Design of motion pattern recognition system based on artificial intelligence methods

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***Abstract*—This paper builds a wearable device that can be used for motion movement recognition based on artificial intelligence technology. Firstly, a human motion data collection device is designed to realise data collection and pre-processing; secondly, the collected data is classified based on artificial intelligence technology to realise pattern recognition of motion states; finally, the results of recognition are analysed and the results show that motion pattern recognition based on artificial intelligence methods is feasible.**

***Keywords*—Artificial Intelligence, Wearables, Pattern Recognition**

I. INTRODUCTION

With the continuous innovation and development of modern technologies such as the artificial intelligence industry, intelligent methods are gradually replacing traditional methods [1-6]. In the recognition of motion patterns by wearable devices, traditional wearable devices mainly rely on the modelling of a single motion to achieve the recognition of multiple motion patterns [7-9]. However, the traditional method requires the establishment of a corresponding mathematical model for each motion pattern and then pattern recognition, which is not only complex but also has corresponding errors [10-12]. With the promotion of artificial intelligence technology, using AI technology for motion pattern recognition in traditional wearable devices will greatly reduce the labour cost and also improve the accuracy of recognition [13-15]. The application of artificial intelligence technology in combination with wearable devices has gradually been developing into a cutting-edge and heated issue in the field of wearable devices [16-18].

Current domestic and international research into wearable devices is focused on optimising the data transmission of wearable devices and other aspects.

Wu [19] et al. propose design techniques for wearable devices in low-power systems to minimize human interaction and keep wearable devices running for as long as possible.Chen [20] et al. address the discomfort caused by wearing multiple sensors on different parts of the body for healthcare applications.Yoon [21] et al. use off-the-shelf ambient light sensors as a smart wearable alternative user interfaces to design and model lightweight user interactions based on typical uses of representative smart wearable devices. Zhang [22] et al. designed a heart rate temperature posture measurement system based on LABVIEW, which enables the measurement and recording of heart rate temperature steps.

There are a series of wearable device systems established by relevant domestic and international workers, but there are some problems and the current research on artificial intelligence techniques for motion pattern recognition systems is not comprehensive enough.

In this work, we use artificial intelligence techniques to improve the traditional method of motion recognition for wearable devices. Firstly, we design a motion information acquisition device, which enables motion information to be collected and transmitted wirelessly to a PC; secondly, we pre-process the data collected based on motion information, and the pre-processing process includes abnormal data rejection, missing data interpolation, high frequency noise filtering and data segmentation; secondly, we recognise motion patterns based on an artificial intelligence method, and build a neural network model for recognising motion states; and finally, We compare the advantages and disadvantages of our proposed method of motion pattern recognition with those of traditional pattern recognition.

The flowchart of our work is shown in Figure 1.

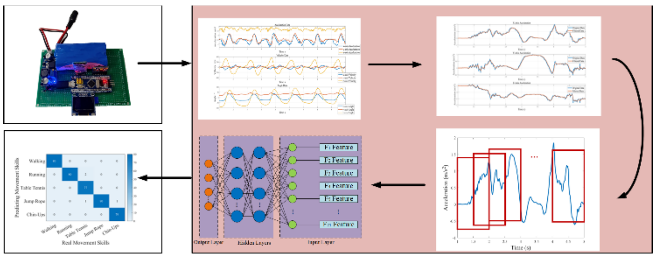


Fig. 1. The flowchart of our work

Our work has the following contributions.

1) A motion information acquisition device was designed, which enables real-time acquisition of motion information.

2)A method for processing the acquired motion information was established, including data smoothing and data segmentation.

3)A method for artificial intelligence recognition of motion patterns was designed.

II. HARDWARE DESIGN FOR MOTION INFORMATION ACQUISITION

A. Block diagram design of the system

The motion information acquisition system needs to collect motion data and send it to the PC. The system block diagram of the motion information acquisition system is shown in Figure 2.

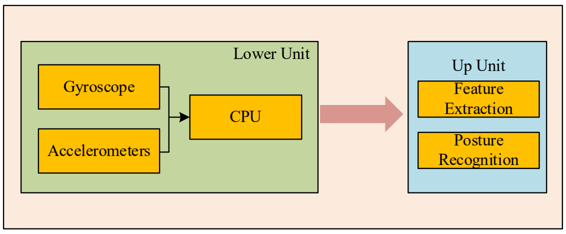


Fig. 2. System Block Diagram of Motion Information Collection Device

As shown in Figure 2, the lower computer includes gyroscopes and accelerometers, and the upper computer implements the functions of feature extraction and pose recognition.

B. Hardware schematic design

The hardware of the motion information acquisition device is designed according to the system block diagram shown in Figure 1 as shown in Figure 3.

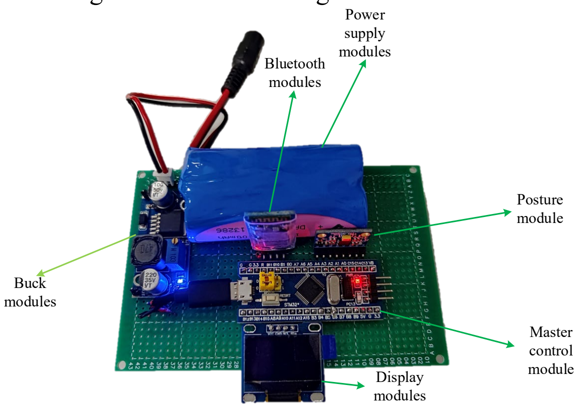


Fig. 3. Schematic Diagram of The Hardware Structure of The Motion Information Collection Device

As shown in Figure 3, the hardware of the motion information acquisition device includes a power supply module, a step-down module, a master control module, a Bluetooth module, a posture module and a display module.

III. DATA PREPROCESSING

As the motion acquisition device has errors in the process of data acquisition and data transmission, the data of the acquisition device needs to be processed accordingly. This paper includes the following steps for the data pre-processing of this data acquisition device: abnormal data rejection, missing data interpolation, high frequency noise filtering and acquisition data segmentation.

A. Abnormal data rejection

There may be some abnormal data in the motion acquisition device which can significantly affect the subsequent processing of the data and therefore needs to be removed.

Outliers are defined by a statistical approach, defining an outlier as a value in a set of measurements that deviates from the mean by more than three times the standard deviation. The motion data collected in this paper varies over time and cannot just be statistically analysed by statistical methods, so this design improves on that method of statistics, and the improved process is shown in Figure 4.

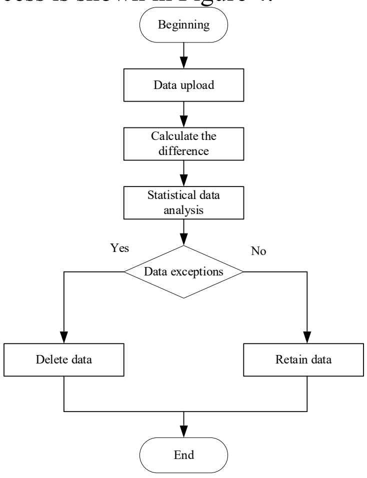


Fig. 4. Abnormal data rejection flow chart

Calculate the first order difference as shown in equation(1).

$$X_i = x_{i+1} - x_i \left(i = 1, 2, \ldots, n-1\right) \quad (1)$$

For $X_i \left(i = 1, 2, \ldots, n-1\right)$, the data within the corridor $\left(EX - 3\sigma, EX + 3\sigma\right)$ is retained and the data outside the corridor X_i and the data corresponding to x_{i+1} are excluded, thus enabling the rejection of abnormal data.

B. Missing data supplement

After removing the abnormal information, the information is sorted out, the missing data is interpolated and smoothed using Lagrange interpolation, and the repaired data is finally output. The specific implementation method is as follows:

For a set of data with outliers removed, the arrangement is denoted as $\left(x_0, y_0\right), \ldots, \left(x_k, y_k\right)$, x_j denotes the position of the independent variable, y_j denotes the value of the function at this position, and all x_j are different, then according to the Lagrange interpolation formula the polynomial of Lagrange interpolation can be obtained as shown in equation(2).

$$L(x) = \sum_{j=0}^{k} y_j l_j(x) \quad (2)$$

In equation(2), each $l_j(x)$ is a Lagrangian fundamental polynomial with the expression shown in equation(3).

$$l_j(x) = \prod_{i=0, i \neq j}^{k} \frac{x - x_i}{x_j - x_i} \quad (3)$$

The Lagrangian fundamental polynomial $l_j(x)$ is characterised by taking the value 1 on x_j and 0 on x_i for $i \neq j$.

Using the fitted Lagrangian polynomial as an estimate of the curve, the data position of the missing value is entered into the polynomial to predict the value of the function at this position, thus enabling data interpolation estimates of the location of the missing data.

C. *High frequency noise filtering*

During data acquisition by motion devices, there is a lot of high frequency noise. To filter out high frequency noise, a first order inertial adaptive filter is used. In this filter, the new output value is defined as a linear combination of the currently sampled value and the previous output value. The specific algorithm is shown in equation(4).

$$Y(n) = m \bullet X(n) + (1-m) \bullet Y(n-1) \tag{4}$$

In equation(4), $Y(n)$ is the filtered output value of this filter, m is the filter coefficient between the interval [0,1], $X(n)$ is the current sample value, and $Y(n-1)$ is the previous filtered output value.

The filter coefficient is the most important parameter of the filter and has a great influence on the filtering effect. In order for the filter to filter out noise more efficiently and accurately, the filter parameters need to be adjusted dynamically. The filter coefficient m is determined and modified as shown in equation (5).

$$\begin{cases} \Delta = Y(n) - Y(n-1) \\ m = \left(1 - \dfrac{\Delta_a}{\Delta}\right) \bullet k_0 \end{cases} \tag{5}$$

As shown in equation(5), Δ is the difference between the current filter Output and the last Filter Output, Δ_a is the conditional threshold for identifying the state of motion, and k_0 is the default filter parameter.

The waveform after anomalous data rejection, missing data interpolation and high frequency noise filtering is shown in Figure 5.

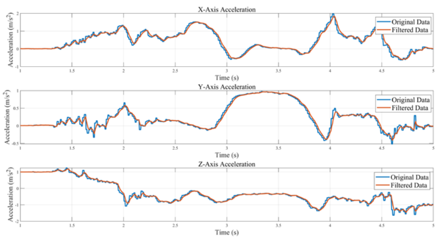


Fig. 5. Data pre-processed images

D. *Collection data splitting*

The acquired motion data is transmitted as a data stream, which cannot be directly pattern recognised and needs to be processed. Therefore, data segmentation of the collected data is required. A common solution for data segmentation is to set a sliding window on the acquired data for processing. The sampling frequency of the data acquisition device is 200Hz, so the sliding window is set to a 2s interval, i.e. 800 sampled data points, while the window coverage is 50%. The sliding window function data segmentation is shown in Figure 6.

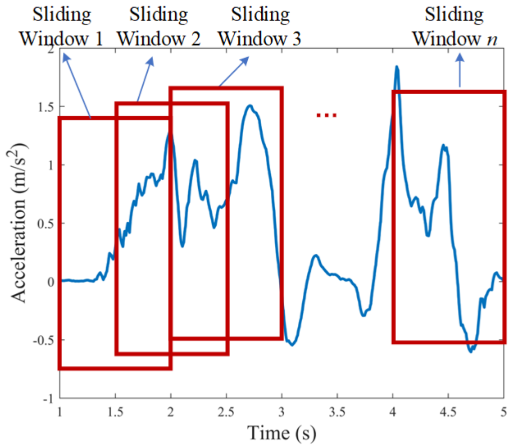


Fig. 6. Data segmentation of images

As shown in Figure 6, after this group data segmentation, the data stream can be split into different data segments. The division of the data stream into different data segments facilitates the subsequent analysis and processing of the data.

IV. Artificial Intelligence Based Motion Pattern Recognition

The collected motion data is pre-processed to achieve data smoothing and data segmentation, at which point the data is divided into 800 data points as a section of data for storage and processing.

A. *Principles of Neural Network Models*

Neural Network Model is a mathematical model that simulates the human brain thinking about a problem. Neural networks have a wide range of applications in the fields of system recognition, pattern recognition and intelligent control.

The neural network model is composed of three parts: the input layer, the hidden layer and the output layer, as shown in Figure 7.

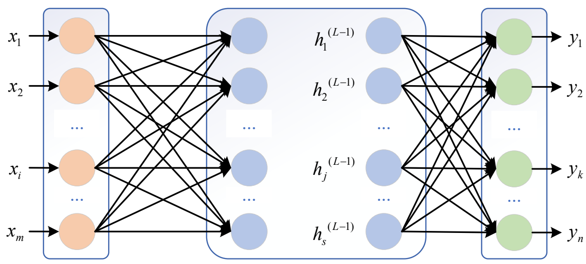


Fig. 7. Neural network models

As shown in Figure 7, the neural network model first establishes the number of layers in the input layer as the input argument affecting the neural network, the middle hidden layer simulates the complex neural network of the real human brain, and finally outputs the prediction result of the income layer in the output layer.

(1) Loss Function

A loss function is a function of non-negative real numbers used to quantify the difference between model predictions and true labels. Common loss functions in neural networks include 0-1 loss function, squared loss function, cross-entropy loss function, and so on. In this paper, the loss function is being defined as the squared loss function, as shown in equation(6).

$$\varepsilon\left(y_i,\hat{y}_i\right)=\frac{1}{2}\left(y_i-\hat{y}_i\right)^2 \tag{6}$$

Then for P sets of neural network samples the total error generated is defined as shown in equation(7).

$$E_p=\frac{1}{2}\sum_{i=1}^{p}\left(y_i-\hat{y}_i\right)^2 \tag{7}$$

(2) Empirical Risk Minimization

The lower the loss predicted by the model, the better the model's predictive ability, so that it can have a lower expected error, by calculating the empirical risk, i.e., the average loss of the training set, as shown in equation(8).

$$R\left(\theta\right)=\frac{1}{N}\sum_{i=1}^{N}\varepsilon\left(y_i,f\left(x_i;\theta\right)\right) \tag{8}$$

(3) Stochastic Gradient Descent

The empirical risk function is a non-convex function that is constructed as an optimisation objective, and the stochastic gradient descent method is used to improve the empirical risk function.

B. Neural network model building

The neural network requires feature extraction of the collected motion data to construct the input features for the neural network to classify the sample data set. The seven features of Mean Value, Variance, Maximum Value, Minimum Value, Root mean square, Crest Factor and Skewness in the three directions of the segmented data are extracted as the input to the neural network.

The output of the neural network is the probability of recognition of the different movements.

The training set is 400 sets, the test set is 100 sets, the learning rate is 0.01, the number of input layer neurons is 23, the number of hidden layers is 2, the number of hidden layer neurons is 120, the number of output layer neurons is 5, the activation function is Softmax function, and the training method is Stochastic Gradient Descent. The corresponding neural network parameters are shown in Table 1.

TABLE I. NEURAL NETWORK PARAMETER SETTING TABLE

Parameter Name	Set Value
The Sample Size of Training Data Set	400
The Sample Size of the Test Data Set	100
Learning Rate	0.01
The Size of Input Nodes	21
The Size of Hidden Layers	2
The Size of Hidden Nodes	120
The Size of Output Nodes	5
Activation Function	Softmax
Training Approach	Stochastic Gradient Descent

The neural network model built after setting the corresponding neural network parameters is shown in Figure 8.

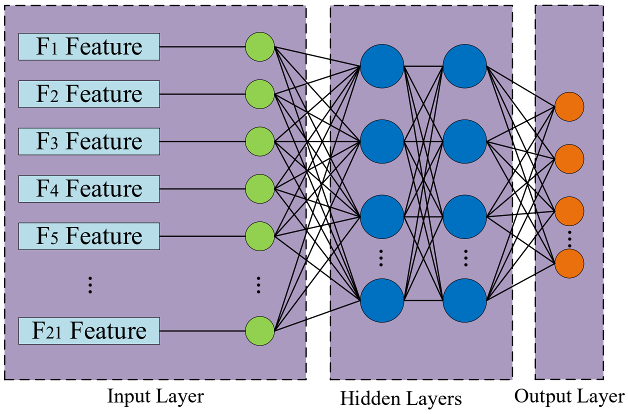
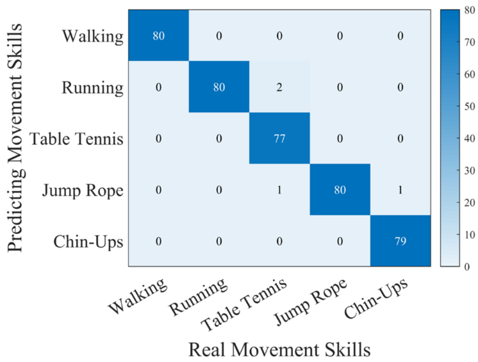


Fig. 8. Neural network structure diagram

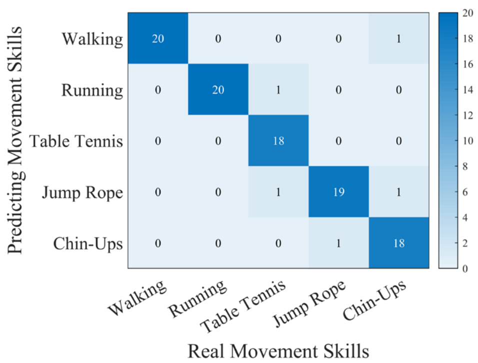
In the neural network structure shown in Figure 7, the inputs are the motion features extracted and the outputs are the single vectors predicting the probabilities of the various classes.

V. RESULTS AND ANALYSIS

The five sports of walking, running, rope skipping, table tennis and pull-ups were identified using the neural network in this paper and their performance on the training and test sets is shown in Figure 9.



a) Training set performance



b) Test set performance

Fig. 9. Performance of neural network models in the training and test sets

Table 2 shows the performance of this neural network model in terms of scores in the training and test sets.

TABLE II. NEURAL NETWORK CLASSIFICATION RESULTS

	Training set Accuracy	Training set Recall	Test Set Accuracy	Test set Recall
Walking	100%	100%	100%	95.24%
Running	100%	97.56%	100%	95.24%
Table Tennis	96.25%	100%	90%	100%
Jump rope	100%	97.56%	95%	90.48%
Pull-ups	98.75%	100%	90%	94.74%
Average accuracy rate	99%	99.02%	95%	95.14%

As shown in Table 2, it can be seen that the classifier built in this paper has a classification effect of over 90% in all five movements, which shows that the classifier can be used to distinguish between different movement patterns.

VI. CONCLUSION

This paper addresses the problem of motion pattern recognition for wearable devices and establishes a motion pattern recognition system. A measurement platform CPU for motion data acquisition and data smoothing and segmentation algorithms are designed, and an artificial intelligence classifier that can be used for motion pattern classification is built. The major contributions of this paper are in the following three areas.

1) A motion data acquisition platform is built.

2) An algorithm for measurement data pre-processing is designed.

3) A classifier for motion pattern recognition was built.

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