possible values, then after one-hot encoding, it becomes m binary features. Moreover, these features are mutually exclusive, and only one is activated at a time. Therefore, the data becomes sparse. This not only solves the problem that the classifier is not good at processing attribute data, but also plays a role in expanding the features to a certain extent.

Figure 9 shows the hierarchical recognition rate of the sensor network. The wireless communication unit consists of the NRF24L01 communication module, which establishes a point-to-point connection with the node's wireless communication unit for node data transmission. The configuration information of the wireless communication unit is determined by the base station configuration unit. In order to establish a wireless connection with the node's wireless communication unit, it is necessary to ensure that the base station wireless communication unit configuration information corresponds to the node wireless communication unit configuration information one-to-one. The acquisition card can be used to collect the voltage signal input of the ruminant detection tag. It is a practical DAQ module that can collect the power consumption of the long jump take-off detection system. It can sample at high speed and ensure the sampling accuracy, which can meet the needs of power consumption measurement of the ruminant monitoring system. Both analog and digital signals can be identified. There is no need to configure a rumination monitoring system to connect to the computer, which solves the inaccurate measurement of the voltmeter. It can be seen that in the real-time monitoring system, the average recall rate of activity recognition is 89.97%. The result of the simulation experiment is slightly lower than that of the simulation experiment. The possible reasons are as follows: during the experiment, the experimenter has shorter exercise time, the number of experiments is less, and the wearable device collides with the outside world or is not firmly worn. In addition, the data collected in this experiment is still quite different from the actual data of human daily behaviors.

4. Conclusion

Considering the complexity of the wearable sensor data and the flexibility of the monitoring program, this paper collects long jump take-off data through acceleration sensors, height sensors, and heart rate sensors and places the sensors on the wrist. Because the sampling frequency of the acceleration sensor is high and there are many random noises, we use the moving average method to smooth the acceleration signal, use the 50% overlapping sliding window to segment the acceleration signal sequence, and extract the mean, variance, and front of the segmented signal segment. The amplitude of 16-dimensional signal components and the extracted data features and height sensor data form a 19-dimensional feature vector to build a long jump take-off feature vector sample set, which lays the foundation for subsequent behavior recognition. When the main factor of packet loss in the network is exceeding the maximum number of retransmissions, ADAPT will change the maximum number of retransmissions. At the same time, an end-to-end long jump take-off recognition system is constructed based on the recursive digital network, through four different types of simple recursive digital network, long short-term memory network (LSTM), bidirectional long short-term memory network (BLSTM), and gated recurrent unit (GRU). The digital network constructs four different long jump takeoff recognition models, conducts experimental verification and analysis on the preprocessed sample data, and obtains the recognition effects, advantages, and disadvantages of these four methods. The experiment uses the feature vector verification set to verify the accuracy of each classifier and defines the classifier as a behavior model. After comparison, the monitoring and recognition rate of the take-off behavior of the long jump finally reached more than 90%.

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 competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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