Motion Recognition for Smart Sports Based on Wearable Inertial Sensors

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Abstract. With the development of wearable technology and inertial sensor technology, the application of wearable sensors in the field of sports is becoming more extensive. The notion of Body Sensor Network (BSN) brings unique human-computer interaction mode and gives users a brand new experience. In terms of smart sports, BSN can be applied to table tennis training by detecting individual stroke motion and recognizing different technical movements, which provide a training evaluation for the players to improve their sport skills. A portable six-degree-of-freedom inertial sensor system was adopted to collect data in this research. After data pre-processing, triaxial angular velocity and triaxial acceleration data were used for table tennis stroke motion recognition. The classification and recognition of stroke action were achieved based on Support Vector Machine (SVM) algorithm after Principal Component Analysis (PCA) dimension reduction, and the recognition rate of five typical strokes can reach up to 96% using the trained classification model. It can be assumed that BSN has practical significance and broad application prospects.

Keywords: Body sensor network · Information fusion · Motion recognition · Wearable computing · Micro-electro-mechanical sensor

1 Introduction

As the earliest innovative Technology in MIT media lab in 1960 s, wearable computing technology is one of the most promising advanced technologies in modern human-machine interaction domain. The technology combines sensors, wireless communication, multimedia, signal process technologies, et al., and is mainly used to provide data monitoring support and auxiliary decision-making for users [1–4]. Traditional optical device based human motion tracking approach and pressure sensor based methods universally suffer from high cost and

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rigorous requirements of testing setup, hence limited the larger scale application in the field [5,6]. Wearable sensors not only have small volume and light weight, but also have the characteristics of low power consumption, simple operation and wireless data transmission, which have been attracting a large number of researchers' attention. In the context of intelligence and big data era, the ultra-miniaturization of electronic devices as well as the continuous progress of forward-looking computing models have boosted microelectronics technology and communication technology. At present, wearable technology is increasingly widely used in intelligent sports, mainly in physical physiological information detection, physical rehabilitation, physical education and research. Initial applications of wearable devices mainly include a simple pedometer, a heart-rate device or other devices to collect various physiological parameters of the exerciser [7,8]. With the continuous development and improvement of inertial sensor technology, inertial sensors have been widely used in smart watches, smart bracelets and other popular personal belongings, which can accurately obtain the inertial data generated by the user's daily activities and provide data for identification and motion analysis [9–16].

As China's "national sport", table tennis is one of the most common sports in Chinese society. According to the survey, there are tens of millions of Chinese people who love playing table tennis, especially among teenagers. It is possible for table tennis enthusiasts to apply wearable sensors during table tennis training to detect and evaluate individual stroke movements, so as to improve their sport skills. In this paper, a wearable sensor system is applied to table tennis training, and the wearer's inertial sensor is used to collect table tennis players' motion throughout the process. Angular velocity and acceleration signals are used to generate the corresponding strokes classifier to complete the recognition of various types of strokes. Recognition algorithm is introduced to classify and recognize the typical stroke action of the players.

As for classification models, researchers have proposed many research methods, such as Decision Trees [17], K Nearest neighbor (KNN) [18], Bayes method [18,19], Hidden Markov Models (HMM) [20], Support Vector Machine (SVM) [21–23] and so on. In literature, various methods for dimension reduction of high-dimensional features of samples in classification and recognition tasks are proposed [24–29]. Current stroke action recognition researches based on wearable sensors is still at an initial stage due to the actual environment variable and the diversity of stroke category, and there are still many problems need to be solved.

2 Methodology and Materials

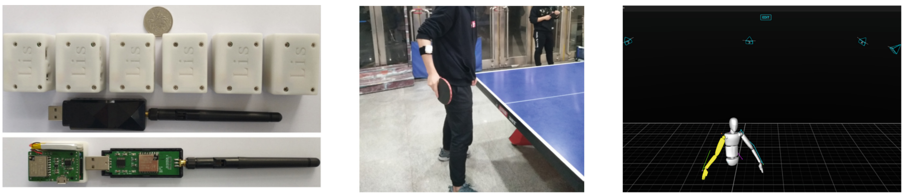
2.1 Hardware Platform Based on Wearable Inertial Sensors

In this paper, the wearable sensor system is used to collect the stroke movement data in table tennis sport. This system consists of low cost six-axis inertial sensor, which can obtain high-precision motion data and well meet the design needs. The research focus on data preprocessing, sample feature extraction, classifier recognition process. Through the reasonable processing of data and classification model training, it is expected to obtain high-precision recognition performance at reasonable processing speed.

Table 1. Inertial sensor array specification

Unit	Accelerometer	Gyroscope
Dimensions	3 axes	3 axes
Dynamic range	±18 g	±2000°/s
Bandwidth (Hz)	50	40
Bias stability (unit 1σ)	0.02	1
Noise density ($units/\sqrt{Hz}$)	0.05	0.05
Alignment error (deg)	0.2	0.2

Figure 1(a) is a the portable motion tracking system developed by Manlyn Ltd (Dalian, China). The lightweight design of sensor module is for the demand of ambulatory and long time monitoring. Sensor array specification is shown in Table 1. Figure 1(b) shows the table tennis stroke assessment scenario, in which the subject may wear sensor nodes on each upper limbs, and their sport activities will not be affected. Movement data from wearable sensors was recorded when the subjects played table tennis. The embedded operating system collect the raw sensor data and transmit the data to the host wirelessly. The 3D human upper limbs model in Fig. 1(c) indicates the ground truth of motion tracking provided by optical device (Made by Optitrack Ltd).



(a) (b) (c)

Fig. 1. Raw data collected from IMU (a) Inertial measurement Unit (b) Sensor installation (c) Ground truth provided by optical device (Made by Optitrack Ltd.)

2.2 Feature Extraction and Selection

After simple extraction, triaxial angular velocity and triaxial acceleration data were used for actual motion recognition. Five typical table tennis stroke movements including forehand stroke, flat push, forehand chop, backhand chop and smash, which are classified and identified respectively based on KNN algorithm and SVM algorithm. The collected raw data needs to be converted into a numerical matrix for subsequent recognition processing. Feature extraction is carried out then and for each data sample we can get a 48-dimensional feature vector, that is to calculate the mean value, variance, kurtosis, covariance, skewness, correlation coefficient, entropy and energy for the angular velocity data and acceleration data in the direction of X, Y and Z axes, as shown in Table 2.

Table 2. Eight features extracted from inertial data

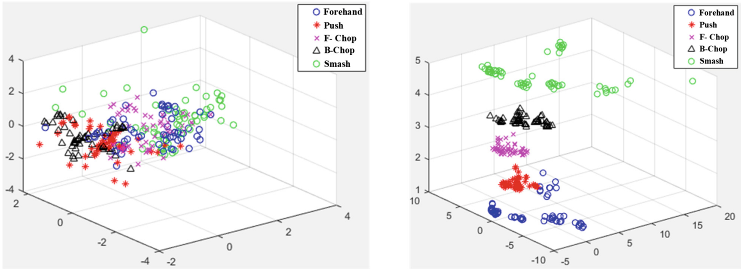
Type of features	Statistical characteristics	Computational formula
Time-domain	Mean value	$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i$
	Variance	$s^2 = \frac{\sum_{i=1}^{n}(X_i - \bar{X})^2}{n}$
	Kurtosis	$K = \frac{\sum_{i=1}^{n}(X_i - \bar{X})^4 f_i}{n\, s^4}$
	Covariance	$\mathrm{cov}(X,Y) = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{n-1}$
	Skewness	$\mathrm{S}K = \frac{n\sum_{i=1}^{n}(X_i - \bar{X})^3}{(n-1)(n-2)\, s^3}$
	Correlation coefficient	$i_{xy} = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}}$
Frequency-domain	Entropy	$H(X) = -\sum_{k=1}^{N} X_i(k)\log X_i(k)$
	Energy	$E = \frac{\sum_{k=1}^{N} X_i(k)^2}{N}$ $(X_i(k) = \sum_{n=1}^{N} x_i\, e^{-j2\pi kn/N}, k = 1, 2, 3, ..., N)$

Feature normalization is normally necessary. Common methods of feature normalization include linear normalization and zero mean normalization as follows:

$$\overset{*}{\underset{linear}{X}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

$$\overset{*}{\underset{zero}{X}} = \frac{x - \bar{x}}{\sigma}. \tag{2}$$

Compare the two normalization method, the linear normalization rely too much on minimum and maximum values, while zero mean normalization can get better recognition performance in the preliminary study. The characteristics of the original sample differ greatly in numerical value. After the normalization and dimensionality reduction, the characteristic values are limited to a certain range with little numerical difference, and the characteristics of the sample data represented by each feature are not changed.



(a) (b)

Fig. 2. Sample characteristic scatter plot (a) before PCA dimension reduction (b) after PCA dimension reduction

The main advantage of PCA (Principal Component Analysis) is that the principal components are orthogonal to each other after dimensionality reduction, which can eliminate the interaction between the components of the original data. In addition, PCA is an unsupervised learning of information measured by variance, which is not subject to sample label limit. Furthermore, its calculation process is simple and easy to realize. Figure 2 shows the effect of PCA dimensionality reduction. Figure 2(b) is the characteristic scatter diagram after dimensionality reduction of PCA. The aggregation number of the same type of stroke data can be seen in the figure, and the degree of differentiation of different actions is large, which lays a good foundation for the subsequent classification by SVM.

Table 3. Recognition rate of classifier using KNN method

K value	1	2	3	4	5	6	7	8	9	10	11	12
Recognition accuracy (%)	93	92	94	92	91	90	89	88	86	84	82	82

When using KNN method, it can be clearly seen from Table 3 that the recognition rate of classifier corresponding to different values of K (from 1 to 12 in this study). the recognition rate of the corresponding classifier is obtained by 10-fold cross validation. It can be concluded that when $K = 3$, the corresponding classifier model has the highest recognition rate. Therefore, in the task of classifying and recognizing the table tennis stroke action of players in this research, $K = 3$ is selected as the optimal value of K when using KNN method. Since the best performance is still less than 94%, SVM method is hence adopted to complete optimize recognition.

SVM based machine learning toolbox Libsvm (Matlab) is adopted in this study. Parameters train were completed through experimental tests. After several experimental tests, parameters and types with better recognition performance were finally selected, it turned out that C-svm was selected as SVM type

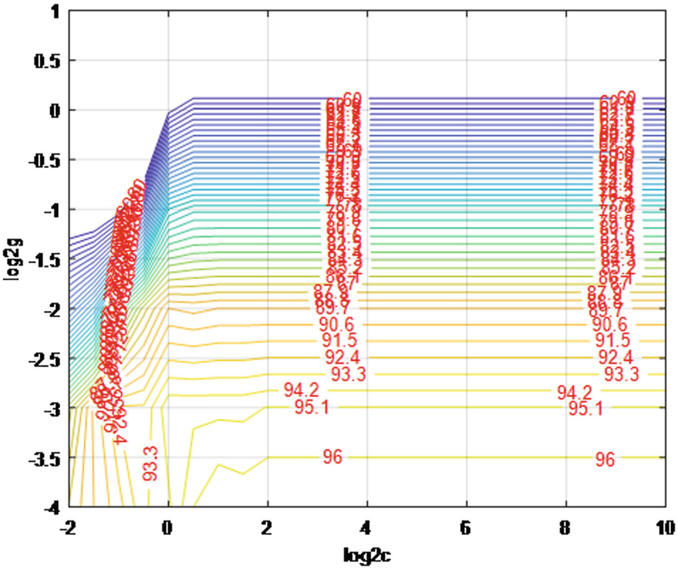


Fig. 3. Contour map of SVM corresponding matrix with different c and g parameters

and Gaussian kernel (as shown in the following formula) was selected as kernel function to achieve optimal recognition performance. Optimal punish coefficient c and kernel function radius g were selected through actual tests where the parameter c and g increasing gradually within a certain range. The test results are expressed in matrix contour plot, as shown in Fig. 3. The horizontal and longitudinal axiss show the parameter c and g taking logarithm of 2, respectively. The red numbers in the figure are recognition rates corresponding to different parameter values of c and g. During actual tests, c and g were increased sharply in the beginning, and the incremental amplitude range were gradually reduced according to the test results. The final result can be seen in the figure. In the end, the optimal output parameters are as follows: $c = 2$, $g = 0.0625$.

$$k(x_i, x_j) = \exp(-\frac{||x - y||^2}{\sigma^2}) \tag{3}$$

When training the classification model, the method of 10-fold cross validation is adopted to randomly divide the sample feature data into ten parts, one part of which is taken as the test set and the other nine parts as the training set. During training, the training set is divided into two parts: feature and label, and the classifier is trained by the classification algorithm. When testing, input the test set to output the recognition result and recognition rate. The flowchart of the proposed recognition process is shown in Fig. 4.

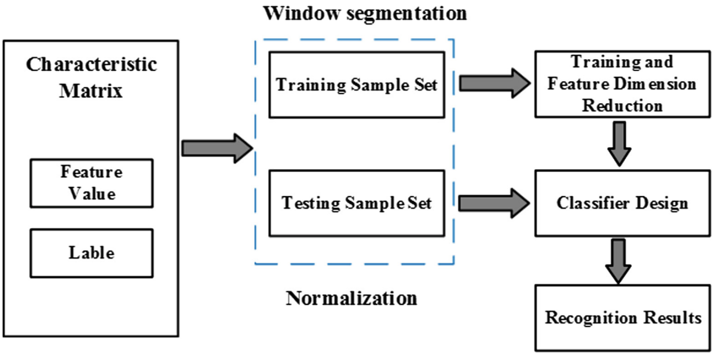


Fig. 4. The flowchart of proposed stroke motion recognition process

2.3 Experimental Results and Analysis

In the experimental stage, five different stroke actions of fifteen subjects were collected with 10 times for each stroke. A total of 750 strokes were collected and analyzed afterwards. The built-in low cost inertial sensor unit can measure the x, y and z axes of acceleration and angular velocity of the player at the same time, as shown in Fig. 5. The synchronization signal can be sent to each acquisition nodes to realize the synchronous measurement of multiple nodes. The data acquisition software can control the acquisition instructions and process the data.

In this paper, the Confusion matrix is used to display the precision of the classification results in a Confusion matrix by comparing the classification results with the actual type. Each column of the obfuscation matrix represents the prediction category, and the total number of each column represents the number of data in that category. Each row represents the true category to which the data belongs, and the total number of data instances for each row represents the number of data instances for that class. The values in each column represent the number of classes that the actual data is expected to be of. The correct classification is located on the diagonal of the confusion matrix, while the wrong classification is located outside the diagonal (Fig. 6 and Table 4).

It can be seen from the above mentioned recognition results that the KNN classification algorithm can not meet the actual application accuracy requirements due to the lower recognition rate (94%). KNN directly compares test samples with training samples without training the model, which is time-consuming and inefficient. In addition, the KNN method is largely dependent on the training sample size and has great limitations in practical application. Therefore, it can be seen from the above that the KNN algorithm can not meet the practical application requirements for the classification and recognition of table tennis stroke actions. With regard to SVM algorithm, satisfactory classification and recognition of stroke actions can be achieved. After the above processing of sample data, the recognition rate of the trained classification model can reach up to

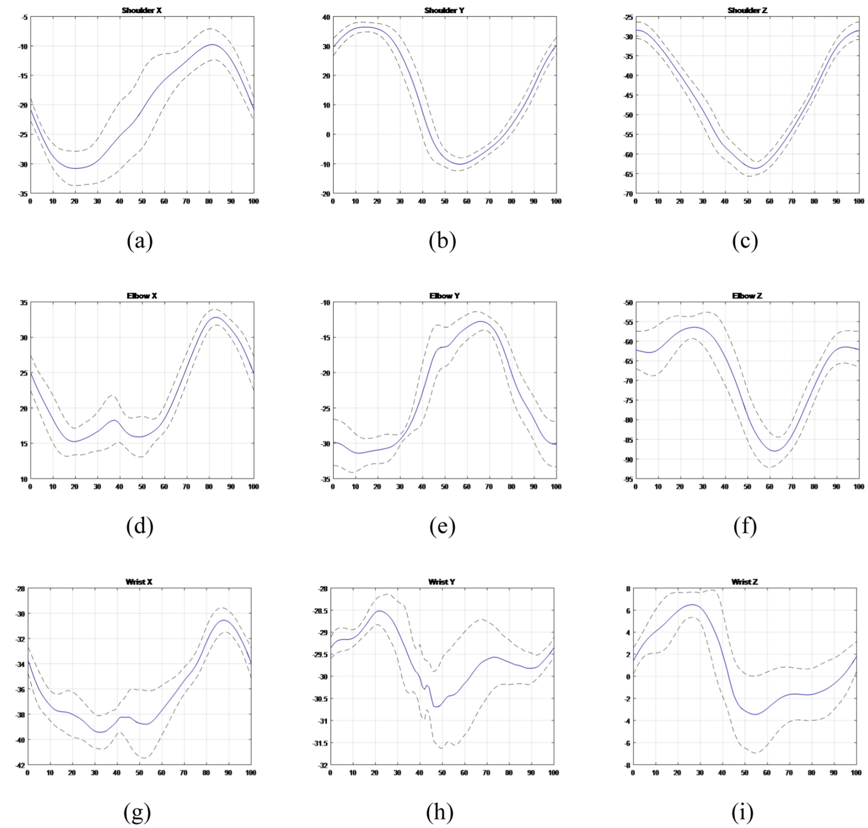


Fig. 5. Raw accelerometer data collected from IMU when a typical subject performs forehand stroke (a) shoulder X axis (b) shoulder Y axis (c) shoulder Z axis (d) elbow X axis (e) elbow Y axis (f) elbow Z axis (g) wrist X axis (h) wrist Y axis (i) wrist Z axis

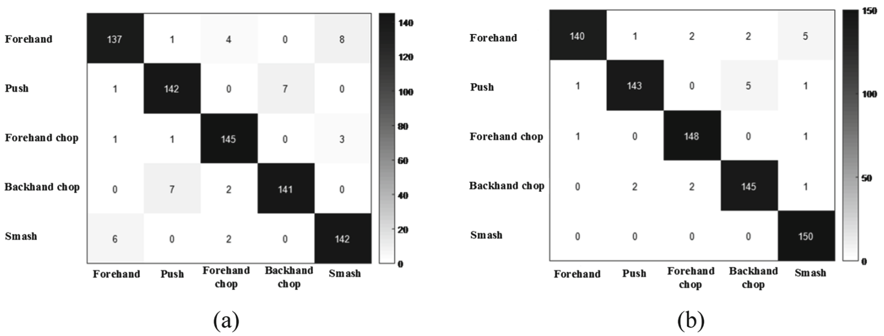


Fig. 6. Table tennis skilled movement recognition results (a) Confusion matrix of five different strokes using KNN classifier (b) Confusion matrix of five different strokes using SVM classifier

96.86%. It is known that KNN method relies too much on the training sample size and has great limitations in practical application. Therefore, SVM is more suitable for the practical application of classification and recognition tasks in the proposed research.

Table 4. Recognition rate of classifier using different feature dimension

Classifier	24 dimensions	48 dimensions	Mean accuracy (%)
KNN	90.86%	94.12%	92.49%
SVM	92.28%	96.86%	94.57%

We can conclued that when using acceleration data and angular velocity data for motion recognition, both algorithms have better performance than merely using acceleration data, and the recognition rate is basically 4% $\sim$ 5% higher. Therefore, this study adopted both triaxial acceleration and triaxial angular velocity data to identify different strokes of table tennis sport, ensuring better recognition performance.

3 Conclusions

In this paper, wearable sensors are applied to table tennis stroke recognition, and the data collected by the wearable sensor is used to realize the recognition of 5 different stroke actions. In the design of recognition process, the method of machine learning is introduced, which reflects the advantage of machine learning method to this kind of recognition task. Through the processing of angular velocity and acceleration data of various kinds of stroke motions collected by inertial sensors, the recognition methods based on KNN and SVM are presented. In the future, various machine learning methods would be studied. Meanwhile, other features can be extracted to explore whether other features can better improve the identification accuracy of the whole system.

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