Recognition of Aerobics Movement Posture Based on Multisensor Movement Monitoring

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Abstract. In the traditional attitude recognition methods, the final recognition rate is low because of the inadequate processing of the motion attitude data. Therefore, based on the multi-sensor mobile monitoring of aerobics movement posture recognition. In the design process of aerobics movement posture recognition method, first of all, based on multi-sensor movement monitoring, collected aerobics movement posture data. Then in order to improve the recognition rate of aerobics posture, the collected data is preprocessed. Will process the good data, according to the time frequency characteristic complete the data characteristic extraction. Comparing the extracted features with the multi-sensor moving monitoring images, through the multi-level attitude recognition algorithm, the movement attitude recognition of aerobics is finally realized. Experimental results show that the proposed method has a higher recognition rate than the traditional method. Even under the influence of changing factors such as penalty factors and kernel parameters, the proposed method is still predominant.

Keywords: Sensor · Mobile monitoring · Attitude recognition · Feature extraction

1 Introduction

The technology of human motion recognition has been developed for many years. It is a kind of pattern recognition method to judge the state of human motion by analyzing the related information reflecting human motion behavior [1]. This technology can provide users with motion state information, so it has a wide range of applications in sports health, sensory games, user social behavior analysis, safety monitoring, patient rehabilitation training, indoor positioning and navigation, personal feature recognition and other fields [2]. The change of living habits and the increase of life stress lead to a variety of diseases troubling people, making people begin to realize the importance of health. A variety of sports should be out of time [3], aerobics has become a popular sport of the masses. Aerobics combines many dance elements, gymnastics, dance, music, fitness, entertainment in one, is conducive to reducing the accumulation of hip and abdominal fat, while the movement of coordination and flexibility improvement [4]. Aerobics to play a role, need

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to complete the movement posture control. In the literature [5], it is proposed to install sensors on human body, fuse information and mine association according to the oscillation amplitude of sensors, and obtain the data of motion posture. The data is monitored by the method of sensor quantification tracking and recognition, and the data is fuzzy adaptive fused by feature clustering, thus realizing the monitoring of motion data. In the literature [6], the recognition of human motion based on data fusion of acceleration sensor and spiral instrument is put forward, which mainly refers to the spiral instrument outputting human motion information, selecting appropriate algorithm to repair and fuse the output information, and realizing accurate measurement of human motion posture.

Therefore, the movement of multi-sensor monitoring as a support to achieve aerobics posture recognition. After the rapid development of sensor technology, it is gradually developing towards miniaturization, digitalization, intelligentization and multifunction, which makes the recognition technology of human daily motion posture based on sensor signal develop rapidly.

In this paper, multi-sensor movement monitoring is applied to aerobics posture recognition. Multi-sensors are used to collect the movement posture, preprocess the collected data, remove the interference of redundant data, extract the data features according to the time-frequency characteristics, and use multi-level posture recognition algorithm to complete the movement posture recognition of aerobics. Experiments show that the designed method has a good recognition rate. It can provide some support for the handling of aerobics posture.

2 Design of Exercise Posture Recognition Method Based on Multisensor Mobile Monitoring

Aerobics movement posture recognition method design, based on multi-sensor movement monitoring. First of all, the typical aerobics movement posture data collection. In order to ensure better recognition effect, the collected data are preprocessed. Then, the data feature is extracted, and a multi-level attitude recognition algorithm is constructed to realize the recognition of the motion attitude.

2.1 Multi-sensor Based Data Acquisition for Aerobics Posture

Because this paper is aimed at a given time series of motion data, stable and accurate pattern recognition is carried out. Mainly based on the sensor movement monitoring, the aerobics movement posture recognition [7]. Taking the posture of human body in aerobics as the key target, a small data acquisition terminal is designed to effectively collect and store the movement information of human body. Multi-sensor mobile monitoring of motion and attitude data acquisition, involving the sensor unit [8], control unit, storage unit and power management unit. The data collection process is shown in Fig. 1.

The sensor module adopts MPU9250 nine-axis sensor chip integrated with many types of sensors, which can be used to extract the acceleration, angular velocity, magnetic field intensity and other related vector information [9]. The MPU9250 chip is composed of a moving attitude module and a magnetic module. The MEMS inertial measurement unit and the MPU6050 six-axis sensor chip can obtain the acceleration, angular velocity

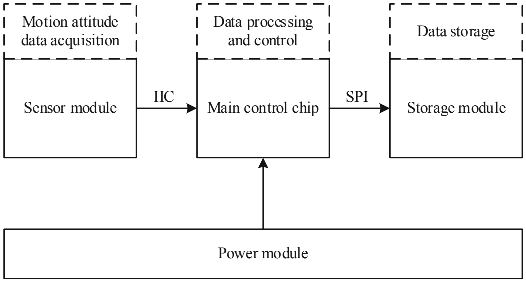

Fig. 1. Motion attitude data acquisition flow

and temperature of the target. The magnetic field intensity and other vector information of the target can be obtained by the AK8963 three-axis magnetometer. According to the motion characteristics of human body, the sample rate of the sensor is 25 Hz, and the sensor data can be read by IIC. So the communication between MPU9250 chip and MCU STM32F103RBT6 is realized by IIC protocol [10]. In the circuit design, the pull-up resistor is used to control the signal line, and the signal line is driven in turn by the IC interface of the main control chip and MPU6050, as shown in Fig. 2.

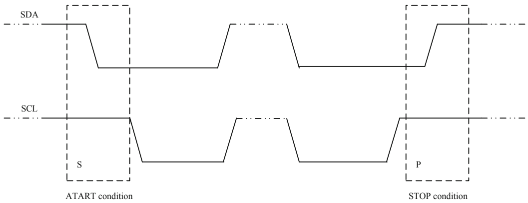

Fig. 2. IIC communication timing block diagram

In the main control chip plate, because the control center needs to carry on the reorganization to the MPU6050 chip data, coordinates between the module the data transmission [11], completes the data on chip storage. For the corresponding requirements of portable devices, the control center needs to have the following characteristics:

(1) Low power consumption.
(2) Fast response.
(3) Stable functions.
(4) Having sufficient communication interfaces.

Based on the above characteristics, this research chooses STM32 chip as the total on-chip control chip. Finally, the storage plate, using MICRO SD CARD as storage media. The layered structure of the medium has the features of low cost, SPI Slave UART, industry-mature interface, compatibility with most devices, and chip solidification of FAT 12/FAT 16/FAT32 file system. Through the combination of the above plates, the joint role of multi-sensor movement monitoring of aerobics movement data acquisition.

2.2 Sample Data Preprocessing

There are always some problems in the collection of motion attitude data by multi-sensor mobile monitoring. The first is that the collected data can not avoid the existence of noise, and prominent noise will affect the recognition algorithm [12]. The second point is due to the difference in the work, the data collected by the data acquisition terminal will have a certain zero deviation error. The third point is that the stability of gravitational acceleration will disturb the posture information of human body. In this study, low-pass filter is used to remove useless noise and extract useful information. The Butterworth filter is used in this paper. The system functions are shown in Fig. 3.

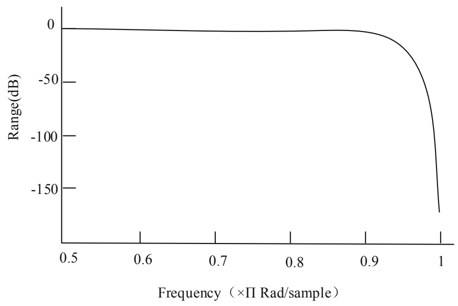

Fig. 3. Filter system functions

According to statistics, the filter has a certain degree of inhibition of interference noise, when the data itself is very stable, its order of magnitude in 10^{-2}–10^{-3} g, and the general movement of the human body in 10^{-1}–100 g change, so the impact of noise is not very large. In addition, the data collected by the terminal should be calibrated. When the objective value of the sensor's data is zero, the actual value of the sensor's data is zero [13]. So it is necessary to calculate the bias error by experiment and compensate the measured signal. In theory, if you put the mpu water at rest, the x-axis, the y-axis reading will be zero, and the z axis will be 1 g or –l g. But this is not the case, each chip due to manufacturing problems, the actual output value of the theoretical value must be deviated, so we need to calibrate the chip.

The calibration formula is:

$$G_x = K \times ADC_x + offset \tag{1}$$

In the formula, ADCX is the actual output of the sensor, GX is the actual sensing data, offset means that the acceleration of 0g is the sensor's actual sensing data, that is, zero bias error. K is the scaling factor. The final step is to remove the gravitational acceleration interference. The gravity acceleration is always included in the human posture data. For the static state, the gravity acceleration is always downward, which makes the three axes of the sensor coordinate system produce stable components. In addition to the gravity acceleration interference filter also used to aerobics posture in the leg, for example, can be filtered before and after the contrast of the time domain, as shown in Fig. 4.

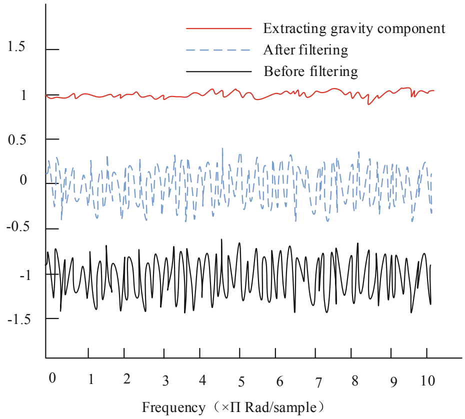

Fig. 4. Comparison of time domain before and after filter of swinging sample

As can be seen from Fig. 4, the motion signal after filtering out the gravity component changes around the zero point, and has a strong regularity, which is convenient for subsequent attitude recognition.

2.3 Feature Extraction of Aerobics Posture Data

It is difficult to get the direct basis of learning decision directly from the original data. Therefore, it is necessary to extract the typical features of various kinds of posture time series to serve the construction and verification of posture recognition algorithms. Before the feature extraction, we need to integrate the initial information to obtain further time series. The acceleration and angular velocity of human body reflect the intensity of human motion to a great extent. Another characterization of human motion is the rate of change of each axis data. It is therefore possible to generate a sequence of differences for each axis. Based on the difference sequence, different motion states can be obtained. In the research of human posture recognition algorithm, its features are generally time-frequency features. The statistical features used in this study include mean value, standard deviation, median absolute deviation, quartile distance, maximum value, minimum value, square and mean value, AR model coefficients with Berg order of 4, correlation of each axis series and information entropy. The formula for calculating mean value is as follows:

$$mean\_accel\_a\_x = \sum\nolimits_n accel\_a\_x_n \tag{2}$$

These formulas represent the total size of the time series. The amplitude of jitter of a signal represented by the standard deviation std. The formula is as follows:

$$std\_accel\_a\_x = \sqrt{\sum\nolimits_n (accel\_a\_x_n - mean\_accel\_x\_a)^2 / N} \tag{3}$$

The two formulas show that the range of motion and intensity of the different postures of the human body are different. Based on this, the salient characteristics of signal frequency can be found. Due to the frequency domain waveform of the moving state, the peak spikes regularly appear on the whole spectrum line. Based on this attitude frequency domain information, including peak frequency point, sub-peak frequency point, peak rising along 3 dB frequency point, descending along 3 dB frequency point, number of outburst frequency point, weighted average frequency point. Peak frequency points represent the most prominent frequency information of attitude. The sub-peak frequency features characterize the attitude sub-salience in the frequency domain, and the peak bandwidth is described along the 3 dB frequency points and the 3 dB frequency points. The number of peak frequency points indicates the frequency richness of human body. The weighted average frequency points represent the average frequency points in the frequency domain. The formula is as follows:

$$\bar{f} = \frac{\sum_{i=1}^{N} \omega_i \times h_i}{\sum_{i=1}^{N} h_i} \tag{4}$$

Under various motion postures, the weighted average frequency maps were compared. According to the contrast graph, it can be seen that this feature can be better classified into aerobics posture categories. To sum up, the peak frequency point, weighted average frequency point and the number of outburst frequency points can all be used as effective data features. These features are numbered in practical applications to facilitate the subsequent expression and application.

2.4 Build a Multi-level Attitude Recognition Algorithm

Aerobics movement posture mainly includes many posture movements, but each movement has its own unique. Therefore, by roughly classifying the movement postures of aerobics, we can narrow the range of gesture recognition, improve the efficiency of the algorithm, and finally achieve accurate recognition of movement postures. Aerobics posture can be seen as a series of coarse classification of movement in space and time, the movement posture in this paper according to the movement intensity, frequency coefficient rough classification of the movement posture. Based on the sports characteristics of aerobics, the paper chooses “kick”, “swing”, “side waist extension”, “high lift leg”, “left and right level lift” five sports posture. Among them, “kick”, “swing leg”, “high lift leg” can be seen as dynamic, “side waist extension”, “left and right level lift” two actions relatively static, called static.

Firstly, the attitude is classified according to the motion intensity. In this paper, the standard deviation of the attitude angles is used to analyze the motion intensity. The standard deviation of the movement attitude angle expresses the change of the movement attitude angle of calisthenics in a certain time, which reflects the movement intensity of the movement attitude; the standard deviation of the combined attitude angle reflects the intensity of the movement attitude angle, which causes the error in order to prevent the special circumstance from separately calculating one angle of the attitude angle; meanwhile, the movement shows the change of the three angles on the attitude angle data, so the value of the combined attitude angle is introduced, and the standard deviation is defined as follows:

$$sum\sigma = \sigma_1 + \sigma_2 + \sigma_3 \tag{5}$$

The σ1, σ2, σ3 in the formula respectively represent the standard deviation of yaw angle, pitch angle and roll angle in the motion attitude angle. According to the experimental analysis, the standard deviation of the combined attitude angle in the rough classification based on motion intensity is set to 1.5°. When the standard value of the combined attitude angle is greater than this value, it is marked as dynamic and less than this value, it is recorded as static.

Secondly, based on the rough classification of pose in frequency domain, it is found that the normal stride frequency of aerobics is not more than 2.5 Hz, and it is periodic. Because the characteristics of aerobics movement in time domain are not obvious, it needs to be analyzed from time domain to frequency domain. When aerobics movements are carried out, the posture recognizer worn on the human body will swing up and down with the movements. Based on the signal of Z-axis acceleration sensor, because the data of Z-axis is affected by gravity field, the Z-axis is filtered at high speed, and the effect of gravity g is filtered out. And the range of exercise energy concentrates on 0–10 Hz, which satisfies the frequency distribution of activity, and the corresponding frequency at the maximum amplitude is 3.972 Hz, which accords with the normal exercise frequency of aerobics. Therefore, the specific action is dynamic.

Finally is the transition movement classification, some movements in the aerobics movement, said separately from the standing posture to the lying posture and the lying posture to the standing posture movement process, because it expresses the movement process, therefore calls it as the transition movement. Compared with other actions, the duration of these two actions is shorter. According to observation and analysis, the duration of transitional actions is usually 3–8 s, and the time is not fixed. In this paper, an adaptive sliding window method is used to segment the data, which can not meet the needs of recognition of transitional actions. Therefore, an adaptive sliding window method is used to segment the data. According to the characteristics of the transition movement, this paper uses the peak-peak and its slope to judge the transition movement of calisthenics. When the peak-peak pitch angle is greater than 34° but less than 50°, whether the peak peak value slope is less than –1.35° is judged. If the slope satisfies the peak value, it is judged to be a suspicious standing movement. Then calculate whether the sum of the standard deviation vectors of the attitude angle in the two time windows is less than 10°, and if it is satisfied, it can be judged to be standing movement. When the peak pitch angle is greater than 50° and its slope is greater than 4.5°, it is judged to be a suspected lying movement. Then calculate whether the sum of the standard deviation vectors of the attitude angle in the two time windows is less than 10°, and if it is satisfied, it is judged to be a lying movement. The algorithm flowchart for the transition action is shown in Fig. 5.

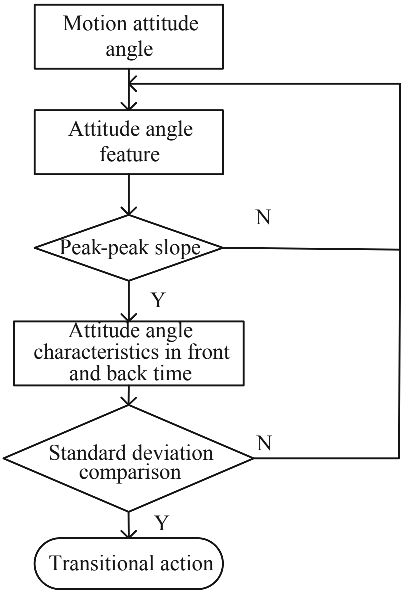

Fig. 5. Algorithm flow for transition action

The attitude recognition algorithm used in this paper is a decision tree method, which can effectively reduce the classification complexity and improve the recognition efficiency by transforming complex multi-classification problems into multi-level binary classification problems. Aerobics movement posture recognition algorithm flowchart is shown in Fig. 6. The attitude data of calisthenics are collected by the attitude recognizer, and the attitude angle is calculated, and the feature is extracted, including mean, standard deviation, frequency domain transform and peak slope. When the standard deviation of the combined attitude angle is higher than 1.5°, the movement is classified as dynamic, otherwise as static. Then the attitude is transformed and the frequency at the maximum

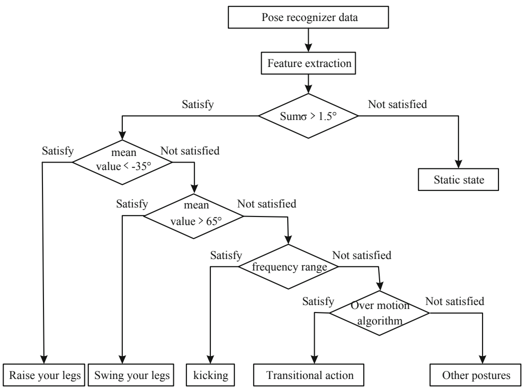

Fig. 6. Flow chart of attitude recognition algorithm

amplitude of the frequency is calculated to classify the motion attitude according to the frequency range.

3 Experiment

3.1 Experimental Environment and Methods

In order to verify the good effect of the proposed method in practice, the experiment is carried out. In order to make the experiment more scientific, this paper chooses two traditional methods as the control group, records and compares the results of the three methods, and analyzes the performance of different methods. The experiment is divided into two parts: training and testing. First, the classification model is trained. In order to intuitively feel the experimental results, this paper selects five kinds of aerobics postures, namely, "kick", "leg", "side waist extension", "high lift leg", "left and right level lift" and posture data, each aerobics movement posture lasts 1 min, according to the sampling rate of 50 Hz, while in most cases, the stability of the human body is about 2 s, the sampling time is set to 1 s, the repetition is 50%. In this experiment, 6 volunteers were selected to complete the whole demonstration of aerobics independently. From the demonstration video, the clear data of 2 h monitoring video were randomly extracted, and a total of 10800 sample window sets were collected. In this paper, the bias error of the sample is calculated, and the static data of the terminal is put horizontally, then the noise is filtered by the filter, and the error is compensated. Complete the de-interference processing, in the time window interception, extraction of sample frames. Using MATLAB software to verify the algorithm, and then use a clear picture of the monitoring video and experimental results were compared.

3.2 Comparison Results of Posture Recognition in Aerobics

After the sample training, three methods are used to recognize the posture. For aerobics posture recognition, the results are shown in Table 1.

Table 1. Comparison of attitude recognition rates of three methods

Movement posture	Methods in the paper (%)	Traditional methods 1(%)	Traditional methods 2 (%)
Kick	92.95	75.42	80.69
Swinging legs	89.91	78.53	86.37
Lateral lumbar extension	90.36	76.09	84.13
Raise your legs	95.27	82.34	84.00
Horizontal lift	96.33	85.29	79.13

According to the table, it can be found that the recognition rate of the proposed method is 96.33%, while the recognition rate of the two traditional methods is 85.29%

and 86.37%. The recognition rate of aerobics posture by this design method is much higher than other methods, which shows that this design method preprocesses the sensor data, can remove redundant data, and provides a good support for the subsequent accurate recognition of sports posture.In addition, the main factors affecting the motion attitude recognition are input feature selection, kernel function selection, penalty factor and kernel function parameters. Taking kicking posture as an example, starting with penalty factor and kernel function parameters, the variable parameters of recognition rate are obtained, as shown in Fig. 7, Fig. 8.

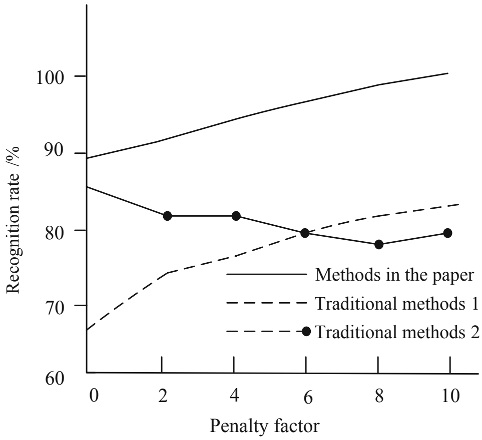

Fig. 7. Position recognition rate with penalty factor curve

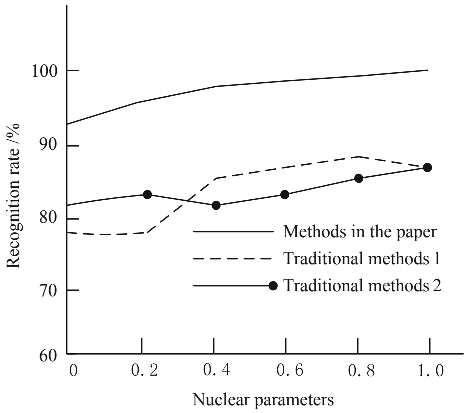

Fig. 8. Curve of gesture recognition rate with nuclear parameters

According to Fig. 7, when Gaussian kernel function is used to recognize posture, the kernel parameter is fixed and the penalty factor is changed. The recognition rate of the three methods is changed as Fig. 7 shows. The recognition rate of the method increases with the increase of the penalty factor, and reaches 100% when the penalty factor is 10. Although the recognition rate of traditional method 1 is also increasing, it is increasing slowly. Traditional method 2 position recognition rate is in a state of continuous decline. It can be found from Fig. 8 that when the fixed penalty factor is 10, the recognition rate of the proposed method is 100% when the kernel parameter is changed and increased to about 0.4, and then stably maintained. The recognition rate of the two traditional methods fluctuates continuously, and the recognition rate reaches 85% at most. To sum up, regardless of the influence factors, the proposed method is always better than the traditional method in the practical application, and can effectively improve the recognition rate. This is because this method can extract the characteristics of aerobics posture according to the time-frequency characteristics, and improve the recognition accuracy of multi-level posture when processing the data of aerobics posture.

4 Concluding Remarks

Based on the multi-sensor mobile monitoring, this paper designs the method of aerobics movement posture recognition. Through the acquisition of motion attitude data, data preprocessing, feature extraction, attitude recognition algorithm construction, the final realization of posture recognition. Through the research of this paper, the recognition rate of human motion posture is improved and the development of human-computer interaction is promoted.

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