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Extreme learning machine classification method for lower limb movement recognition

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Abstract In order to identify the lower limb movements accurately and quickly, a recognition method based on extreme learning machine (ELM) is proposed. The recognizing target set is constructed by decomposing the daily actions into different segments. To get the recognition accuracy of seven movements based on the surface electromyography, the recognition feature vector space is established by integrating short-time statistical characteristics under time domain, and locally linear embedding algorithm is used to reduce the computational complexity and improve robustness of algorithm. Compared with BP, the overall recognition accuracy for each subject in the best dimension with ELM is above 95%.

Keywords Movement recognition · Surface EMG · ELM-LLE · Multi-classification

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1 Introduction

Stroke is characterized by high rates of morbidity, mortality and disability, and accompanied by various complications, which accounts for more than 1 million deaths per year in China [1]. With the aim of enhancing people's capacity of impaired mobility, restoring their normal social life and improving their psychological and physiological state, intelligent assistant system for limbs are innovated. This system can greatly enhance human exercise ability and retain flexibility and direct operational feeling [2]. Motion recognition technology, one of the most crucial techniques in the design of this system, can maintain the consistency of execution and action, and also prevent interference to human body's free movements.

At present, there are three methods used to accomplish the action recognition: The first method is mainly focused on the analysis of non-invasive evoked Electroencephalogram (EEG) [3] which is obtained directly from the human motor nervous system. There are still many confusions of the working mechanism of the brain to be solved, and the action recognition and control for EEG is only limited to simple body movements. The second one is human motion information method, which is indirectly acquired by means of some information sensing devices placed in the user or the auxiliary equipment [4–6]. However, because of the increase of the number and type of sensors, the complexity and the cost of this system has risen rapidly. The third way is that the human body model is used for motion prediction [7]. The implementation of a certain action by the redundancy of human joints creates unlimited possibilities. Currently, different optimization algorithms based on possible trajectory are discussed under the specified user body function; the prediction accuracy will be affected by the accuracy of the simulation model, mathematical opti-

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mization method, assumptions of the research and other factors.

Human movements are usually accompanied by bioelectric changes in muscles. Electromyogram (EMG) signal is a characteristic display of muscular activities in time and space, which has the advantages of non-invasive measurement and simple operation. Now, motion recognition based on the surface electromyography (sEMG) technology has been widely used in the control of robots and artificial limbs as well as human body rehabilitation. Khezri et al. [8] designed the hand gesture recognition system by using artificial neural nets (ANN) and fuzzy inference model. Phinyomark et al. [9] improved the recognition rate of 10 upper limbs' movements by comparing different feature sets. Khushaba et al. [10] used different features and LIBSVM [11] classifier to recognize finger movements successfully. Chen et al. [12] explored the Support Vector Machine (SVM) classification method to improve the accuracy of upper limb motion recognition and the efficiency in real-time control. Young et al. [13] introduced successfully a novel classifier based on Bayesian theory to provide classification of simultaneous wrist and hand movements. Naeem et al. [14] built a new Back-Propagation (BP) model to estimate human arm muscle force. Wang et al. [15] proposed an on-line myoelectric control system based on the linear discriminant analysis (LDA) classifier that can classify eight prehensile hand gestures. Kiguchi [16] also used EMG to recognize the hand posture and developed the corresponding power-assist exoskeleton robot. However, the current studies of motion recognition are merely focused on the human upper limb, which are not enough to study lower limb, and it lacks satisfying recognition accuracy in sEMG signals. Lower limb EMG signal is a typical time-varying non-stationary signal, and usually generates large motion noise. So it is difficult to identify the action pattern of the lower limb quickly and accurately using the surface EMG signal.

Extreme learn machine (ELM), neural networks with single hidden layer, has the advantages of high efficiency and fast speed, and is well improved and applied in recent years [17–20]. ELM can randomly generates the connection weights between input layer and hide layer as well as thresholds in hide layer neuron, and it only need to set the number of hidden layer neurons without adjustment in the course of training that can get the only optimal solution. BP method utilizes the errors to update the neural weight, which requires the results of each forward calculation. Moreover, it can fall into the local minimum easily, which is not the optimal solution. Compared with the traditional BP neural network, ELM has strong generalization ability and fast learning speed. Furthermore, it has also been proven that the solution space of SVM is the same as the subspace of ELM [21] and also requires to set many parameters.

In this paper, surface EMG signal is used as the source of information, combining the time-domain characteristics to build the recognition vector space. Local linear embedding (LLE) [22,23] algorithm is used to reduce dimension, and extreme learning machine (ELM) as a classification method to identify standing up, constant speed walking and stair activity, which are target actions to carry on the research.

2 Materials and methods

2.1 Construction of target actions

From the perspectives of human kinematics, a complex body movement is composed of some simple movements based on certain rules. For instance, stair activity can be simply divided into two simple action segments, swing and support movement. Those simple action segments can be effectively identified and could provide clear control instruction for the intelligent aided rehabilitation system. According to the recognition target set, the primary task is built to identify lower limb movements. As shown in Table 1, the daily lower limb activities, including standing up, walking and stair activity have been decomposed into seven segments.

2.2 Feature extraction

When the human body completes different lower limb movements, excitation time and excitation grade for the corresponding muscles are different too [24]. Since short-time statistics have the advantages of minor calculation, the statistical features of the segmented signals can approximately reflect the variation laws of statistical characteristics over time. Different muscular activities produce different sEMG lengths, the wave of EMG approximates to sine function with a higher signal-to-noise ratio, which is applicable for ZC index. RMS can reveal mainly the number of motor units being activated during muscle movement, etc. In this paper, the characteristic vector space is composed of different time-domain features to reflect the amplitude of the sEMG signal. Mean absolute value (MAV), variance (VAR), the fourth-order autoregressive (the 4th AR), zero crossings (ZC), root mean square (RMS) are adopted in the recognition of lower limb movements. Hudgins et al. [25] used mean absolute value (MAV) and zero crossings (ZC) to recognize four forearm motions successfully. Wang et al. [26] has proven that VAR and the 4th AR and the other methods are effective in recognition of postures by comparing the different feature sets under the condition of time domain, frequency domain and time-frequency domain respectively.

Table 1 Decomposition of the daily lower limb activities

Number	Motion	Description of action and main functions
A	Standing up	Lift hips out of the seat, keep standing posture/move entire body upwards
B1	Walking (support state)	One heel touch the ground and the other toe leaves the ground/support the body and keep balance, let the other leg and the body forward
B2	Walking (swing state)	One toe leaves the ground and the other heel touch the ground/let one leg forward when the other supports the body
C1	Up stairs (support state)	One heel touches the steps and the other toe off the steps/support the body and keep balance, let the other leg and the body upwards
C2	Up stairs (swing state)	One toe leaves the steps and the other heel touches the steps/let one leg upwards when the other supports the body
D1	Down stairs (support state)	One heel touches the steps and the other toe leaves the steps/support the body and keep balance, let the other leg and the body downwards
D2	Down stairs (swing state)	One toe leaves the steps and the other heel touches the steps/let one leg downwards when the other supports the body

2.3 Feature reduction by locally linear embedding

Roweis and Saul successfully explored LLE, a nonlinear dimensionality reduction algorithm [27], which has been widely used in the field of classification and clustering for image data, character recognition, Bioinformatics, etc. It can keep the high-dimensional distribution and structure of data, and put similar data closer. However, in some cases, LLE method is not applicable. For example, if the data are distributed in a closed sphere, it cannot be mapped to the two-dimensional space, and maintain the original data manifold. In this paper, since too much vector dimensions will increase the complexity of the recognition algorithm, LLE is adopted to reduce the dimensionality of vector space .

The main methods of LLE algorithm can be described as follows:

Step 1 Compute K neighbors of each data point, $\overrightarrow{X_l}$. The closest K sample points around the solving sample points are defined as the K neighbor points, and K is a predefined value.

Step 2 Compute the weights W_{ij} that best reconstruct each data point $\overrightarrow{X_l}$ from its neighbors. First, an error function is defined here:

$$min\ \varepsilon(w) = \sum_i \left|\overrightarrow{X_l} - \sum_j W_i j \overrightarrow{X_j}\right|^2 \tag{1}$$

Local covariance matrix C:

$$C_j k = (\vec{x} - \vec{\eta}_j) \cdot (\vec{x} - \vec{\eta}_{jk}) \tag{2}$$

x represents a specific point, its K neighbor points are represented by η.

Step 3 Compute the vectors $\overrightarrow{Y_l}$ best reconstructed by the weight W_{ij} , all the sample points are mapped to D-dimension space. The mapping condition is denoted as:

$$min\ \varepsilon(Y) = \sum_i \left|\overrightarrow{Y_i} - \sum_j W_{ij} \overrightarrow{Y_j}\right|^2 \tag{3}$$

where $\varepsilon(Y)$ is the cost function, $\overrightarrow{Y_l}$ is the output vector of $\overrightarrow{X_l}$, $\vec{Y}_j (j = 1, 2, \ldots, k)$ is the k neighbors of $\overrightarrow{Y_l}$, which is satisfied with conditions: $\sum_{i=1}^{N} \vec{Y}_i = \vec{0}$, $\frac{1}{N}\sum_{i=1}^{N} \vec{Y}_i \vec{Y}_i^T = I$, I is $m \times m$ unit matrix. Through the above steps, we can get the reconstructed data in low dimensional space. Here, the value of K is 25.

2.4 Motion recognition by extreme learning machine

In recent years, as a new learning method of single-hidden layer feed forward neural networks (SLFNs), extreme learning machine (ELM) has a good generalization performance to improve the learning speed of the neural network. The main principles of ELM can be described as follows:

Given arbitrary and distinct training samples of N elements, where

$X_i = [x_{i1}, x_{i2}, \ldots, x_{in}]^T \in R^n$ and
$Y_i = [y_{i1}, y_{i2}, \ldots, y_{im}]^T \in R^m$.

Assuming the activation function of hidden layer is denoted as $g(X)$, the mathematical expression of SLFN with L hidden layer neurons can be written as:

$$\sum_{i=1}^{L} \beta_i g(X_j) = \sum_{i=1}^{L} \beta_i g(w_i \cdot X_j + b_i) = Y_j (j = 1, 2, \ldots, N) \tag{4}$$

$w_i = [w_{i1}, w_{i2} \ldots w_{in}]^T (i = 1, 2, \ldots, L)$ is the weight vector connecting the ith hidden neurons and input neurons; denotes the weight vector connecting the i^{th} hidden neuron and output neurons; $\beta_i = [\beta_{i1}, \beta_{i2}, \ldots, \beta_{in}]^T (i =$

$1, 2, \ldots, L)$ is the bias of the ith hidden neuron; denotes the inner product of w_i and X_j, $\mathrm{Y_j} = [\mathrm{y_{j1}}, \mathrm{y_{j2}}, \ldots, \mathrm{y_{jm}}]^{\mathrm{T}}$ is the corresponding target vector, and the active function is g(x).

Thus, to tain the output weights β, which is given by calculating the least-square solution from the given equation group, it can be simplified as:

$$H\beta = Y \tag{5}$$

$$H = \begin{bmatrix} g(w_1x_1 + b_1) & \cdots & g(w_Lx_1 + b_L) \\ \vdots & \ddots & \vdots \\ g(w_1x_N + b_1) & \cdots & g(w_Lx_N + b_L) \end{bmatrix}_{N\times L} \tag{6}$$

So,

$$\hat{\beta} = H^{+}Y \tag{7}$$

where H^{+} is the Moore–Penrose generalized inverse of matrix H. The solution is also the only global optimal solution by using SLFNs. Meanwhile, good general performance and fast training speed are its great advantage.

2.5 Recognition method of lower limb movement

During the process of moving lower limb consistently, both legs have the function of balancing body and shifting weight. If lower limb actions are divided into different segments that are only based on a single source of information, the efficiency and precision of classification will be affected in a certain degree. Because various lower limb actions (including standing up) can be classified simply and accurately with the plantar pressure information, the recognition goals can be decomposed into swing motion set and support motion set by means of pressure data. On this basis, the EMG signals are used for further subdivision within each motion set.

The characteristic values of sEMG signal in five muscles include eight time-domain features aimed to build feature vector space for movement identification. 40 dimensions (5×8) can increase the complexity of the recognition algorithm, so it is necessary to reduce the dimension of the signal feature vector. As the main dimension reduction algorithm, Principle Component Analysis (PCA) [28] has been used in practical research widely. However, PCA is a linear dimension reduction, which is not good for the final classification. Some useful classification features may be lost by using this method to determine the principal component, if the research only taking top K (K is the default value) as the most contributive feature components which is merely based on the biggest change in data features. On the contrary, the LLE algorithm is a nonlinear dimension reduction, which is effective for the classification task. Further discussions about LLE algorithm are shown in Sect. 2.3. Figure 1 shows recognition process of lower limb movements.

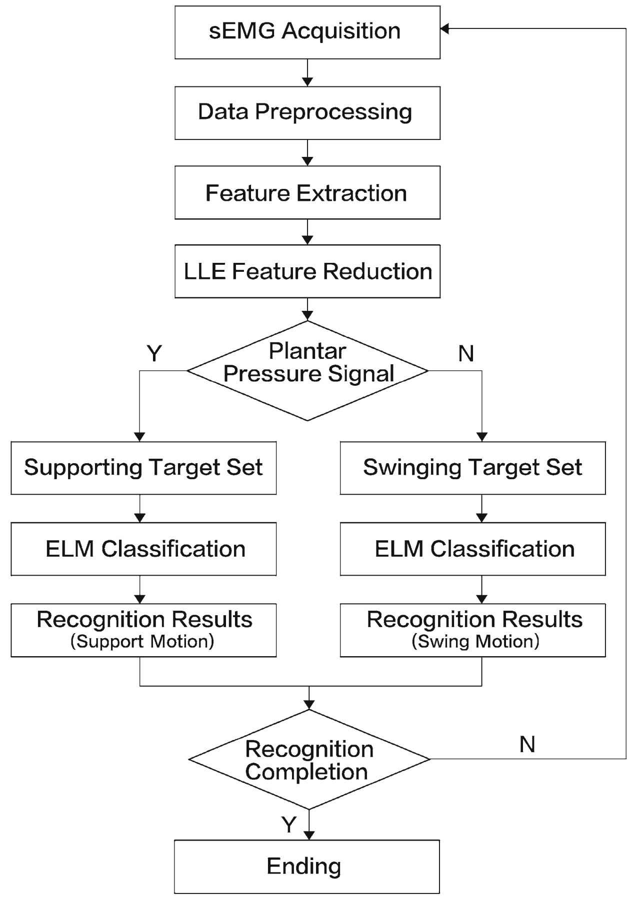

Fig. 1 Flow chart of sEMG motion recognition

2.6 Participants

In this paper, 5 male students of Zhejiang Sci-Tech University are chosen as the experimental subjects to avoid the influence of gender and age on the EMG signals. Their heights and Weights are listed in Table 2.

Every subject is in good physical condition during the experimental process. They have no injury or disease in lower limb, and did not do any strenuous exercise within 24 h before

Table 2 Basic information of subjects

Subject	Age	Height (cm)	Weight (kg)
1	24	172	62
2	27	168	58
3	25	175	68
4	28	180	71
5	25	177	65

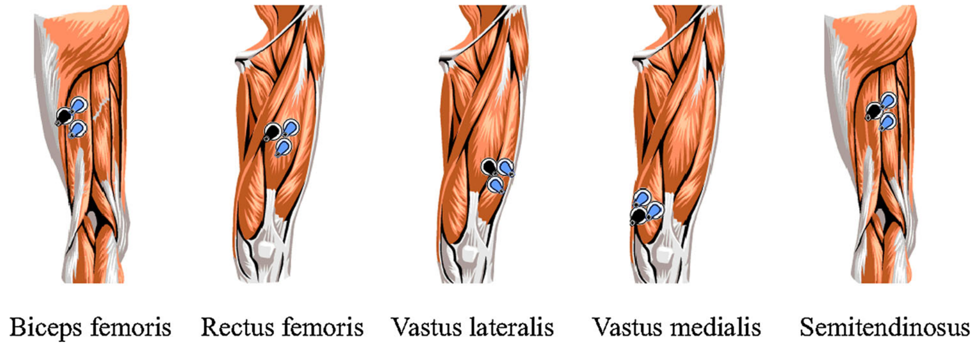

Fig. 2 The selected muscles and position of electrodes on the lower limb

the experiment, so that their postures are normal without any muscle fatigue. In this way, the objectivity of the experimental data has been ensured and the interference of muscle fatigue has been prevented as well.

2.7 Experimental process

(1) Rectus femoris, vastus lateralis, vastus medialis, biceps femoris and semitendinosus, the signal change of those muscles in different lower limb movements is extremely obvious while maintaining a strong stability [24]. Therefore, 5 kinds of muscles are selected for action recognition in practical application. The skin surface of the selected muscles is cleared with fine gauze and medical alcohol cotton. The positions of those electrodes on the lower limb are shown in Fig. 2.

(2) The plantar pressure measurement shoe-pads are placed on the pelma after the electrodes are attached to the body. The subjects needed to test the EMG signal in static and vigorous states before the task, and two states are recorded for 5 s respectively. This process is used to eliminate individual differences. The normalization process is performed:

$$P_{normalization} = \frac{P}{P_{max} - P_{static}} \tag{8}$$

(3) Experimental observer use the metronome to guide subjects to complete 7 lower limb movements, such as standing up, constant speed walking and walking up and down stairs. The relevant data are collected by Motion Lab Systems with 8-channel and plantar pressure measurement system at the same time, and the sampling frequency on each channel is set to 1000 HZ, real-time EMG signal waveforms are displayed on computer screen. Each task is repeated for 30 times. (The subjects are required to complete three gait cycles and walk at a normal pace in each experiment. Besides, the number of steps is 3 in stair activities.)

(4) The experiment is over after the 7 lower limb actions are completed. The experimental data processing is realized based on Matlab (2010b).

3 Results and discussion

The amplitude and frequency of EMG signal will change with time in the process of human activities, and the time varying gives a strong basis for motion recognition. Using the effective identification strategy, the pattern of continuous human action can be recognized. Generally, when using the recognition strategy of action pattern, a length of time should be chosen in advance. After the information sampling is completed in this time period, the feature of the collected data has been extracted, and then seven motions are identified. Through this method, this study has put the feature extraction and motion recognition together in a period of time to process. However, in the sampling process, the processor is only used to control the A/D conversion for sampling, so the reaction time of the system is increased too. A recognition strategy with segmentation of data stream and moving window for lower limb movements as shown in Fig. 3 is proposed.

In Fig. 3, T_d is the length of time for pattern recognition, and t is the length of the moving window, which is also the time of the window conversion. The strategy does not use pattern recognition in each sampling window, but just calculates the characteristic value of the window informa-

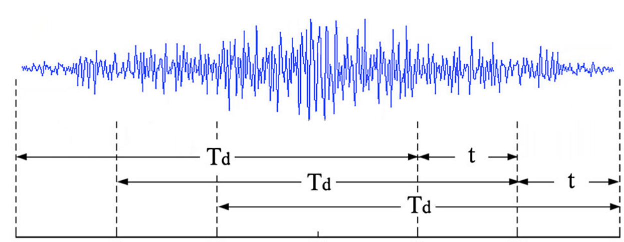

Fig. 3 Recognition strategy for lower limb movements

tion. After T_d, classification model is selected for movement identification by using the feature vectors of all the window segments. On the one hand, taking sample while the processor in feature extraction and computation can make full use of the computing power of the processor; on the other hand, "moving window" generates overlapping time periods, which increases the length of time used to identify motions, thus improving the robustness of the algorithm.

In the experiment, 600 data points are extracted from the motions of each subject. According to the moving window method, the selected period of RMS, MAV, VAR, ZC and the 4th AR is 100 sampling points, which forms different data segments. So the length of time is 400, the moving size is 100. From the 600 data points from the motions of 5 lower limb muscles, 3 data segments are obtained by moving window

$$\text{Accuracy} = \frac{\text{training number of correct prediction} + \text{testing number of correct prediction}}{60}$$

in each time. Thus all motions would generate in total 3150 ($5 \times 3 \times 7 \times 30$) samples. The first 30% samples are used for testing and the rest 70% samples are used for training. Here, training epochs are 500 with mini-batch gradient descent.

This paper presents ELM model that is neural networks with single hidden layer. Hidden layer node L can greatly affect the correct rate and the generalization ability of neural network model, which has been proved by Huang et al. [29]. The hidden node L is searched from 1 to 300 to obtain the best-hidden node at the highest accuracy rate, and the generalization ability of neural network is the best at this time. Figure 4 shows that the trend of testing accuracy and training accuracy remain essentially the same, which explains that the integrity of sample data is better. In the research, when the node is more than 70, the accuracy rate reaches to a satisfactory state. With the increase of the node, the accuracy is improved correspondingly, but the increase of the amplitude is very subtle and the complexity of compute nodes is getting higher and higher. In order to reduce the computational complexity, one of the optimal hidden layer nodes is randomly selected among 150–200 nodes. Here, ReLU (f (x) = max (0,x)) is the activation function, and the hidden layer node L is 160.

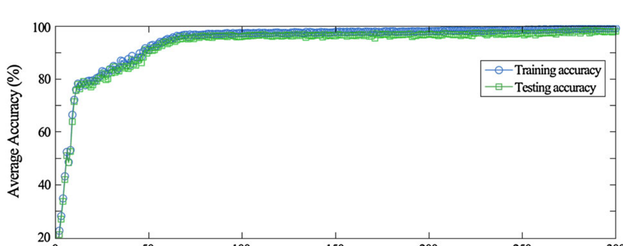

Fig. 4 The trend of the accuracy of the hidden layer nodes

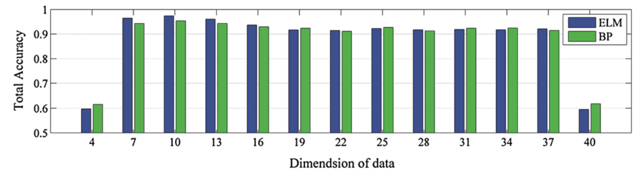

Fig. 5 The recognition accuracy of different dimensions

After using LLE to reduce dimension, Fig. 5 gives the recognition accuracy based on ELM and BP in different dimensions for 5 subjects, and BP model uses the neural network toolbox of Matlab software. The training accuracy and testing accuracy are integrated into the total accuracy:

Several conclusions can be drawn from Fig. 5 and Table 3:

(1) Limited by time and experiment condition, and the differences among individuals, there are some disturbances in the results of motion recognition. Moreover, the sample size are not enough to collect enough effective sampling points, which leads to misrecognition. In Table 3, we can see that in demonstration of leg-supporting motion while coming down the stairs, the accuracy of all subjects can achieve 100%, and the overall recognition accuracy of each subject is above 95%, which indicates that lower limb motions can be identified rapidly and accurately by using LLE-ELM classification method. Due to large movement range and different gait for lower limb, artificial errors also lead to the poor accuracy of recognition for some motions.
(2) In the identification of specific motion status, the accuracy of standing up (A) is relatively low. Subject leaning forward in different degrees can easily leads to standing with inertia force, and a decrease in the leg muscle force can lead to the difference of EMG signal, which complicates recognition for lower limb motions.
(3) Figure 5 displays the recognition accuracy of different dimensions, which shows the dimensions of the highest accuracy are 10 by using ELM, and after that the accuracy rate is decreased. With the increase of dimensions, the difference between ELM and BP is narrowed. The recognition accuracy of ELM under the simple computing method is higher than that of BP. An intuitive picture in 10 dimensions shows the state of the data distribution for different actions, and 50 points are arbitrarily selected form each action to display. The distribution of

Table 3 Recognition accuracy of ELM (%)

Subject	A	B1	B2	C1	C2	D1	D2	Average
1	100	75.56	98.89	98.89	100	100	98.89	96.04
2	87.78	94.44	91.11	94.44	98.89	100	98.89	95.08
3	83.33	96.67	94.44	98.89	100	100	100	96.19
4	93.33	100	100	98.89	92.22	100	92.22	96.67
5	96.67	100	100	100	100	100	100	99.52
Average	92.22	93.33	96.89	98.22	98.22	100	98.00	

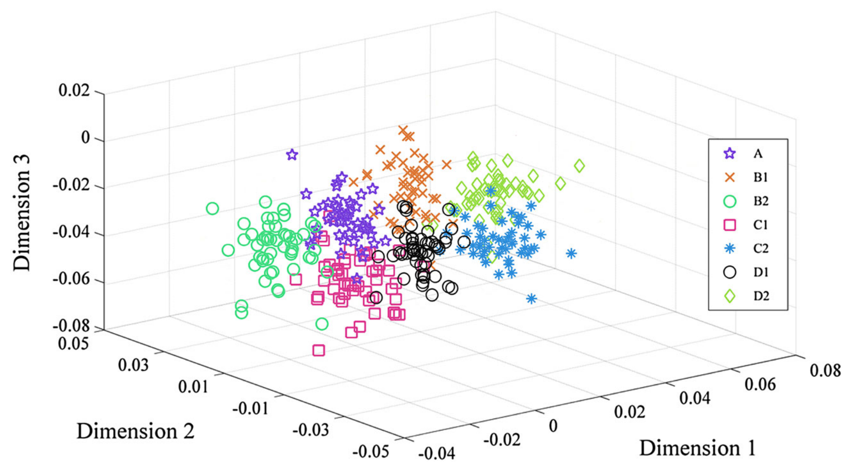

Fig. 6 Distribution of data points for different actions

data points based on LLE-ELM method is obvious in Fig. 6.

4 Conclusions

In this paper, a recognition algorithm based on LLE-ELM hybrid model for lower limb motion is proposed. The sEMG signals of 5 lower limb muscles, including rectus femoris, vastus lateralis, vastus medialis, biceps femoris and semitendinosus, are selected as the information source. Besides, 8 time-domain features like RMS, MAV, VAR and others are chosen to establish the feature vector space. The daily lower limb movements like standing up, constant speed walking and stair activity are decomposed into different segments to accomplish the recognition goals. The results of the experiment confirmed that the presented method is correct and effective through the comparison between ELM and BP algorithm, which enriched recognition methods for the human lower limb motions. It provides a theoretical basis for the research and development of intelligent aided device for human lower limb.

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