Research on Action Recognition of Multi-Component Motion Sensors Based on FPCA and Ensemble Learning

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Abstract. In the cutting-edge fields of health monitoring, intelligent security, and human - computer interaction, the technology for recognizing human motion states plays a crucial role. However, there is an inherent contradiction between the continuity of human motion and the discrete data collection, which restricts the accuracy and operational efficiency of recognition algorithms. In light of this, this study innovatively introduces the functional data analysis method.Firstly, it transforms the human motion sequence into a functional form through the innovative application of functional data analysis, and precisely locates the starting point of the cycle based on the minimum extremum point, achieving efficient extraction of single - cycle function data. Then, the functional principal component basis expansion method is adopted to reasonably approximate the motion function, effectively capturing the key features of the data.Moreover, to address the challenge of selecting the number of principal components to truncate, this study innovatively introduces the Stacking ensemble learning strategy, constructing a two - layer model architecture: the output of the first - layer model serves as the input of the second - layer model, replacing the traditional model selection process through model aggregation, significantly enhancing the stability of the prediction model.The effectiveness of the proposed method is verified based on the WARD dataset. Compared with four common ensemble learning models such as principal component analysis combined with GBDT, the results of the Monte Carlo simulation experiments show that the method proposed in this paper demonstrates significant advantages in both recognition accuracy and stability, providing more reliable technical support for the practical application of human motion behavior recognition technology in multiple fields.

Keywords: Sports Behavior Recognition; Functional Principal Component Analysis; Ensemble Learning; WARD Dataset.

1. Introduction

In the current digital era, wearable devices have been widely applied in daily life and scientific research due to their portability, real - time monitoring capabilities, and continuous data collection features, greatly facilitating the collection of human motion data. Hao Guozhang[1] conducted research on gesture recognition based on multi - sensor fusion, while Yang Jing[2] focused on exploring human motion recognition methods using wearable motion sensors. Han Wenjie [3] delved into triboelectric joint sensors and their application in knee joint assistive devices. Additionally, many scholars have devoted themselves to this field. For instance, Wang Yufei [4] conducted an in - depth discussion on the application of wearable sensors in motion detection, covering aspects such as the collection and analysis of athlete training signals. Sun Jun [5] investigated feature extraction methods for human motion data based on wearable devices to better identify different motion behaviors. These diverse and rich studies have made human motion behavior recognition a cutting - edge and hot topic in the fields of artificial intelligence and pattern recognition.

However, the data in wearable motion recognition databases present numerous challenges. Human daily behaviors are periodic, resulting in these data having approximately periodic features and varying lengths for each sample. Traditional data processing methods, such as principal component analysis (PCA), have shown limitations when dealing with such data characterized by continuous changes. As Du Jing et al. [6] pointed out, the linear dimensionality reduction approach of PCA is inadequate in capturing complex patterns in nonlinear data scenarios, leading to significant performance fluctuations and insufficient feature discrimination ability. Liu Lei [7] also mentioned that in practical applications, PCA performs poorly in processing human motion data with complex periodic features, failing to fully exploit the effective information within the data.

To more efficiently and accurately identify motion behaviors, this paper proposes an innovative method based on functional data analysis. Su Benyue et al. [8] proposed the idea of transforming original data into continuous periodic functions through Fourier fitting, and this method draws on this idea.By precisely selecting the appropriate starting point of the period and the truncation length, the data is preprocessed to better depict the continuity and periodicity of the data. Meanwhile, functional principal component analysis (FPCA) is adopted for dimensionality reduction. Compared with traditional methods, FPCA can better capture the functional features in the data, as verified in the relevant research by Bao Lihong [9]. Additionally, to further enhance the stability of the prediction results, this paper introduces the Stacking ensemble learning framework. Li Mu [10] expounded on the advantages of ensemble learning, this framework combines the strengths of multiple models for motion behavior recognition. Through a comprehensive comparison with machine learning models based on traditional PCA, the significant advantages of the proposed method in terms of accuracy and stability are fully verified, aiming to open up new ideas and methods for the field of human motion behavior recognition.

2. Theory and Methodology

Due to the periodic nature of human daily activities such as walking, the data in wearable motion recognition databases all have approximately periodic features. To better demonstrate these characteristics, the Fourier fitting method is used to transform the original data into continuous periodic functions. The discrete points on this data are taken as the motion behavior data to be recognized, which can better reveal the patterns of human movement. It is observed that the length of each sample in the original data varies, so it is necessary to consider truncating the time series of each sample to the same length while maximizing the retention of sample information. Therefore, approximately one cycle of the motion sequence is considered to be extracted for each sample. For each sample, the key to truncating a sequence of one cycle lies in the starting point of the sample's cycle and the length to be truncated. To align all sample data, for the continuous function $f(t)$ fitted for each sample sequence, all the extreme points are found, and the time corresponding to the minimum extreme point is taken as the starting point of the cycle for that sample. In other words,

$$\min_{t} f(t) \quad s.t.\ f'(t) = 0 \tag{1}$$

This also constitutes a unified standard for selecting the starting points of each sample period. Regarding the length of the period, the data in the WARD dataset is received from the sensors at a frequency of 20 times per second. Combined with the observation of each sample data and the characteristics of human behavior, the 45 time points after the starting point of each sample period are taken as the extracted data for subsequent processing.

To be able to conduct behavior recognition by using the functional features in the sequence of human motion data, functional data analysis is adopted to transform the discrete data sequence into functions. As for a regression problem,

$$Y = \int_{t \in T} X(t)\beta(t)dt + \varepsilon \tag{2}$$

Here, the method of basis expansion is adopted for $X(t)$, that is, for a function, it can be expressed as a linear combination of a set of basis functions:

$$X(t)=\sum_{i=1}^{I}a_i\phi_i(t)=\boldsymbol{a}^T\boldsymbol{\Phi},\ a_i\in\boldsymbol{R},\ i=1,2,\cdots,J \tag{3}$$

Here, $\boldsymbol{a}=(a_1,a_2,\cdots,a_I)^T$, $\boldsymbol{\Phi}=(\phi_1(t),\phi_2(t),\cdots,\phi_I(t))^T$.

As for the solution of $\boldsymbol{a}$, the least - squares method can be used to solve the following problem:

$$\hat{\boldsymbol{a}}=\arg\min_{\boldsymbol{a}}\sum_{k=1}^{k}\left(X(t_k)-\sum_{i=1}^{I}a_i\phi_i(t_k)\right)^2 \tag{4}$$

It can be obtained that

$$\hat{\boldsymbol{a}}=\left((\boldsymbol{\Phi}')^T\boldsymbol{\Phi}\right)^{-1}\left(\boldsymbol{\Phi}'\right)^T\boldsymbol{X} \tag{5}$$

Here, $\boldsymbol{X}=\left(X(t_1),X(t_2),\cdots,X(t_k)\right)^T$, that is, the basis expansion form of the function is obtained. For each curve $X_j(t)(j=1,2,\ldots,k)$ in the sample and $\beta(t)$ substituted into equation (2), the same smoothing process can be obtained that

$$Y=\boldsymbol{a}^T\int\boldsymbol{\Phi}(t)\boldsymbol{\Phi}^T(t)dt\boldsymbol{b}+\varepsilon=\boldsymbol{a}^T\boldsymbol{W}\boldsymbol{b}+\varepsilon \tag{6}$$

Among them, both $\boldsymbol{a}$ and $\boldsymbol{b}$ are obtained by basis expansion of $\boldsymbol{X}(\boldsymbol{t})$ in the data and $\boldsymbol{\beta}(\boldsymbol{t})$. At this point, the original data can be replaced by the basis expansion coefficients of the function for prediction, and the problem is transformed into solving $\boldsymbol{b}$ through the basis expansion coefficients of the function in the samples. Here, the mean squared error minimization is adopted to solve it:

$$\begin{aligned}\beta(t)&=\arg\min_{\beta}\frac{1}{n}\sum_{i=1}^{n}\left(y_i-\int X_i(t)\beta(t)\right)^2\\&=\arg\min_{\beta}\frac{1}{n}\sum_{i=1}^{n}\left(y_i-\boldsymbol{a}_i^T\int\boldsymbol{\Phi}\boldsymbol{\Phi}^Tdt\ \boldsymbol{b}\right)^2\\&=\arg\min_{\beta}\frac{1}{n}\sum_{i=1}^{n}\left(y_i-\boldsymbol{a}_i^T\boldsymbol{W}\boldsymbol{b}\right)^2\end{aligned} \tag{7}$$

At this point, it can be solved for

$$\hat{\boldsymbol{b}}=\left(\boldsymbol{A}^T\boldsymbol{W}\boldsymbol{W}^T\boldsymbol{A}\right)^{-1}\boldsymbol{A}^T\boldsymbol{W}\boldsymbol{Y} \tag{8}$$

Here, $\boldsymbol{A}$ is the matrix composed of the basis expansion coefficients of the functions in the sample.

When the basic functions are orthogonal to each other, $\boldsymbol{W}$ becomes an identity matrix, which greatly simplifies the original problem. At this point, for a new sample, the corresponding response variable can be obtained through its predictor variables.

In practical situations, the basis expansion coefficients of functions in the sample are still high-dimensional data. To reduce the complexity of the data, dimensionality reduction processing is required. Here, to capture the functional features in the data, the commonly used method of applying principal component analysis (PCA) to the data is changed, and functional principal component analysis (FPCA) is considered to process the basis expansion coefficient matrix. Compared with principal component analysis, functional principal component analysis has a better dimensionality reduction effect in data scenarios with continuous variation characteristics.

The traditional principal component analysis involves transforming a k-dimensional data set into a p-dimensional one (where p is much smaller than k). Specifically, the original data $\boldsymbol{X}$ is multiplied by the direction matrix $\boldsymbol{W}$ to obtain the new data $\boldsymbol{Z}$, that is

$$\boldsymbol{X}\boldsymbol{W}=\boldsymbol{Z} \tag{9}$$

Here, $\boldsymbol{W}$ represents some of the directions with the highest information content in the original data, and they are sorted. The purpose of principal component analysis is to ensure that the new data still contains the vast majority of the information in $\boldsymbol{X}$. The solution for each column of $\boldsymbol{W}$ can actually be transformed into the eigenvalue decomposition of the covariance matrix of the original data:

$$\boldsymbol{\Sigma} w_d = \boldsymbol{X}^T \boldsymbol{X} w_d = \lambda w_d,\ d = 1, 2, \cdots, p \tag{10}$$

At this point, the eigenvectors corresponding to the largest p eigenvalues of the covariance matrix $\boldsymbol{\Sigma}$ are the columns of matrix $\boldsymbol{W}$. In functional data analysis, an analogy can be drawn to the equation (9), and here the covariance function is used to describe the covariance matrix. The form of the eigenvalue decomposition is:

$$\int \Sigma(s,t) w_d(t) dt = \lambda w_d(s),\ d = 1, 2, \cdots, p \tag{11}$$

Here, $\Sigma(s,t)$ is the covariance function. To simplify the covariance function, one can consider centering $\boldsymbol{X}$, such that the covariance function $\Sigma(s,t)$ can be estimated:

$$\Sigma(s,t) \approx \frac{1}{n} \sum_{i=1}^{n} X_i(s) X_i(t) \tag{12}$$

Here, n represents the sample size. To solve for $w_d(t)$, a basis expansion is performed on it, it is obtained that:

$$\frac{1}{n} \sum_{i=1}^{n} a_i a_i^T \int \boldsymbol{\Phi}(t) \boldsymbol{\Phi}^T(t) dt\, \boldsymbol{b}^T \boldsymbol{\Phi}(s) = \lambda \boldsymbol{b}^T \boldsymbol{\Phi}(s) \tag{13}$$

Let $\boldsymbol{Q} = \frac{1}{n} \sum_{i=1}^{n} a_i a_i^T \int \boldsymbol{\Phi}(t) \boldsymbol{\Phi}^T(t) dt$, then at this point, the eigenvalue decomposition can be obtained

$$\boldsymbol{Q} \boldsymbol{b}_d^T = \lambda \boldsymbol{b}_d^T \tag{14}$$

Sort the eigenvalues of $\boldsymbol{Q}$ in descending order and take the first p eigenvalues. The corresponding eigenvectors are the basis expansion coefficients of $w_1(t), w_2(t), \dots, w_p(t)$, and thus $w_i(t)$ can be obtained. Following the form of equation (9), $\boldsymbol{W}(t) = (w_1(t), w_2(t), \dots, w_p(t))$ can be used to process $\boldsymbol{X}$:

$$\int \boldsymbol{X}(t) \boldsymbol{W}(t) dt = \boldsymbol{Z} \tag{15}$$

For the n samples in the dataset, the data after dimension reduction by FPCA can be obtained as

$$\boldsymbol{Z} = \begin{bmatrix} \int X_1(t) w_1(t) dt & \int X_1(t) w_2(t) dt & \cdots & \int X_1(t) w_p(t) dt \\ \int X_2(t) w_1(t) dt & \int X_2(t) w_2(t) dt & \cdots & \int X_2(t) w_p(t) dt \\ \vdots & \vdots & & \vdots \\ \int X_n(t) w_1(t) dt & \int X_n(t) w_2(t) dt & \cdots & \int X_n(t) w_p(t) dt \end{bmatrix} \tag{16}$$

The matrix $\boldsymbol{Z}$ can then be used as a predictive variable for the recognition of human body movements and behaviors in later stages.

To improve the stability of prediction results, instead of training data with a single model, a Stacking ensemble learning framework is introduced. The idea of Stacking ensemble learning lies in combining multiple models. The general steps are as follows: first, the samples are divided into several parts, which take turns as training sets and test sets for model training to obtain test results, and new samples to be predicted can also be input into these models to get results. This process can be repeated multiple times, and then the obtained results are input into a second-layer learner for training and prediction to get the final predicted value. In general, stacking ensemble learning combines algorithms of multiple different models, uses the output of the first-layer models as the input of the meta-predictor of the second-layer model, and the output of the meta-predictor is the final prediction result. The flowchart representation of the above process is as follows:

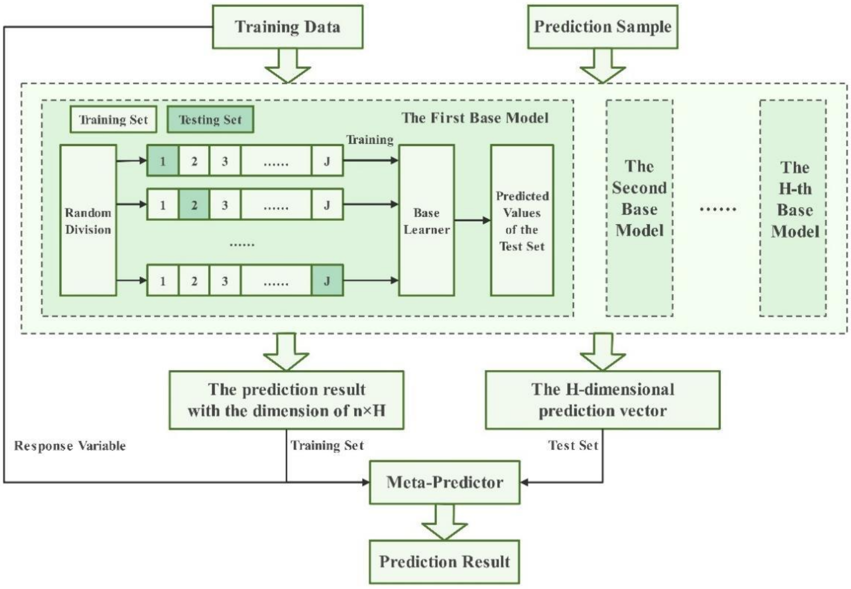

Figure 1. Stacking Ensemble Learning Process Diagram

The training data is randomly divided multiple times, and in each division, multiple trainings are conducted through cross-validation. For new samples to be predicted, each division requires them to be input into the J models of cross-validation, and the results are averaged. Under H divisions, a total of H-dimensional prediction data is obtained, which serves as the input for the meta-predictor. Additionally, to fully leverage the diversity of models and adapt to different data scenarios, the Stacking ensemble learning framework is generally free in terms of base models.

3. Experiment and Analysis

3.1 Dataset Description

The dataset used in this experiment is the publicly available "Wearable Activity Recognition Dataset (WARD)" provided by the University of California, Berkeley [11], and the dataset is described in the following table.

Table.1. Basic Information of the WARD Dataset

Category	Description
Experimental personnel	Thirteen men and seven women (a total of 20 people, with age differences)
Action type	Daily actions such as walking forward, going upstairs and going downstairs.
Number of repetitions of the movement	Repeat each movement five times.
Duration of a single experiment	Each action takes more than 10 seconds to execute.
Sensor configuration	Five motion sensors (left wrist, right wrist, waist, left ankle, right ankle)
Sensor functions	Each sensor includes: ·Three - axis accelerometer ·Dual - axis gyroscope
Data collection frequency	20 times per second (20Hz)
The composition of single-action data	Each action data contains the readings of 5 sensors: ·Each sensor has 5 columns of data (3 - axis acceleration + 2 - axis gyroscope). ·A total of 25 data streams (5 sensors × 5 columns)

In daily life, human body movements are approximately periodic behaviors [8], that is, each time series recorded in the dataset is composed of multiple approximately periodic data. Therefore, to avoid the negative impact of redundant data on the experimental results and in consideration of the approximately periodic characteristics of the data, this paper uses Fourier fitting to convert the discrete motion sequences into continuous periodic functions and extracts the values of approximately one period from the function. Then, the vertical upward acceleration sequences of the left and right feet of each subject during upright walking and stair climbing are collected. These motion sequences are used as predictor variables, and the specific actions performed by the subjects are used as response variables for classification and recognition. For each pair of actions to be classified and recognized, 20 subjects each conducted 5 experiments. Therefore, theoretically, each classification task has 200 samples; however, considering possible battery failures of the sensors and network data packet losses, some data in the dataset may be missing. The missing motion sequences are not included in the data used for classification and recognition, so the sample size for each classification task is less than or equal to 200. Moreover, since each subject performed the same number of trials for each action during data collection, the sample size for each action is almost the same in each experiment.

3.2 Data analysis

This study mainly processed the data of three motion states (going upstairs, walking, and jogging) of 20 subjects. Firstly, the data were checked for validity, then the mean was subtracted to eliminate baseline shifts. Next, a 4th-order Fourier series was used for curve fitting, and then the derivative was taken to find the extreme points of the motion curves. In this study, the function values of the minimum point and the 45 points following it were extracted as feature vectors and labeled according to the motion type (e.g., walking as 1, going upstairs as 0). Then, functional principal component analysis (FPCA) was conducted on the data to smooth the data and calculate the 25 most representative principal components, which not only retained the original data information but also significantly reduced the data dimension.

In the following ensemble learning experiments, the performance of functional principal component analysis (FPCA) was compared with that of four machine learning models based on traditional PCA (GBDT, XGBoost, random forest, and LightGBM). The performance evaluation metrics included accuracy, F1 score, and AUC. Accuracy is the proportion of correctly classified samples, F1 is the harmonic mean of precision and recall, and AUC is the area under the ROC curve. The range of values for all three metrics is [0, 1], with higher values indicating better overall performance of the classifier. The formulas for the metrics are as follows:

$$\text{Accuracy}=\frac{Number\ of\ correctly\ predicted\ samples}{Total\ number\ of\ samples}\times 100\% \tag{17}$$

$$\text{F1} = 2\times\frac{Precision\times Recall}{Precision+Recall} \tag{18}$$

Among them, precision indicates the proportion of samples predicted as positive by the model that are truly positive, and recall indicates the proportion of actual positive samples that are correctly predicted. Two experiments were conducted by comparing the three states of motion (going upstairs, walking, and jogging) in pairs. The means and standard deviations were calculated respectively. The results are shown in Table 2, and a boxplot is drawn using these results, as shown in Figure 2.

Table.2. Results of Walking and Jogging Recognition Based on Vertical Upward Acceleration of the Right Arm

	Accuracy		F1 score		AUC	
	Mean value	SD	Mean	SD	Mean	SD
FPCA-Emodel	0.9650	0.0099	0.9648	0.0099	0.9645	0.0095
PCA-GBDT	0.6225	0.3253	0.6027	0.3483	0.6021	0.3755
PCA-XGBoost	0.6712	0.2906	0.6334	0.3342	0.6233	0.3664
PCA-RF	0.6650	0.2377	0.6184	0.2927	0.6068	0.3353
PCA-lightGBM	0.6425	0.3094	0.6138	0.3409	0.6085	0.3696

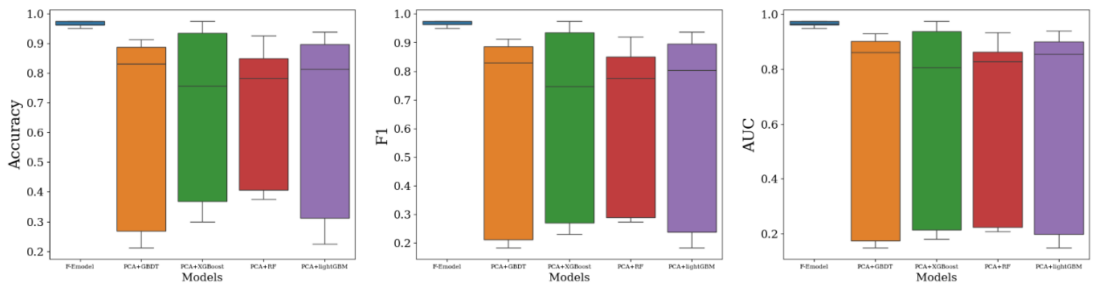

Figure 2. Box plot of walking and jogging recognition results based on the vertical upward acceleration of the right arm

The acceleration data of the right arm sensor in the horizontal direction during the subjects' walking and jogging were selected. From the chart results, it can be seen that FPCA (F-Emodel) is significantly superior to various methods based on PCA (PCA + GBDT, PCA + XGBoost, PCA + RF, PCA + LightGBM) in the three key indicators of accuracy, F1 score, and AUC.

Specifically, the mean accuracy of FPCA reached 0.9650, which is far higher than the highest value of 0.6712 among the PCA-based methods; the mean F1 score was 0.9648, also significantly better than the highest F1 score of 0.6334 in the PCA series; the AUC index also shows the same trend, with FPCA's value of 0.9645 being much higher than 0.6233. Moreover, the standard deviation range of FPCA was (0.0095, 0.0099), which was significantly lower than that of PCA (0.2377, 0.3755), indicating that the features extracted by FPCA have stronger discriminative power and stability. The vertical acceleration data of the sensor at the left ankle of the subjects when they were going upstairs and walking were also selected. The results further confirmed the superior performance of FPCA. The results are shown in Table 3, and a boxplot is drawn using these results, as shown in Figure 3.

Table.3. Results of Walking and Stair Climbing Recognition Based on Vertical Upward Acceleration of the Left Foot

	Accuracy		F1score		AUC	
	Mean	SD	Mean	SD	Mean	SD
FPCA-Emodel	0.7587	0.0373	0.7569	0.0377	0.7630	0.0403
PCA-GBDT	0.5212	0.1039	0.5206	0.1039	0.5258	0.1042
PCA-XGBoost	0.5188	0.1009	0.5173	0.1009	0.5280	0.1000
PCA-RF	0.5137	0.0927	0.5086	0.0926	0.5164	0.0963
PCA-lightGBM	0.4550	0.1157	0.4486	0.1157	0.4664	0.1297

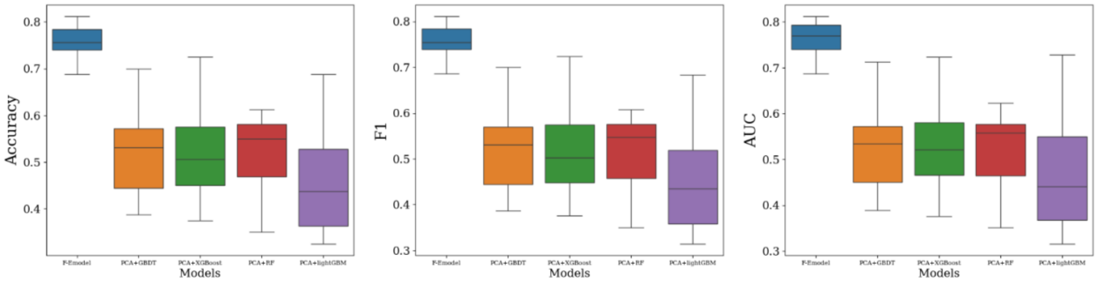

Figure 3. Box plot of walking and going upstairs recognition results based on the vertical upward acceleration of the left foot

FPCA captures the continuous variation patterns of data more effectively through functional data analysis and demonstrates significant advantages in complex classification tasks. In contrast, the PCA method, due to the limitations of linear dimensionality reduction, shows considerable fluctuations in nonlinear data and has obvious deficiencies in feature discrimination ability. It is more suitable for linearly separable scenarios, and its performance is greatly influenced by data distribution. In summary, compared with the PCA dimensionality reduction method that does not consider functional features, the ensemble learning effect of FPCA, which extracts functional features, is better.

4. Conclusions

This paper employs functional data analysis, functional principal component analysis (FPCA), and Stacking ensemble learning methods to process wearable motion recognition data, aiming to achieve precise recognition of human movement behaviors. It can be seen from the experimental results that by using FPCA and introducing the framework of Stacking ensemble learning, compared with some existing mainstream machine learning methods, its prediction accuracy has been significantly improved. This indicates that a more suitable usage method for this type of data scenario has been found here. It also provides a better research perspective for the analysis of discrete time series data.

Functional Principal Component Analysis (FPCA), leveraging functional data analysis, delves deeply into the functional features within data and can effectively capture the continuous variation patterns. When dealing with human motion data that has complex patterns, FPCA overcomes the limitations of traditional PCA in linear dimensionality reduction and demonstrates significant advantages. For instance, when confronted with motion data that is nonlinearly distributed, traditional PCA struggles to accurately extract key features, leading to a decline in model performance; in contrast, FPCA, through the functional processing of data, can better preserve the intrinsic structure of the data, providing more representative features for subsequent classification tasks.

The Stacking ensemble learning framework enhances the stability of prediction results by combining the algorithms of multiple different models, using the output of the first - layer models as the input for the second - layer models. In experiments, by repeatedly dividing the dataset for training and prediction, different models leverage their respective strengths in different subsets, ultimately leading to more reliable prediction results.

However, there are still some deficiencies in this paper: (1) During the research process of this paper, the settings of some parameters are too objective. For example, the number of principal components in FPCA and the number of basic functions in Fourier basis expansion, these parameters are not necessarily the most suitable for this data context; (2) The models in the Stacking ensemble learning framework are too monotonous. This paper only finds through experiments that in Stacking ensemble learning, when both the base learner and the original learner are set as support vector machine models, the prediction accuracy is higher than that of other common models. However, such situations have not been strictly confirmed. As for how to optimize the Stacking ensemble learning framework and identify the sub-models that are most suitable for the corresponding data scenarios, it will be one of the urgent problems to be solved.

In conclusion, this study provides an efficient and stable method for human motion behavior recognition. In practical applications, this method is expected to play a significant role in fields such as intelligent healthcare, health monitoring, and sports training, helping doctors to more accurately assess patients' rehabilitation conditions and providing personalized exercise advice for fitness enthusiasts. At the same time, this research also points out the direction for future studies. In the future, the scale and diversity of the dataset can be further expanded, and more optimized model combinations and parameter settings can be explored to promote the wide application and in - depth development of human motion behavior recognition technology in more practical scenarios.

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