Exploration of new community fitness mode using intelligent life technology and AIoT

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Abstract: The purpose is to better mine the fitness motion data for intelligent wearable devices and promote the development of the new community fitness mode. First, the defects of the traditional fitness motion recognition system are analysed. Then, software engineering technology and Deep Learning (DL) technology are used to build a multi-layer fitness motion monitoring system. Finally, the data of running, riding, race walking, and rope skipping in the PAMAP2 data set are used for system evaluation. The results show that the proposed motion data monitoring system has an average accuracy of 97.622%, an average precision of 96.322% and a recall rate of 96.021% for fitness data recognition. The experimental results suggest that intelligent wearable devices with the proposed monitoring system can effectively mine wears' motion data and promote the development of the new community fitness mode.

Keywords: AIoT; motion recognition; intelligent life technology; intelligent wearable device.

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1 Introduction

The Artificial Intelligence of Things (AIoT) integrates the Artificial Intelligence (AI) technologies into the Internet of Things (IoT) and can be vividly expressed as an equation, AIoT=AI+IoT (Ometov et al., 2019). AIoT derives from the IoT and can collect and store massive data through the cloud centres and the edge devices, which can be further analysed through AI and big data technologies, thereby digitising and intelligently connecting all things. The AIoT intelligent HW (Hardware) with sensors and communication modules can modularise a complex urban management system into the urban infrastructure module and the urban service module (Debauche et al., 2020). With the AIoT technological advancement, the AIoT products are spreading widely. For example, the smart bracelet can record and analyse motion information and has gained its popularity among fitness people for health data monitoring and customised fitness plan. Community fitness aims to tame professional sports for people's daily life. Community fitness is supported by the mass grassroots, and the venues are often founded upon public places in urban areas (Liu et al., 2019). Community fitness is the civilisation and the future of professional sports. Meanwhile, many researchers are exploring the role of community fitness as a healthy lifestyle (Yao and Tseng, 2019).

Nowadays, various affordable intelligent devices with high accuracy have appeared because of cheaper gyroscope, accelerator and optical heart rate sensor, simplifying the acquisition of human motion data. Consequently, sports

Applications (APPs) have gone viral, and fitness is becoming a national lifestyle, thus promoting the development of the sport. However, the intelligent wearable devices on the market have some shortcomings. Specifically, fitness data are simply presented to users without being analysed in-depth, which consumes energy and time while reducing the efficiency and limiting the applicability of the intelligent wearable devices. Therefore, an innovative fitness data monitoring system should be proposed to mine, analyse, and utilise user data through AI technologies.

As intelligent equipment prevails, the application of high-performance sensors has infused all social spheres. Intelligent devices embedded with sensors can count step or control gestures. Yet, the overall application scenarios of sensors are very limited, wasting a huge amount of data that can be mined through Deep Learning (DL) technologies. DL technology is the core of many state-of-art algorithms. Compared with traditional ML (Machine Learning) algorithms, DL algorithms can process more complex with larger capacity. Many research works have been done on fitness development to construct a sports wearable device, yet few researchers have explored the information mining dimension of sports wearable devices to help fitness people regulate their fitness actions. Therefore, a multi-layer system for fitness data recognition with the data acquisition, data calculation and data application layers is proposed to store and segment the relevant information of athletes. Moreover, features are mined, motions are recognised and substandard actions are fed back in real-time.

2 Related works

With the widespread of wearable devices, the research of human motion recognition has attracted more and more researchers' interest in recent years. Thanks to technological advancement, much sophisticated human motions can now be recognised, as compared to the single gesture recognition in the initial stage. Many fields, such as medical monitoring, sports training, human interaction and Virtual Reality (VR) have seen the utilisation of human motion recognition. Domestic and international research analyses human motion recognition from three aspects: the recognition algorithm of the classifier, the extraction of motion features, and the number, type and placement of sensors.

Gao et al. reviewed the concept of dynamic mapping in human motion recognition based on DL, believed that dynamic mapping recursion could encode the spatial, temporal and structural information in video sequence into dynamic motion images, and pointed out that the common Convolutional Neural Network (CNN) model could recognise 3D human motions (Gao et al., 2020). Fu et al. (2020) proposed an attitude estimation method for embedded devices. The model transformed the previous single-stage Kalman filter into a two-stage Kalman filter, then judged the attitude of the carrier through the adaptive adjustment algorithm based on fuzzy logic, and then adjusted the covariance matrix of the filter. The adaptiveness of the sensor could be identified as the object state. Zou et al. (2020) found that substandard strength training caused serious injury to fitness people. Therefore, Zou et al. (2020) designed a set of intelligent fitness gloves for real-time monitoring in strength training through AIoT technologies. The gloves could identify various training items, detect substandard behaviours, and evaluate the exercise quality of glove wearers. The experimental results showed that the intelligent fitness glove system had high accuracy and reliability (Zou et al., 2020). Kao et al. (2019) discovered that few researchers had studied the application factors of a wearable health tracker. Thus, Kao et al. (2019) defined an analysis framework to explore the application factors of wearable health trackers and deduced the analysis framework of influence diagram through decision experiment and analysis experiment. Then, based on the relationship graph, the Partial Least Squares (PLS) structural equation model was chosen to verify consumers' willingness to wear wearable health trackers (Kao et al., 2019). Pal et al. (2019) established an experience quality model based on the perception of end-users to smartwatches and fitness trackers and evaluated the experience quality model from data quality and information quality. To sum up, although the effect of human motion will be affected by many factors, most of them follow the process of the recognition chain in the field of human motion recognition. This process can be described as a general framework. Sample data can be obtained through this framework to construct a recognition system and recognise motion. The accelerometer has become the mainstream of research because of its low price, small size, and handy portability. The wavelet transformation is the most commonly used recognition algorithm to extract motion data features, and the popular classification algorithm is often chosen.

3 Method

3.1 Architecture of fitness data monitoring system

The architecture of the fitness data monitoring system is analysed. Although the architecture of different fitness data monitoring systems varies, they all contain fitness data exchange, analysis, and processing modules. The proposed system aims to identify and help adjust the user's fitness actions timely (Takizawa, 2018; Grzybowska et al., 2019), so the system time response is not a major factor, which is quite different from the previous fall detection system. LV et al. (2019) proposed the storage management model of Building Information Modelling (BIM) geospatial big data based on the research on the spatial distribution characteristics of BIM geospatial big data. Inspired by this idea, a multi-layer fitness data monitoring architecture is proposed based on the research of other system architectures (Mirza et al., 2019; Elfaramawy et al., 2019), as shown in Figure 1.

Figure 1 Architecture of fitness data monitoring system

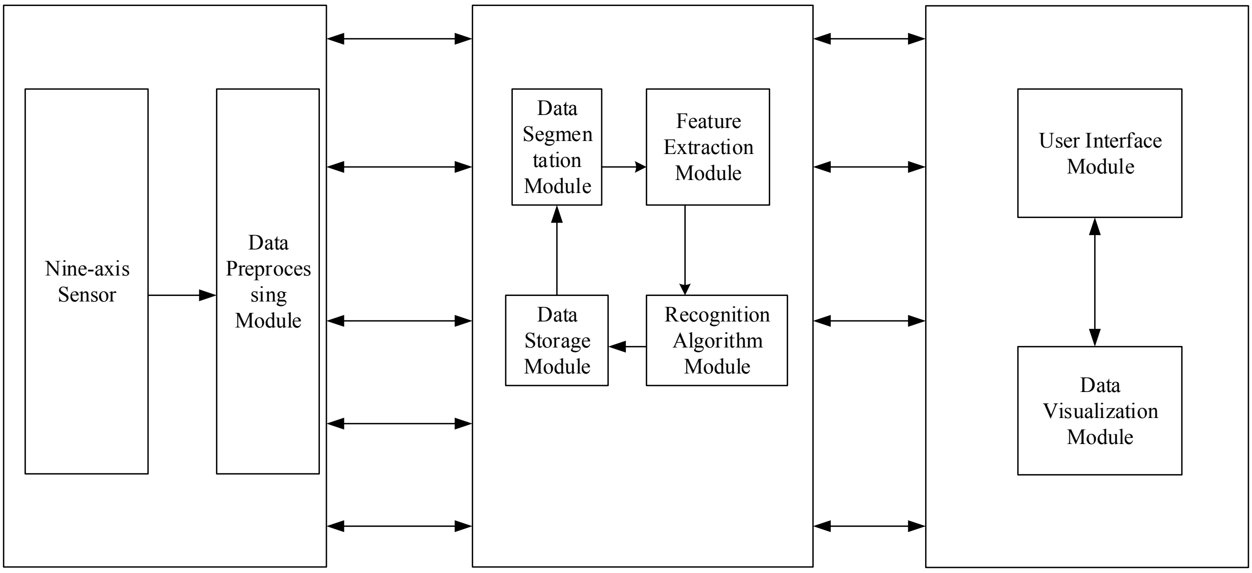
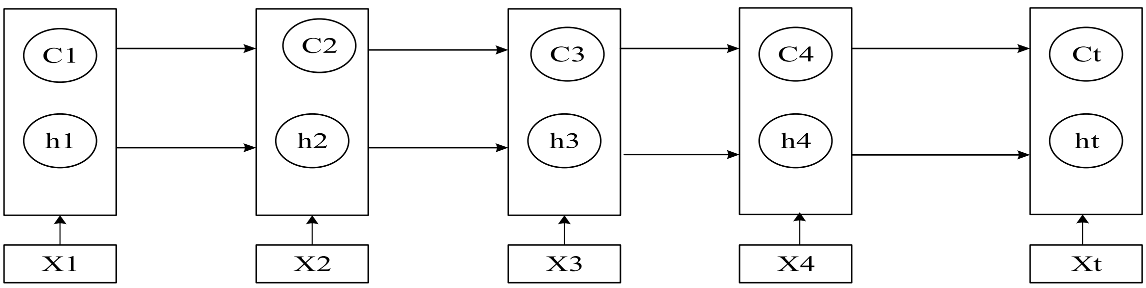


Figure 1 shows that the architecture of the fitness data monitoring system is divided into three layers. The leftmost part is the data collection layer and can be further divided into motion sensor modules and data pre-processing modules according to the SW and HW. Here, a nine-axis sensor module composed of a three-axis accelerator module, three-axis gyroscope module and three-axis magnetometer module is chosen (Akira and Keizo, 2018; Ayazli et al., 2019). The data pre-processing module is divided into noise filtering, missing value processing, and data normalisation/standardisation submodules. The noise filtering submodule can remove noises in the human motion information, such as system vibration noise. The common removal methods are median filtering, Gaussian filter and Kalman filtering. In the missing value processing submodule, the commonly used methods can be roughly divided into deletion method, interpolation method, and prediction method. Deletion method deletes unnecessary missing values; interpolation method can be divided into mean interpolation, median interpolation, and Lagrange interpolation; prediction method establishes a prediction model with existing variables. When high-intensity exercise is performed, sensors' acquisition data fluctuate terribly. Therefore, to minimise the influence of extreme values and compare different dimensional data, the data should be standardised for pre-processing through the nine-axis sensor module (Tortora et al., 2020). The data calculation layer consists of a data storage module, data segmentation module, feature extraction module, and recognition algorithm module, of which the recognition algorithm module is the core of the fitness data monitoring system. The data application layer is at the top of the system architecture and is the intermediary between the system and the outside world. Users can access and operate the system through the World Wide Wide (WEB) browser and system interface. The data application layer is divided into user interface modules and data visualisation modules. The user interface is constructed through the HTML (HyperText Markup Language) technology, CSS (Cascading Style Sheets) technology and JavaScript. The data visualisation module can transform the data into a visual interface and present users with intuitive motion data and analysis results (Wang and Yan, 2020; Shukla et al., 2019).

3.2 *Construction of fitness data computing layer*

Long Short-Term Memory (LSTM) Neural Network (NN) is an effective variant of Recurrent Neural Network (RNN). In LSTM structure, the hidden layer at each moment contains multiple memory modules, each module contains one or more memory cells, and each memory cell contains three memory gates. It effectively solves the problem of gradient explosion or gradient disappearance which often occurs in the simple RNN, and Figure 2 shows the schematic diagram of expanding it according to the time sequence (Czajkowski and Kretowski, 2019; Guo et al., 2019).

Figure 2 LSTM structure diagram



In Figure 2, $X_1, X_2, X_3, ..., X_t$ represents the input of the network at each time, $C_1, C_2, C_3, ..., C_t$ represents the internal state of the network at each time, and $H_1, H_2, H_3, ..., H_t$ represents the external state of the network at each time.

Compared with the simple RNN, there are two improvements in LSTM (Manonmani and Balakrishnan, 2020; He et al., 2019). The first improvement is to introduce the internal state variable c_t especially for linear loop information transmission, as shown in equation (1), and output information to the external state h_t at the same time, as shown in equation (2) (Wang et al., 2019).

$$c_t = f_t \odot c_{t-1} + i_t \odot c_t' \tag{1}$$

$$h_t = o_t \odot \tanh(c_t) \tag{2}$$

In equations (1) and (2), o_t means different gate structures in LSTM, $\odot$ is the product of vector elements, c_{t-1} is the memory unit at the last rising time, and $c_t^{'}$ is the candidate state obtained by nonlinear structure.

The second improvement is the introduction of the forget gate f_t, the input gate i_t and output gate o_t can control the information transmission path. The function of the forget gate is to control how much information the internal state needs to forget at the last time, which can be calculated through equation (3). The function of the input gate is to control the candidate states at the current time and how many states need to be saved, which can be calculated through equation (4). The function of the output gate is to control how much information of the current internal state needs to be output to the external state. Equation (5) shows its calculation (Mekruksavanich and Jitpattanakul, 2021; Yu et al., 2020).

$$f_t = \delta\left(W_f x_t + U_f h_{h-1} + b_f\right) \tag{3}$$

$$i_t = \delta\left(W_i x_t + U_i h_{t-1} + b_i\right) \tag{4}$$

$$o_t = \delta\left(W_o x_t + U_o h_{t-1} + b_o\right) \tag{5}$$

In equations (3), (4) and (5), $\delta(.)$ represents the Logistic function, x_t denotes the input of the current time and h_{t-1} is the external state of the previous time. U_f represents the variable value, and b_i stands for the weight coefficient.

LSTM can quickly and effectively process massive data and intelligently learn features of unlabelled data, thus greatly improving the human motion recognition system. First, the content of feature extraction is simplified. For the traditional ML algorithm, feature extraction is a complex and tedious work, and researchers often need to design feature sets based on experience. However, LSTM can mine the internal relationship between features and recognition targets and combine multiple simple features into new complex features, simplifying the updating process of weight matrix and enhancing system efficiency. In terms of feature extraction, LSTM automatically extracts multi-dimensional features based on basic features, avoiding the extraction of time-domain and frequency-domain features of time series data, and minimising information loss of dimension reduction. Therefore, LSTM is chosen as the classifier in the fitness data computing layer. Jie et al. (2021) proposed a CL-LDA topic model based on the research of lexical co-occurrence analysis and the Latent Dirichlet Allocation (LDA) topic model. Similar to the LSTM model, the CL-LDA model could mine the short text topic with sparse semantics and missing co-occurrence information (Jie et al., 2021).

Figure 3 shows the structure of the constructed LSTM in RNN.

Figure 3 Schematic diagram of the improved LSTM RNN structure

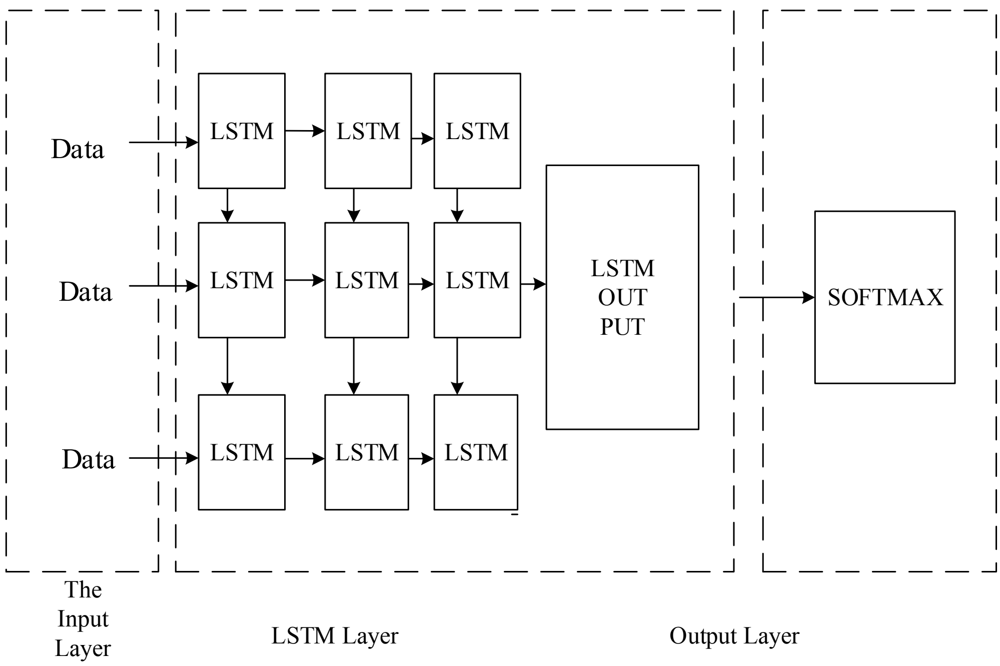
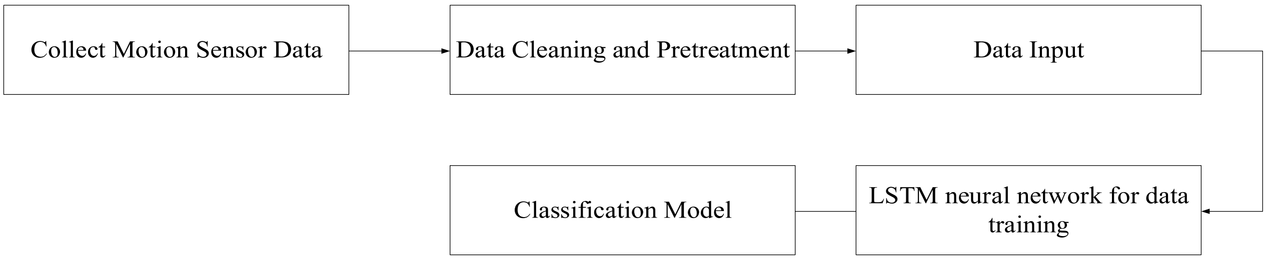


Figure 4 Flow design of human body fitness recognition information system



Here, the input layer of LSTM NN is composed of three channels: *X*, *Y* and *Z*. The data collected by sensors in *X*-, *Y*- and *Z*-directions are input, respectively. The input layer of LSTM NN is a buffer memory of the whole network for data addition. In the previous work, the data collected by the sensors in *X*-, *Y*- and *Z*-directions have been combined into a three-dimensional vector with a sliding window, the width of which is 200. Thus, a three-dimensional matrix with the size of n*200*400 is input into the LSTM layer. According to basic DL theory, the more the number of nodes and hidden layers are, the lower the training speed of NN is. Consequently, an LSTM NN is designed with three hidden layers. The number of nodes in the first LSTM layer is 128, the number of nodes in the second LSTM layer is 64, and the number of nodes in the third LSTM layer is 12. Under the LSTM layer is the dropout layer with a dropout ratio of 0.5, and the classification output layer is the softmax layer.

3.3 Process design of fitness data monitoring system based on LSTM RNN algorithm

The workflow of the designed human body fitness recognition information system can be divided into five steps: 1) collecting the sensor data of different people in the community; 2) data cleaning and pre-processing; 3) inputting the data into PC; 4) using the designed LSTM NN to train the processed data and 5) getting the corresponding motion classification model.

3.4 Experimental data set and system environment

Table 1 shows the system HW and SW configuration.

Table 1 Experimental environment configuration

HW environment	Species	Parameters
	HD (Hard Disk)	1500G
	Memory	24G
	GPU (Graphics Processing Unit)	GT×2060
SW environment	OS (Operating System)	Ubuntu 18.04
	Database	Mysql 5.8
	Development language	Python3.4
	DL framework	Tensorflow

The recognition effect of the model determines the system performance and is affected by many factors, such as the training data set. For this purpose, the PAMAP2 body motion data set, proposed by the University of California, Irvine, is used. The data set contains measurement data of 12 sports, including walking, lying flat, standing, cleaning the room, ironing, cycling and race walking. Data types include acceleration data, angular velocity data and magnetic field azimuth data. The relevant data in the data set are recorded by the inertial measurement unit located in the hands, feet, and chest of the subjects. The total recording time is more than 10 hours, the data sampling interval is 0.01s, the total amount of data is 2.87 million, and the data dimension is 54 columns. According to the actual needs, the data of running, riding, race walking, and rope skipping are selected as the experimental data of fitness project. The selected data are divided into training set and verification set by 8:2 ratio. After the visualisation of the original data extracted from PAMAP2, attribute values of some data are missing, while most of the data have few attributes missing. However, the inconsistency of sampling frequency between heart rate sensor and other sensors will lead to heart rate loss, which occurs in about 8 out of every 9 sets of heart rate data. Thus, the average known heart rate can estimate the missing heart rate. After the missing data are completed, the data are normalised. To simplify the recognition data, the sliding window technology can segment the data. A sliding window with a width of 200 and a moving step of 100 is designed accordingly, which can correspond to a person's physical activity data in 2 seconds.

3.5 Test environment configuration and evaluation index

A medium-sized community is selected for the experiment to evaluate the performance of the proposed system and verify its substandard actions recognition capacity in fitness motion. According to the community fitness advocates, most fitness people don't have a clear understanding of standard fitness motions and volunteer to try the proposed system. Here, BWT901CL can collect the actions of the subjects. The subjects are five male and five female community residents, aged between 35 years old and 45 years old. The experimental environment is a space in the community, and the sensors are attached to the experimenters. Then, the Bluetooth module can connect the sensor and computer to realise data transmission. The subjects are requested to do the foot sliding, foot side, and non-sliding step under the guidance of the relevant personnel.

The performance of the proposed system is tested through accuracy (see equation (6)), precision (see equation (7)), recall (equation (8)), and F1 score (equation (9)).

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN} \quad (6)$$

$$Precision = \frac{TP}{TP + FP} \quad (7)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (8)$$

$$F1 = \frac{2TP}{2TP + FP + FN} \quad (9)$$

In equations (6), (7), (8) and (9), TP means a positive example is positively classified; TN means a negative example is negatively classified; FP means a negative example is positively classified and FN means a positive example is negatively classified.

4 Results and discussion

4.1 Model performance evaluation

The test results of the model suggest that, for the fitness motion of subject 1 to subject 5, the recognition accuracy of the model is more than 97%, the recognition precision of the model is more than 96.5%, the average recall rate of the model is 0.962, and the average F1 value of the model is 0.964. The four test results show that the performance of the proposed model is excellent, which can accurately identify all kinds of fitness motions and achieve the expected requirements.

4.2 Performance test comparison of model parameters

Figure 6(a) shows the loss value and accuracy value of the NN model with three LSTM layers, and Figure 6(b) shows the loss value and accuracy value of the NN model with four LSTM layers. Thus, for both the LSTM NN model with three LSTM layers and four LSTM layers, after 140 times of iterative training, the accuracy curve and loss value curve of the model tends to be stable and convergent, proving that the proposed model is stable and effective. However, the accuracy of the NN model with three LSTM layers is slightly higher than that of the NN model with four LSTM layers. The training time of NN model with four LSTM layers is much longer than that of the NN model with three LSTM layers. Therefore, the model with three LSTM layers is selected, which can meet the requirements of the system.

To further evaluate the performance of the proposed model, the proposed algorithm is compared with the *K*-NN (*K*-Nearest Neighbour) algorithm in the classical supervised classification model algorithm and the Backpropagation (BP) NN model with two hidden layers. Figure 7 shows the experimental results.

Figure 5 Model test results

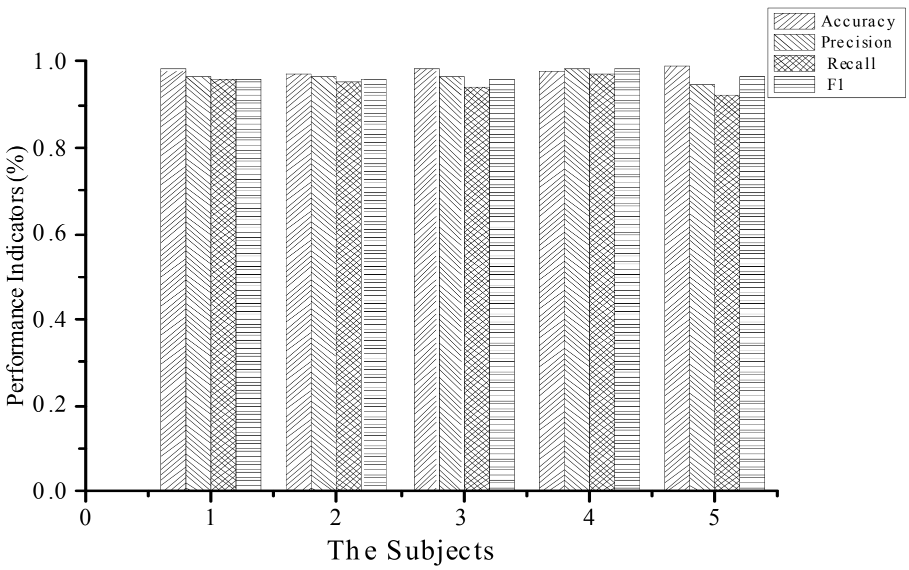
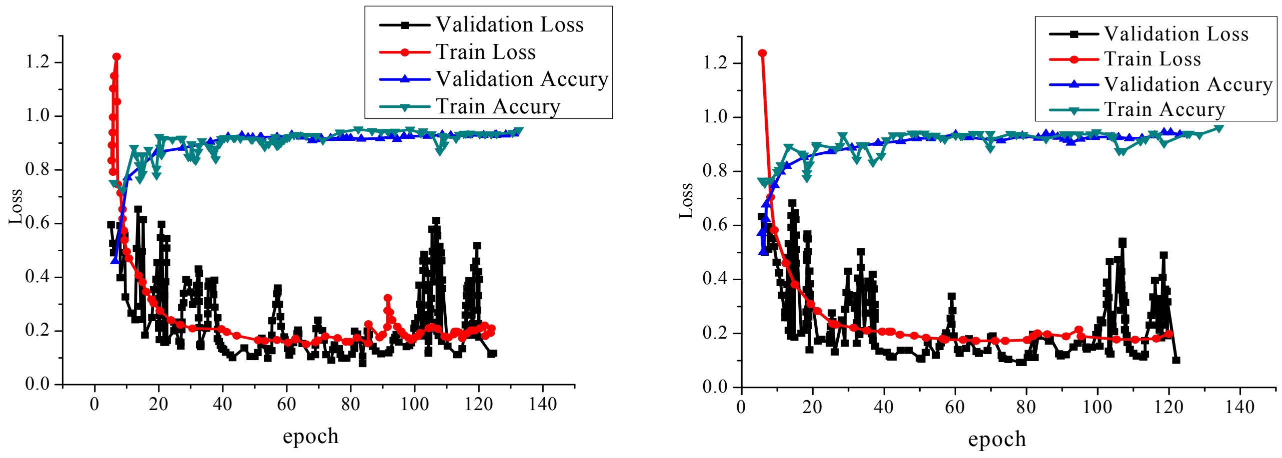


Figure 6 Test indexes of LSTM NN model (a) shows the LSTM NN model with three LSTM layers and (b) is the LSTM NN model with four LSTM layers



(a) (b)

Figure 7 Comparison of model accuracy

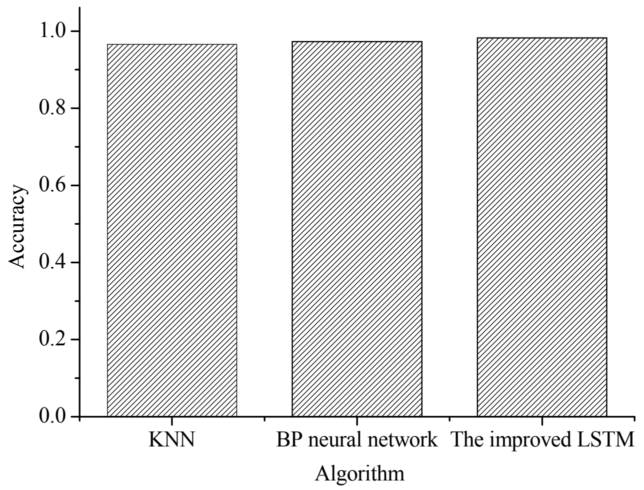


Figure 7 suggests that in the data set used, the recognition accuracy of the KNN model for fitness motion is 95.344%, the recognition accuracy of the BP NN model for fitness motion is 96.344% and the recognition accuracy of the proposed LSTM NN model for fitness motion is 97.622%. It shows that the LSTM NN with the ability to capture data time series has higher recognition accuracy than the KNN model and BP NN model. The proposed model can better recognise and monitor the fitness motion data.

To further prove the effectiveness of the proposed model, the proposed model is compared with the multi-layer CNN model and the multi-layer CNN model with attention mechanism under the WISDM data set, and the experimental results are compared. The experimental results show, under the WISDM data set, the accuracy of the multi-layer CNN model is 91.2%, the accuracy of the multi-layer CNN NN model with attention mechanism is 96.4% and the accuracy of the proposed LSTM NN model is 97.5%. The overall recognition rate of the proposed LSTM NN model is higher than that of the multi-layer CNN NN model and multi-layer CNN NN model with an attention mechanism.

4.3 Discussion

The proposed LSTM NN model overcomes the inconvenience of manual feature extraction in the traditional human motion model and simplifies the recognition process, thus improving system efficiency. But the proposed LSTM NN model consumes more training time and resources. Here, the training time of the proposed LSTM NN model is 869.7 s, the average training time of each epoch is 9.23 s, and the average recognition time of human motion recognition on the test set is 0.00031 s. The model LSTM NN proposed has a high recognition rate for motions with high complexity, but a low recognition rate for motions with high acceleration similarity.

4.4 Actual system effect display

Figure 8 shows the recognition results of the model for unlabelled data by inputting the collected human data annotation into the NN model for learning.

Figure 8 System test results

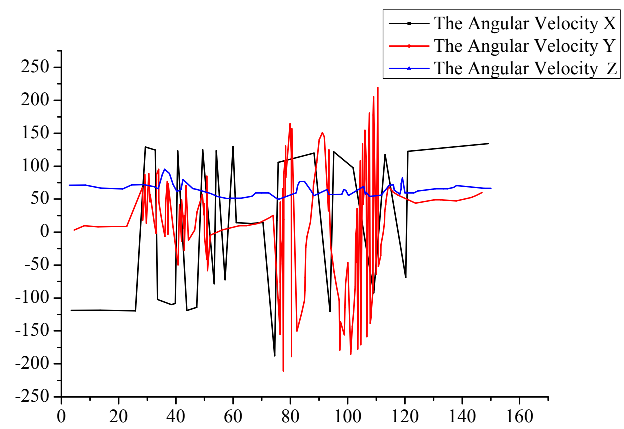


Figure 8 shows that when the sensor obtains the 0th to 60th values, the angular velocity in the *X*-direction, *Y*-direction and *Z*-direction has no obvious changes, so it can be judged that the subject is in a normal state of motion; when the sensor obtains the 80th to 100th values, the angular velocity in the X-direction, Y-direction and Z-direction have obvious changes, so it can be judged that the subject has the phenomenon of sideslip. At this time, the system should remind the user in time. When the sensor obtains the 100th to 160th values, the angular velocity in the X-direction, Y-direction and Z-direction fluctuate less, and the user returns to the normal motion state.

5 Conclusions

Currently, the intelligent wearable device system of community fitness people cannot mine motion data and has a low recognition rate for the fitness category. Consequently, a motion data monitoring system with multi-layer architecture is proposed. The proposed motion data monitoring system overcomes the inconvenience of manual feature extraction in previous systems and improves the recognition accuracy of the system.

But the proposed motion data monitoring system still has some shortcomings. Fitness motion data need to preprocessed before they are input into the proposed LSTM NN model and then are uploaded to the OS, which reduces the real-time response of the system. In the follow-up study, the LSTM NN will be further explored. For example, the Gru NN algorithm can be included, which is a simplified version of LSTM NN and can simplify the training model and consumes less training time and resources. The proposed LSTM NN model can be used in the field of intelligent assistant training and exert its application value.

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