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Feature extraction and quantitative analysis of smart wearable exercise data based on CNN

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Abstract The main advantages of smart wearable devices are their convenience and real-time nature, making them a great potential for the quantitative management of daily sports activities. In this study, a sports pattern recognition model based on smart wearable devices is proposed, which aims to recognize and classify different sports activities by collecting accelerometer and gyroscope sensor data, combined with feature extraction and classification algorithms. First, pre-processing operations such as denoising and normalization are performed on the collected data, and time domain features such as variance and peak are used for feature extraction. Then, Particle Swarm Optimization Support Vector Machine (PSO-SVM) model is used for training and classification. The experimental results show that the PSO-SVM model has a significant advantage over the traditional GS-SVM model in action recognition. Specifically, the average recognition rate of 14 sports actions is 94.55%, and the recognition rate of each sport is more than 85%. In addition, the training time of PSO-SVM is also significantly shortened compared to GS-SVM. Based on these results, this paper demonstrates that the proposed model has higher accuracy and practicality in practical applications, especially in the quantitative management of daily sports activities. The findings provide strong support for the application of smart wearable devices in the field of health management.

Index Terms Smart Wearable Devices, Sports Pattern Recognition, Particle Swarm Optimization, Support Vector Machines, Feature Extraction, Classification Models

I. Introduction

The construction of a higher level of public service system for sports is an important cornerstone for accelerating the construction of a strong sports country, and also an important element in promoting the common prosperity of all people to make more obvious and substantial progress [1]. At present, the scientific and technological revolution led by the innovation-driven development strategy provides stronger scientific and technological support for sports development. Accompanied by the development of domestic information technology, sports and information technology are gradually integrated to promote the development of intelligent sports, and the quantitative management of the user's daily sports activities is also one of the important practices of intelligent sports development. Intelligent technology can use a variety of sensors with high technology to achieve an all-round perception of people's movement, and then flexibly use a variety of modern information technology means to process and analyze the collected information, so as to realize the intelligent service and management of sports, which largely makes up for the shortcomings of the development of digital sports [2]-[5].

Among them, the emergence of smart wearable devices boosts the management of sports activities for all people in the direction of scientific and intelligent development [6]. Smart wearable devices are electronic devices with intelligent functions that can be worn or worn on the human body [7]. As an electronic device that can realize the real-time detection of sports data, directional quantitative development of guidance programs, sports scene human-computer interaction and other functions, it is increasingly widely used in sports [8]-[10]. Smart wearable devices provide hardware support for user sports, and their main function in sports is to monitor the body condition and provide data analysis [11]-[13]. At the same time, smart wearable devices can provide personalized services according to the individual differences of different wearers, which facilitates the formation of targeted training programs and improves the scientific and targeted nature of sports training [14]-[16]. Under the new situation, the exploration of the application path of smart wearable devices in sports management has become a popular research topic nowadays.

This study is divided into three parts: first, the smart wearable device is used to collect motion data, and the data are preprocessed using methods such as filtering and normalization to ensure high quality data; Second, the time-domain features of the sports data are extracted, including variance, peak, interquartile spacing and other features, to form a high-dimensional feature vector; third, the PSO-SVM model is used for training and testing, and the effectiveness and advantages of the model are verified through experiments. The experimental results show that the proposed method exhibits high accuracy in the recognition of different sports categories, especially in the quantitative management of daily sports activities, which has a wide range of application prospects.

II. Human motion pattern recognition model based on smart wearable devices

With the popularity of wearable devices such as smart watches and bracelets, it is of great significance to use them in the field of human behavior recognition and decode human behavioral activities from them to realize the recognition of human movement patterns for applications such as the quantitative management of daily sports activities.

II. A. Human motion action recognition

II. A. 1) Data acquisition

In the data acquisition phase, the sensors in the wearable device convert the information it senses about the human body's movements into electrical signals that can be easily transmitted, stored and processed according to specific rules. In addition to the wearable device as the hardware base, the data acquisition also requires an application on the smartphone or a web page on the computer as the console of the data acquisition process. Since the inertial sensors in the wearable device contain three-axis accelerometers and three-axis gyroscopes, the raw sensor data collected by the wearable device will contain three-axis acceleration data and three-axis angular velocity data.

The set consisting of the categories of sports actions used for recognition can be denoted as $M = \{m_1, m_2, \cdots, m_n\}$, where m_1, m_2, $\cdots$, and m_n each represent an action.

II. A. 2) Data pre-processing

Data preprocessing refers to denoising or standardizing the raw sensor data collected.

The purpose of denoising is to remove the components of the original sensor data that have nothing to do with the action itself, and the sources of noise include the irregular jitter produced by the human body during movement and the measurement error of the sensor equipment itself, etc. The existence of these noise components in the original sensor data will have an impact on the recognition effect of the action.

Normalization (also known as normalization) operation is a crucial part of action recognition. After normalization, the effect of the scale between acceleration and angular velocity data is eliminated, and the data from each axis will be of the same order of magnitude, thus reducing the effect of the above factors on the accuracy of action recognition. Commonly used normalization operations include Z-score normalization and min-max normalization.

The Z-score normalization uses the mean and standard deviation of the raw sensor data to process the data into data that satisfies a standard normal distribution (mean zero, standard deviation one). Assuming that the vector X represents the raw sensor data from an inertial sensor for a particular axis, the data obtained after the normalization operation is:

$$X' = \frac{X - \overline{X}}{S} \tag{1}$$

where $\overline{X}$ and S are the mean and standard deviation of the original sensor data X, respectively.

The min-max normalization, also known as divergence normalization, is based on the principle of mapping the original sensor data into values located in the $[0,1]$ closed interval with the help of linear transformations:

$$X' = \frac{X - \min}{\max - \min} \tag{2}$$

where $\max$ and $\min$ are the maximum and minimum values in the original sensor data X respectively. When using this method, if new data need to be added to the data X, then $\max$ and $\min$ may change, and the normalization results change accordingly.

Indicators of the choice of the two standardization methods: when using distance as a measure of similarity between data or when PCA techniques are needed to assist in classification or clustering tasks, Z-score standardization is appropriate; whereas when distance, covariance, or data not obeying a normal distribution are not used, min-max standardization or other standardization methods are more appropriate.

A segment of inertial sensor data of duration $T(T = \{1, 2, \cdots, t\})$ can be represented after pre-processing operations such as denoising and normalization as (the original text does not give the complete form of the representation here):

$$D=(A_x,A_y,A_z,G_x,G_y,G_z)=\begin{pmatrix} A_x^1 & A_y^1 & A_z^1 & G_x^1 & G_y^1 & G_z^1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ A_x^t & A_y^t & A_z^t & G_x^t & G_y^t & G_z^t \end{pmatrix} \tag{3}$$

Among them, the column vectors A_x, A_y and A_z are obtained by preprocessing a piece of sensor data from the accelerometer X, Y and Z axes with a duration of T, respectively. The column vectors G_x, G_y, and G_z are obtained by preprocessing a piece of sensor data from the gyroscope X, Y, and Z axes with a duration of T, respectively. A_x^t, A_y^t, and A_z^t represent the data values of data A_x, A_y, and A_z at time t, respectively. G_x^t, G_y^t, and G_z^t represent the data values of data G_x, G_y, and G_z at time t, respectively.

II. A. 3) Data slicing

Due to the large number of actions performed continuously by the exerciser during data acquisition, a segment of sensor data with a duration of T will likely contain multiple actions. For more convenient labeling and feature extraction, a single data segment used to feed into the model to recognize an action should contain fewer action data sample points. Therefore, after the data preprocessing operation, the data D obtained from the preprocessing operation needs to be sliced into a series of data segments S:

$$S=\{s_1,\cdots,s_k\} \tag{4}$$

where the data segment s_i represents a piece of data that lasts from moment $t_{i,start}$ to moment $t_{i,end}$.

II. A. 4) Feature extraction

Feature selection and feature extraction are a pair of interrelated but vastly different steps. The task of the feature extraction step is to extract feature vectors from the original sensor data segments that are representative of the data segments, while the task of the feature selection is to eliminate useless feature vectors from the set of feature vectors described above. Here, the feature extraction step and the feature selection step are connected to form a feature extraction and selection model φ, and the feature vectors obtained from the data fragment s_i extracted by the model φ can be represented as:

$$F_i=\varphi(D',s_i) \tag{5}$$

All the extracted features constitute the feature space. The first N feature vectors F_i (where $i=1,2,\cdots,N$) and their corresponding labels m_i are selected to form the training dataset $\tau=\{(F_i,m_i)\}_{i=1}^N$, and the remaining feature vectors and their corresponding labels collectively form the test dataset v.

II. A. 5) Model Training and Action Recognition

Action recognition belongs to the classification task, which is accomplished through two phases: the model training phase and the model testing phase.

The goal of the model training phase is to learn an optimal model that can be used to recognize actions using the labeled action data in the training dataset. In the model training phase, an optimization algorithm is used to update the model parameters θ so as to maximize the recognition accuracy of the model on the training dataset τ, and finally the classification model Φ is obtained.

And the goal of the model testing phase is to recognize the unlabeled action data in the test dataset using the action recognition model learned in the model training phase. In the model testing phase, i.e., the action recognition phase, the model Φ maps the feature vector F_i in the test dataset v to each action $m_j \in M$ with confidence $P\left(m_j/F_i,\theta\right)$:

$$P\left(m_j/F_i,\theta\right)=\Phi(F_i,\theta),m_j\in M \tag{6}$$

Eventually, the action $\hat{m}_j$ corresponding to the largest confidence level $P_{\max}$ is identified as the action to be predicted:

$$\hat{m}_j = \underset{m_j \in M}{\operatorname{argmax}} P\left(m_j / F_i, \theta\right) \tag{7}$$

In the step of feature extraction and selection, the test data set formed at last contains label information corresponding to the action data. The above action recognition result can be compared with its corresponding label in the test data set, and if it is consistent, it is recognized correctly, otherwise it is recognized incorrectly.

II. B.Human Movement Action Feature Extraction

In order to extract the time-domain features of the motion sensor, it is necessary to filter the raw data of the sensor to remove the noise and burrs in the original signal. In this paper, median filtering and smoothing filtering are used to preprocess the data, and the median filtering process is carried out once every 5 data points, and let $x_1, x_2 \cdots x_n$ be a sample of the sensor data x, and the mathematical model of smoothing filtering is [17]:

$$x_i = 0.01x_{i-2} + 0.01x_{i-1} + 0.9x_i + 0.03x_{i+1} + 0.05x_{i+2} \tag{8}$$

II. B. 1) Feature extraction

Among the three-axis MEMS acceleration sensor signals and three-axis MEMS angular velocity sensor signals acquired by the inertial measurement unit, different feature quantities can be extracted from each axis data. Feature extraction has a great impact on the accuracy of multi-motion pattern recognition. The extraction of time-domain features is of low computational complexity and short time-consuming, and in this paper, we finally select a variety of time-domain features suitable for systems with high real-time requirements.

II. B. 2) Extraction of Acceleration Sensor Time Domain Features

(1) Variance

Variance is the extent to which the data deviates from the mean, the larger the variance, the greater the deviation of the data, i.e., the tester carries out a larger range of actions in the behavioral pattern. When describing the volatility of the data, the variance and the standard deviation have the same function, but the standard deviation needs to open the root sign of the variance, and the amount of arithmetic is larger than the variance. The combined acceleration is the scalar sum of the three-axis acceleration, which is more stable than the data of a single axis and will not be limited by the way the sensor is worn, so the combined acceleration variance is used in this paper for the recognition of standing and running. The formula for the combined acceleration is shown below:

$$A = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{9}$$

where, A is the combined acceleration of three-axis acceleration; a_x, a_y, a_z are the accelerometer three-axis data, respectively.

Let $x_1, x_2 \cdots x_n$ be a sample of the angular velocity sensor data x, the variance formula is shown below:

$$Var = \frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2 \tag{10}$$

where, Var is the variance; $\overline{x}$ is the mean of the n observations of the sample.

(2) Quartile Spacing

Quartile spacing is also one of the characteristics used to measure the strength of signal variation, which is not affected by anomalous signals and peaks. The data a_x of accelerometer x-axis is arranged from smallest to largest as $b_1, b_2, \cdots, b_n$, and $b_1, b_2, \cdots, b_n$ are divided into four, and the quartile spacing is the difference between the third quartile and the first quartile, which is calculated by the formula shown in the following equation:

$$IQR = Q_3 - Q_1 \tag{11}$$

where, IQR is the interquartile spacing; Q_1 is the first quartile; Q_3 is the third quartile.

(3) Peak

Peak value is used to describe the intensity of the signal change in a cycle, there are positive and negative, the larger the peak value, the greater the amplitude of the movement. The peak size of the three axes of the accelerometer represents the movement of the tester in different directions, such as forward, backward, left and right, respectively. The moment the tester falls forward, the peak data of the accelerometer in the x-axis is larger than that of the daily mode, and the change of the peak value of the three axes of the accelerometer can be used to recognize the specific way of the tester's fall. The peak value is simpler to calculate and can truly reflect the behavioral pattern of the tester, this paper adopts the peak value as the feature quantity to identify the sprawling and lying down.

II. B. 3) Extraction of time-domain features of the angular velocity sensor

(1) Mean value

Mean value is an indicator to reflect the intensity of change in a set of data, its advantage lies in the ability to make full use of the characteristics of the data, and the calculation is simple, the calculation is small, the shortcomings are susceptible to the influence of extreme data. The formula for the mean value is shown below:

$$M=\frac{1}{n}\left(x_1+x_2+\cdots+x_n\right) \tag{12}$$

where, M is the mean; n is the number of samples; x_i is the sample data.

(2) Skewness

Skewness is used to measure the direction and degree of data skewness. Let $x_1, x_2 \cdots x_n$ be a sample of angular velocity sensor data x, then the skewness of angular velocity sensor data x can be estimated as:

$$k_s=\frac{n\sum(x_i-\overline{x})^3}{(n-1)(n-2)d_s^3} \tag{13}$$

In Eq. (13): k_s is the skewness; x_i is the sample observation; n is the number of samples; $\overline{x}$ is the average of n observations of the sample; d_s is the sample standard deviation.

Aiming at the problem of the difficulty of recognizing the motion action, this paper adopts the mean, variance and skewness of the angular velocity sensor as the feature parameters of the secondary recognition while the acceleration quartile spacing is selected as the feature parameter.

II. C. Classification of human locomotor movements

II. C. 1) Feature Fusion

In order to amplify the difference of information characterizing different actions, feature fusion can be carried out to amplify the difference by fusing the features with higher intensity of information characterizing the actions, and finally realize action recognition. When fusing features, the most important thing is to judge the distinguishability of the fused features. And judging the distinguishability can be solved by quantifying an index, commonly used indexes are relative entropy, Sammon's stress, Davies-Boulding clustering index (DBI), etc., and among them, DBI has the strongest intuition, so this topic chooses to adopt DBI indexes for evaluating the fusion of features.

When using DBI index for evaluation, there are mainly the following steps:

(1) Define a decentralized value S_{i}:

$$S_{\mathrm{i}}=\left[\frac{1}{n}\sum_{j=1}^{n}\left|X_j-A_i\right|^q\right]^{\frac{1}{q}} \tag{14}$$

Eq. (14) represents the degree of dispersion of the data, where X_j represents the j data point in the i class, A_i represents the center of the i class, the values of q have 1 and 2, and when q =1 represents the mean value of each point to the center point; q =2 indicates the standard deviation from each point to the center point, and in order to better measure the degree of data dispersion, q =2 is selected for this topic.

(2) Define the value of a distance S_{ij}:

$$D_{\mathrm{ij}}=\left[\sum_{k=1}^{n}\left|a_{ki}-akj\right|^2\right]^{\frac{1}{2}}k \tag{15}$$

a_{ki} denotes the value of the k th attribute at the center point of the i th class, and D_{ij} is the distance between the center of the i th class and the k th class.

(3) Define a value of similarity R_{ij} by the value of dispersion and the value of distance:

$$R_{\mathrm{ij}}=\frac{s_i+s_j}{D_{ij}} \tag{16}$$

(4) The DBI index is obtained by calculating and selecting the maximum value in R_{ij} and averaging the maximum similarity values for each class:

$$DBI=\frac{1}{N}\sum_{i=1}^{N}R_{ij}(\max) \tag{17}$$

The above is the calculation process of DBI index, and in the definition, the larger the value of DBI index represents the larger the similarity, so its representative significance is smaller.

II. C. 2) Classification Methods for Support Vector Machines

SVMs dealing with multiclass problems need to be constructed from a single classifier to a multiclassified one. There are two methods, direct and indirect. Direct modification of the objective function is the direct method; the combination of multiple is the indirect method. The indirect method is mainly categorized into one-to-one (OVO) and one-to-many (OVR).

Suppose there are 4 classes of samples categorized according to OVO and OVR respectively. As shown in the figure it can be seen that for the classification of 4 classes of samples OVO requires 6 classifiers while OVR requires only 4. However, it is not comprehensive enough to consider only the number of classifiers, but also the amount of computation of each classifier. In the training of OVR classifiers need all the data involved in training, when more than one classifier test results are positive, but also consider their pre-confidence, while OVO each time only two types of according to the training, so a comprehensive comparison of the OVO classifiers of the arithmetic is smaller.

Because this paper will be nine action classification, sample data is more, so the comprehensive consideration of processing speed and accuracy of the problem finally chose the classification method of OVO.

II. C. 3) Optimization of Support Vector Machines by Particle Swarm Algorithms

As can be seen from the previous section, SVM classification performance is mainly dependent on g and C. g: the construction of the kernel function; C the value of the penalty factor, g affects the distribution of high-dimensional spatial data, and the parameter C mainly mediates the empirical risk and confidence range. Therefore, in order to improve the classification ability of SVM it is necessary to optimize these two parameters and find the best combination of them.

In the search for the optimal combination of the two parameters, there are mainly grid methods based on cross-validation and algorithms such as genetic algorithms and particle swarm algorithms. These three methods can find the optimal parameters, but the grid method search time is too long, especially for the large amount of data in this topic, so this topic mainly uses the faster search speed of genetic algorithm (GA) and particle swarm algorithm (PSO) two methods for the search of the two parameters of the search for the optimal, after the experimental validation of the optimization of PSO on the SVM is known to make the classifier better, so the next step is to only introduce the optimization principles of PSO optimization principle for SVM [18], [19].

PSO, is designed by simulating the feeding behavior of bird flocks. This model compares the birds in the flock to a volume-less and mass-less particle, and the best position in space is found by searching, competing, and coordinating, which has the advantages of simplicity, searching the whole globe, fast speed, and insensitivity to the size of the population.

(1) The basic PSO algorithm is as follows:

Let the particle population size be N, the number of iterations M, and the particle dimension S-dimensional, then the coordinates of particle $i(i=1,2,\cdots,N)$ can be written as $x_i=(x_{i1},x_{i2},\cdots,x_{is})$, and substituting the coordinates into the objective function to calculate the fitness, which will in turn select the optimal position of the particle individual $p_i=(p_{i1},p_{i2},\cdots,p_{is})$ and the global optimal position $p_g=(p_{g1},p_{g2},\cdots p_{gs})$. $v_i=(v_{i1},v_{i2},\cdots,v_{is})$ is the particle velocity, and its product with time is the distance traveled, and let $f(x)$ be the objective function for minimizing this particle swarm for adaptation:

$$p_{id}^{k+1}=\begin{cases}p_{id}^{k}, & f(x_{id}^{k+1})\geq f(p_{id}^{k})\\ x_{id}^{k+1}, & f(x_{id}^{k+1})<f(p_{id}^{k})\end{cases} \tag{18}$$

$$p_{gd}^{k+1}=\begin{cases}p_{gd}^{k}, & f(p_{gd}^{k+1})\geq f(p_{gd}^{k})\\ p_{id}^{k+1}, & f(p_{gd}^{k+1})<f(p_{gd}^{k})\end{cases} \tag{19}$$

Each particle gets a new position and velocity in the new $d=(1,2,\cdots,S)$ -dimensional subspace, which can be updated as:

$$x_{id}^{k+1}=x_{id}^{k}+v_{id}^{k+1} \tag{20}$$

$$v_{id}^{k+1}=\omega^{*}v_{id}^{k}+c_1r_1(p_{id}^{k}-x_{id}^{k})+c_2r_2(p_{gd}^{k}-x_{id}^{k}) \tag{21}$$

In Eq. (20), $k(k=1,2,\cdots,M-1)$ is the current iteration number, p_{id}^{k} is the optimal position of the particle history of i, while p_{gd}^{k} is the optimal position of the particle swarm, ω^{*} is the inertial weight, which can be used to control the velocity of the particles, and c_1, c_2 are the acceleration constants. which can influence the individual and global learning factors; $r_1,r_2\in[0,1]$, and so on, iterating until the fitness is satisfied, then the search for the optimal end, you can get the optimal parameters after the search.

The above is the basic algorithm structure of PSO, when PSO optimizes SVM, it is necessary to reconstruct the PSO-SVM classifier, and optimize the two parameters C and g, so as to get the smallest error of a group of parameters to make the best classification effect. The specific steps are shown below.

(2) PSO-SVM algorithm is as follows:

a) Particle swarm initialization: because of finding the two optimal parameters C and g, the particle swarm is 2-dimensional, so that $C\in[0.1,100]$, $g\in[0.1,1000]$, so that the size of the population is chosen to be 50, and the number of iterations is 100, so that the particle swarm is initialized, and the velocity and position are updated as:

$$v_{ij}^{0}=v_j^{\min}+r(0,1)(v_j^{\max}-v_j^{\min}) \tag{22}$$

$$x_{ij}^{0}=x_j^{\min}+r(0,1)(x_j^{\max}-x_j^{\min}) \tag{23}$$

The superscript on the left side of the equation denotes the generation of the swarm, the subscript ij denotes the i particle j-dimensional position, and i takes a natural number from 1 to 50, $j=1$ or 2. $x_j^{\max}=(1000,100)$, $x_j^{\min}=(0.1,0.1)$, $v_j^{\max}=0.6*x_j^{\max}$, $v_j^{\min}=-v_j^{\max}$.

b) Select the fitness function: take the fitness value of the parameter as $err=1-CV$, CV is the recognition rate of the action under the parameter, and err is the error rate of the action. The PSO takes the same value of fitness as that of the GA, which is the error rate.

c) Calculate the fitness value.

d) Determine the global optimal position again based on the individual optimal position determined first.

e) Parameter update: The parameters of Eqs. (24) and (25) are updated by deriving the position from (4):

$$x_{ij}^{k+1}=x_{ij}^{k}+v_{ij}^{k+1} \tag{24}$$

$$v_{ij}^{k+1}=\omega_i^{*}v_{ij}^{k}+c_1r_1(p_{ij}^{k}-x_{ij}^{k})+c_2r_2(p_{gj}^{k}-x_{ij}^{k}) \tag{25}$$

$$\omega_i^{*}=\begin{cases}\omega_{\min}+\dfrac{(\omega_{\max}-\omega_{\min})*(f_i-f_{\min})}{f_{avg}-f_{\min}} & f_i\leq f_{avg}\\ \omega_{\max} & f_i>f_{avg}\end{cases} \tag{26}$$

ω_i^{*} is the adaptive weight coefficient of the i th particle and $\omega_{\min}=0.4$, $\omega_{\max}=0.9$, which is calculated as (26).

Let $C_1=1.2$ and $C_2=1.7$, and then the execution of (3) to (5) is repeated successively according to the loop condition, and finally the termination condition is reached.

III. Daily physical activity quantitative management application practice

In this chapter, the human movement pattern recognition model based on smart wearable devices proposed in this paper will be applied to the quantitative management of daily sports activities to explore its practical application performance.

III. A. Experimental design

III. A. 1) Experimental Objects

A total of 8 healthy testers were invited to participate in this experiment. The testers were not allowed to do strenuous exercise recently and were guaranteed to have enough sleep to ensure that they could efficiently complete the acquisition task during the action data collection process. The testers will perform running, jumping rope, push-ups, deep squats, pull-ups, basketball dribbling, soccer passing, badminton long jump, standing long jump, flat support, boxing straight punch, hurdles, bicycle pedaling 14 types of sports movements, numbered from 1 to 14 in order.

III. A. 2) Experimental data collection

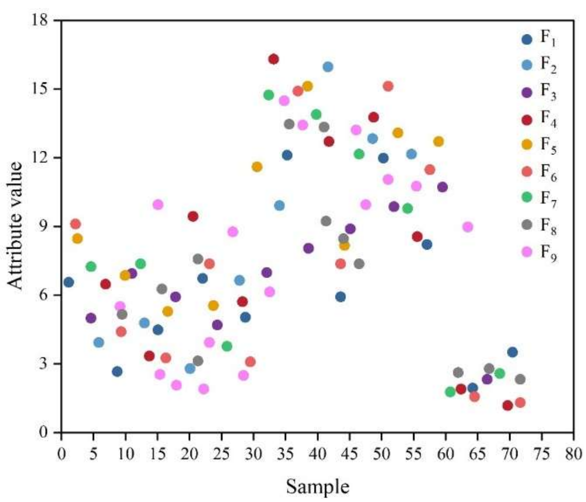
In this paper, we use the program developed by Android Studio to record multiple acceleration data changes of real-time smart wearable devices. Based on the frequency of daily human activities and the fact that the smart wearable device in this study needs to be placed on the wrist where the frequency of movement is high, the sampling interval in this study is chosen to be 30ms.

When the user clicks on the “Record” button, all the data displayed on the screen starts to be automatically generated into a txt file and stored in the device. When the recording is completed, click the stop button to finish the recording, and automatically change the line in the txt text to distinguish and wait for the next recording. In order to prevent unnecessary acceleration caused by the user's redundant movements at the beginning and end of data collection, the data collected in the first 2s and the last 2s were discarded and not considered. The moment when the experimenter clicked the “Record” button was recorded at the same time as the motion states were recorded, so that the motion states of the recorded data could be distinguished during data processing.

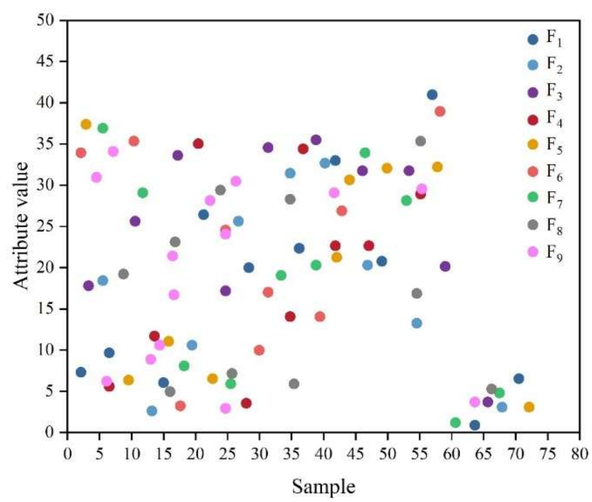
One-half of each type of motion state was randomly selected as the training set, and the remaining one-half as the test set, so as to ensure that the data in the training set and the test set did not overlap with each other. Each data set has 9 feature values (corresponding to F_1~F_9).

III. B. Visualization of experimental data

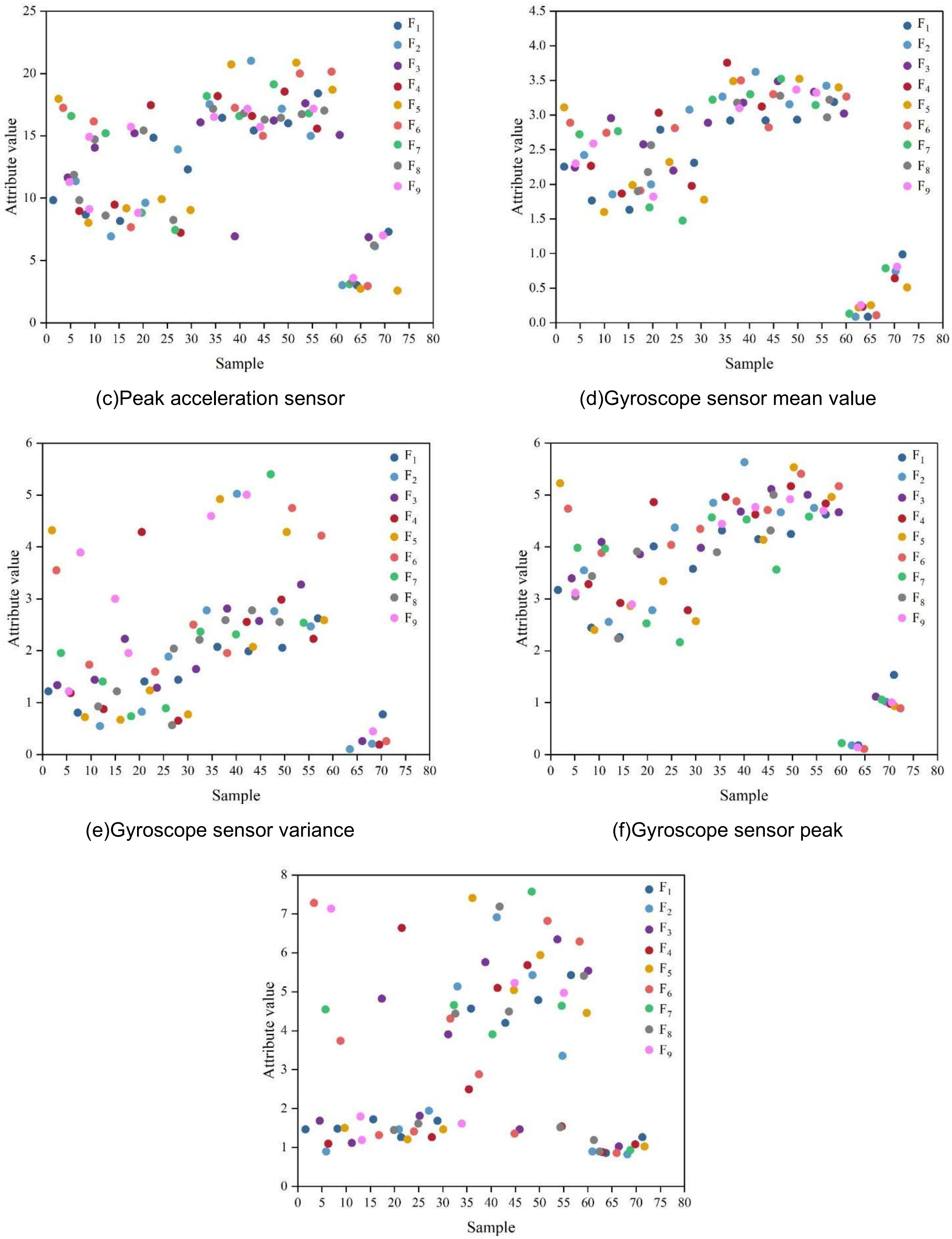
The distribution of eigenvalues of all sports action samples obtained in MATLAB is specifically shown in Fig. 1. Figures (a) to (g) correspond to the accelerometer sensor mean, accelerometer sensor variance, accelerometer sensor peak, gyroscope sensor mean, gyroscope sensor variance, gyroscope sensor peak, and covariance values, respectively. The acceleration sensor mean value in the figure can better avoid the influence of single data on the results, and the peak specificity of different sports actions is stronger, the behavioral pattern is distinguished obviously, which is convenient for the analysis of the experimental results data later.



(a)Mean of acceleration sensor



(b)Acceleration sensor variance



(c)Peak acceleration sensor

(d)Gyroscope sensor mean value

(e)Gyroscope sensor variance

(f)Gyroscope sensor peak

(g)Covariance value.

Figure 1: Distribution of eigenvalues of sports action samples

III. C. Experimental results and analysis

The feature vectors F_1, F_2, F_3, F_4, F_5, F_6, F_7, F_8, F_9 obtained by fusion according to the separability index are sequentially inputted into the two classifiers PSO-SVM adopted in this study and GS-SVM as a comparison to carry out parameter optimization, model training, and classification for action recognition, and the resulting results of the average test recognition rate under different feature fusion vectors are shown in Table 1.

From the table, it can be seen that with the increase of the number of fused features:

(1) In terms of the average recognition rate of the 14 types of upper limb actions, PSO-SVM is larger than GS-SVM; both classifiers show a trend of increasing and then decreasing, and when the feature fusion vector is F_6, both GS-SVM and PSO-SVM have the largest average recognition rate of the 14 types of actions at this time, and the highest average recognition rate of GS-SVM and PSO-SVM classifiers are respectively 91.82% and 94.55%; after reaching the maximum recognition rate, with the increase of the number of fusion features, the recognition rates of both classifiers appear to decline. although F_9 contains a total of 10 relatively high separability features in the time domain, frequency domain, time-frequency domain, and entropy features, the recognition results of F_9 are not ideal, and even the effect is the worst, which means that it is not the case that the higher the number of fusion features, the higher the recognition rate.

(2) The training time of both trainers shows a growing trend; the training time of PSO-SVM is much better than that of GS-SVM.

Table 1: Average test recognition rate under different feature fusion vectors

Fusion feature vectors	SVM type	Training time(s)	Test average recognition rate(%)
F_1	GS	885	88.13
	PSO	797	88.57
F_2	GS	1141	88.93
	PSO	878	89.91
F_3	GS	1310	89.64
	PSO	956	91.52
F_4	GS	1671	90.09
	PSO	1111	91.88
F_5	GS	2440	90.45
	PSO	1316	92.41
F_6	GS	2865	91.82
	PSO	1433	94.55
F_7	GS	3859	90.63
	PSO	1658	90.36
F_8	GS	4427	89.02
	PSO	1700	88.75
F_9	GS	4421	86.88
	PSO	2973	87.32

In order to further consider the recognition rate of each action, the recognition rates of 14 kinds of actions under different fusion features are collated, and the collation results are specifically shown in Table 2. It can be seen that when F_6 is used as an input feature, the recognition rate of individual actions at this time are all higher than 82%, there is no phenomenon that a certain action has a lower recognition rate, and the number of action categories with a recognition rate higher than 90% is more than the rest of the features as input features.

Table 2: Recognition rate of 14 kinds of actions under different fusion feature vectors

Action category	SVM type	Fusion feature vectors								
		F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9
1	GS	88.77	88.59	91.45	89.84	93.82	95.11	91.11	89.81	87.39
	PSO	89.98	92.42	93.94	96.33	97.39	96.24	93.81	88.84	92.46
2	GS	96.25	96.19	94.87	96.41	95.04	96.37	90.11	91.19	91.36
	PSO	97.39	97.53	97.48	94.93	93.94	93.65	91.24	88.77	91.14
3	GS	84.98	83.68	81.34	82.43	80.16	82.63	84.83	83.63	78.63
	PSO	81.08	81.45	83.55	86.19	85.06	88.86	85.14	85.05	78.74
4	GS	87.35	86.29	84.95	88.67	86.35	91.09	87.31	85.04	87.39

	PSO	84.96	83.82	87.42	92.56	94.84	92.31	86.23	86.31	86.3
5	GS	92.69	94.98	96.17	95.06	96.44	93.87	92.32	93.64	91.08
	PSO	96.2	96.28	96.37	97.56	94.95	95.13	94.87	90.2	88.71
6	GS	87.46	91.07	91.08	93.94	93.76	92.63	94.97	91.4	89.97
	PSO	86.17	92.5	92.37	94.83	92.36	95.1	91.15	91.1	88.56
7	GS	76.28	78.66	77.59	81.31	77.42	81.45	83.95	79.89	75.05
	PSO	74.93	79.8	83.75	84.91	82.41	82.85	82.36	80.15	74.9
8	GS	96.39	94.9	92.4	93.59	92.53	97.6	93.81	93.92	90.02
	PSO	98.87	97.54	97.44	94.91	93.94	95.07	92.49	91.38	90.16
9	GS	90.1	91.12	94.84	87.69	85.15	80.84	84.96	81.14	78.63
	PSO	91.11	93.7	92.65	84.9	89.89	89.94	86.05	83.76	82.38
10	GS	91.41	92.55	93.84	92.45	93.56	93.39	92.36	89.84	88.58
	PSO	91.41	90.19	91.39	90.09	92.48	96.59	96.2	89.92	91.06
11	GS	89.99	91.13	92.55	93.9	95.17	93.87	94.82	94.94	91.05
	PSO	91.4	90.16	91.2	92.3	93.72	97.46	93.61	95.06	90.17
12	GS	87.56	88.63	89.92	91.08	92.3	94.99	96.07	92.66	88.55
	PSO	88.58	92.54	93.76	92.69	94.86	95.13	92.47	96.09	91.44
13	GS	82.33	81.34	87.55	87.57	92.59	91.43	91.3	88.55	87.41
	PSO	87.44	85.03	92.68	91.29	92.45	92.51	87.48	87.51	87.57
14	GS	82.55	85.14	86.29	87.61	92.36	83.71	89.94	89.95	89.85
	PSO	80	86.11	87.39	92.51	95.04	97.3	91.05	88.95	88.68

In order to further visually compare the recognition rate of each action in GS-SVM and PSO-SVM for the F6 fusion feature vector inputs, the test classification results are plotted specifically as shown in Figure 2. From the figure, it can be seen that the PSO-SVM used in this paper has a single recognition rate of more than 85% and a recognition rate of 90% for 13 actions, while the recognition rate of GS-SVM is lower than 85% for four actions, such as action 3, action 7, action 9, and action 14, and the PSO-SVM is lower than the GS-SVM only in the recognition rate of two actions, such as action 2, action 8, and so on.

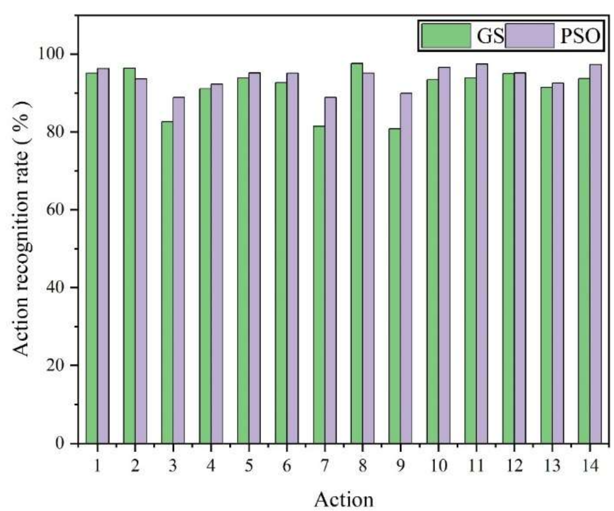


Figure 2: Comparison of action recognition rate under F_6 fusion feature

Therefore, considering the training time, the average recognition rate of 14 kinds of actions, the recognition rate of single kinds of actions and other factors, the PSO-SVM classifier adopted in this paper was proved to have the optimal performance through comparative analysis, and the optimal fusion feature F6 was used as the final input feature, and the test recognition of 14 kinds of actions was specifically shown in Table 3. Compared with other feature types such as time domain and entropy features, the average action recognition rate of multi-feature fusion adopted in this paper is the highest 94.55%, which significantly improves the performance of action recognition types and can better meet the diverse needs in the quantitative management of daily sports activities.

Table 3: Comparison of recognition rate of different features

Type of characteristics	Average action recognition rate(%)
Horizon	92.6
Frequency domain	89.08
Time-frequency domain feature types	91.06
Entropy characteristics	86.68
Multi-feature fusion	94.55

Overall, the human movement pattern recognition model based on smart wearable devices proposed in this paper can play a better role in the quantitative management of daily sports activities and has good application effects.

IV. Conclusion

In this paper, the proposed method of sports pattern recognition based on smart wearable devices adopts the particle swarm optimization support vector machine model to classify the sports data efficiently. In the experiments, 14 different sports activity data are used and the PSO-optimized SVM model shows better performance than the traditional GS-SVM model. With the input of the optimal feature fusion vector F6, the PSO-SVM model achieves an average recognition rate of 94.55%, which is significantly better than other feature fusion methods. Especially in terms of action recognition accuracy, PSO-SVM shows high accuracy in the recognition of multiple motion types.

Specifically, among the 14 types of motions, the PSO-SVM model's recognition rate exceeds 85% for 13 types of motions, and the recognition rate of several of these motion categories exceeds 90%. In addition, the training time of PSO-SVM is relatively short, which further improves the usefulness of the model. In the experiments comparing different feature fusion methods, the multi-feature fusion-based approach demonstrated more excellent performance, especially when dealing with motion patterns with large differences, the fused features significantly improved the recognition effect of the model.

In summary, the smart wearable device-based exercise pattern recognition method can be effectively applied to the quantitative management of daily physical activities with high recognition accuracy and strong application capability, providing new ideas and methods for personalized health management.

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