Hand Gesture Recognition of Double-Channel EMG Signals Based on Sample Entropy and PSO-SVM

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Abstract. Considering wearable device requirements, such as injury-free, comfortable and light, a new method based on sample entropy and PSO-SVM for double-channel EMG signals recognition is proposed. First, the signal is segmented by using a non-overlapping adjacent sliding window. And the sample entropy of the valid information after signal in each window is decomposed by EMD is fast calculated to obtain a feature vector. Then the paper improved the PSO algorithm from two aspects. On the one hand, using a dynamic topology improved the impact of “premature” by replacing the global optimal value with neighborhood optimal value. On the other hand, in order to increase the probability of particles jumping out of local optimum, according to the principle of partition crossover, reset the particles that are trapped in local optimum. Next, the multi-window fusion decision result of the adaptive weight voting is used to identify the gesture. Finally, five methods are used to classify the five combined fingers movements about pinch gestures and compare with each other. The experimental results show that the algorithm (IPSO-SVM-WMV) combined sample entropy has strong robustness, real-time and anti-interference ability in double-channel EMGs signal recognition and the classification accuracy is better than PSO-SVM.

1. Introduction

The recognition of surface Electromyography (sEMG) signals has received more and more attention in recent years. Different movements have different muscle contraction states. And the characteristics of surface EMG signals are different. By analyzing these characteristics, different motion patterns can be distinguished. Remotely operated robots in the nuclear industry for remote operation through surface EMG signals for maintenance of critical equipment. In human-machine collaboration systems, EMG signals have become one of the widely used biological signals for human motion intent prediction. In the field of medical rehabilitation, the study of upper and lower extremity exoskeleton and artificial hand prosthesis for rehabilitation therapy are mostly based on surface EMG signals [1].

In these fields, the full implementation of high-precision gesture recognition requires a large number of EMG sensors, which greatly increases the cost and complexity of device development. Recently, a gesture recognition arm ring MYO was sold well [2]. And the arm ring included 8 EMG channels inside. However, it is relatively bulky as a wearable device. This paper studies the gesture recognition method based on double-channel EMG signals.

In terms of physiological time series (EEG, sEMG), sample entropy has a good application for the evaluation of its complexity and pathological state [3]. The calculation of sample entropy does not depend on the length of the data. The calculation speed is fast, the real-time performance is good and the anti-noise ability is strong. The sample entropy has good consistency. The lower the sample
entropy value is, the more self-similar the signal sequence is. The higher the sample entropy value, the more complex the signal sequence. Therefore, this paper uses sample entropy to extract the characteristics of EMG signals.

The PSO algorithm is an evolutionary algorithm, which belongs to the unconstrained optimization problem. It uses real numbers to solve the problem. It has strong versatility and requires fewer parameters to adjust. It is easy to implement collaborative search. At the same time, using individual local information and the particle swarm global information to guide the search, it is easier to leap out of the local optimaums, which is less restricted by experience. However, the disadvantage is that it is easy to fall into “premature” and slow down the convergence speed and the local search ability of the algorithm is poor in the late stage of evolution. It is a probability-based optimization method, and the algorithm cannot guarantee the search for the global optimal solution [4].

At present, the SVM multi-classification method mainly uses the indirect method that uses multiple simple SVM classifiers for multi-classification. One-to-one Multi-classifier is that K simple classifiers is used for K classification. the unknown samples are classified by maximum of the classification function value. The number of classifiers is small in this method and the classification speed is relatively fast. However, this method has a large deviation. Later, a multi-classification method based on decision trees was derived, but this method will accumulate errors in each layer of the classifier; One-to-many Multi-classifier is that K(K-1)/2 simple classifiers is used for K classification. Each classifier votes on the class of the unknown sample, and the class with the most votes is the classification result. And the multi-classification in LIBSVM uses this method [5].

EMG classification accuracy is usually smoothed using majority voting (MV)techniques [6]. But although this method of majority voting is effective in smoothing classification, it handles output decisions in a naive way without considering the actual possibility of mis-classification. Therefore, in this paper, we design a method based on Multi-sliding window fusion decision to further improve classification.

This paper proposes an improved PSO algorithm and fuses the optimized PSO algorithm with the SVM (IPSO-SVM). Considering the case of the single SVM classifier identifying the error rate, an adaptive weight majority voting decision method fusing Multi-sliding window decision is proposed (SVM-WMV) in the post-generalization process. The accuracy of the classifier in the training process is used as the weighting factor. The adaptive weighting factor is used to fuse the identification information of multiple windows to make decisions, which significantly improves the result of gesture recognition. The recognition of the five combined fingers movements about pinch gestures is used to verify the performance of proposed algorithm (IPSO-SVM-WMV).

The experimental results show that the improved PSO algorithm improves the “pre-mature” convergence of the particle swarm, and the Multi-sliding window fusion decision reduces the misclassification, and significantly improves the recognition rate of the SVM multi-classification. Making the operation of devices based on the surface EMG signals is more accurate in the application of wearable devices. This research has certain application value.

2. Method

2.1. Feature Extraction
Empirical mode decomposition is a new adaptive signal time-frequency domain processing method, especially used for the analysis and processing of non-stationary signals. This paper, adaptively decompose the nonlinear, non-stationary EMG signals in the 125ms window into several different modal functions (IMF) and one residual component by EMD. As shown in the following equation (1):

\[
E(t) = \sum_{j=1}^{n} c_j(t) + r_n(t)
\]  

(1)
The frequency of these IMFs varies from large to small and contains time-scale information of different characteristics. By calculating the average frequency of each IMF $c_j(t)$, the IMF with the range falling between 20Hz and 450Hz is selected as the effective IMF for the extraction of the EMG information. In this paper, the signal in the sliding window is first decomposed by EMD, then the effective IMFs are weighted and fused to obtain a valid information sequence $E(t)$. As shown in the following equation (2).

$$E(t) = \sum_{j=t}^{n} \delta_j c_j(t)$$

The calculation method of Fast sample entropy is as follows.

Set the EMG effective information sequence as following equation (3).

$$\{N_i\} = \{\bar{E}(t)\}, \{N_i\} = N(1), N(2), N(i), ..., N(n)$$

Group the EMG effective information sequence in vectors about $m$ Dimension as following equation (4).

$$N_m(i) = [N(i), ..., N(i + m - 1)], 1 \leq i \leq n - m + 1$$

Define the distance between two vectors as the absolute value of the maximum interpolation of the corresponding elements in vector as following equation (5).

$$d[N_m(i), N_m(j)] = \max_{k=0,...,m-1}([N_m(i+k) - N_m(j+k)])$$

Calculate the number of distances between two vectors in the vector groups of $m$ and $m+1$ Dimension that are less than the threshold $A^{m+1}_t, A^m_t$ as following equation (6).

$$A^m = \sum_{i,j=1}^{n-m+1} d_{ij} / 2, A^{m+1} = \sum_{i,j=1}^{n-m} d_{ij} / 2 \left\{ \begin{array}{ll} d_m = 1, & d[N_m(i), N_m(j)] \leq r, 1 \leq i, j \leq n - m + 1 \\ d_m = 0, & d[N_m(i), N_m(j)] > r, 1 \leq i, j \leq n - m + 1 \end{array} \right.$$

where, $\{d_{ij}\}$ is statistical sequences. Calculation the average of all $A^m_t$ as $A^m_t$. Calculation the average of all $A^{m+1}_t$ as $A^{m+1}_t$. As shown in the following equation (7).

$$A^m_t = \sum_{i=1}^{n-m+1} A^m_t / n - m + 1, \quad A^{m+1}_t = \sum_{i=1}^{n-m} A^{m+1}_t / n - m$$

where, $A^m_t$ is the probability of matching of Two sequences of $m$ dimension in similar tolerance $r$, $A^{m+1}_t$ is also. Calculate sample entropy magnitude as following equation (8):

$$E_{sp}(n, m, r) = -\ln[A^m_t / A^{m+1}_t + C]$$

where, $C$ is a tolerance to avoid unsolvable situations.

2.2. SVM

SVM is a new machine learning method based on statistical learning VC theory and structural risk minimization principle [7]. For the nonlinear separable case, its main idea is to map the sample into the high-dimensional linear space by the idea of maximizing the plane partition interval, so that the classification plane can correctly segment the samples. In the case of nonlinear separability, a nonlinear function in the SVM can be used to map the data to a high dimension feature space, and then an optimized hyperplane is established in the high dimension feature space, and the classification function becomes as following equation (9):

$$f(x) = \text{Sgn} \left[ \sum_{i=1}^{\alpha} \alpha_i \exp(-\|x_i - x\|^2 / \sigma^2) + b \right]$$
where the dot product operation can be directly given by its corresponding kernel function. This paper chooses the radial basis kernel function because theoretically the radial basis can be projected into the space of any dimension. $\sigma$ is the parameter of the RBF kernel. At the same time, there are inseparable situations in the segmentation process. In order to ensure the accuracy of the classification and tolerate some noise and misclassification. The SVM method introduces slack variables $\xi_i$ and penalty coefficients $C$, and the problem of finding the largest geometric separation interval can be transformed into the following optimal problem as following equation (10).

$$\text{Max } J(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j K(x_i, x_j), 0 \leq \alpha_i \leq C, \sum \alpha_i y_i = 0, \alpha_i \geq 0, \gamma_i + \alpha_i = 0, \gamma_i \geq 0$$

The problem is solved by the best method of the SMO algorithm. In addition, there are some suitable tools that can be useful, such as the QP toolkit. After solving values of $\alpha$, values of $b$ can be obtained by $\alpha$. There is a key problem in the SVM. How to choose the parameters of the radial basis kernel function and how to design the penalty factor in the classification process. Reasonable selection of the radial basis parameters and the penalty parameters in the cost function can greatly improve the performance of the classifier. This paper chooses the improved PSO algorithm to search for matching kernel function parameters and penalty factors.

### 2.3. PSO

The particle swarm optimization (PSO) algorithm is derived from the simulation of bird predation behavior in nature. It is a global optimization evolution algorithm. Each particle has only two variables of velocity and position, ignoring mass and volume, and multiple particles composing particle swarm. The particle swarm has three key parameters of population size, particle dimension and the number of iteration [8].

In the $D$ dimensional solution space, there are $n$ particles forming a swarm, and the position, velocity of each particle, the speed and location of the swarm are as following equation (11).

$$x_i = (x_{i1}, x_{i2}, \ldots, x_{id}, \ldots, x_{id}), v_i = (v_{i1}, v_{i2}, \ldots, v_{id}, \ldots, v_{id}), \ X = \{x_i\}, \ V = \{v_i\}$$

The particle position and velocity update equation (12) is as follows.

$$v_{id}^{t+1} = w v_{id}^t + C_1 \text{rand}_1 (P_{\text{best}_{i}} - x_{id}^t) + C_2 \text{rand}_2 (G_{\text{best} - x_{id}^t}), \ x_{id}^{t+1} = x_{id}^t + \beta v_{id}^{t+1}$$

where, $w$ is the Inertia factor; $\beta$ is the Constraint factor; $C_1$ and $C_2$ are the Acceleration coefficient; $\text{rand}_1$ and $\text{rand}_2$ are the random number between 0 and 1; $P_{\text{best}_{i}}$ is the value of the $dth$ dimension of the $ith$ particle history optimal position. $G_{\text{best}}$ is the value of $dth$ dimension of optimal position in the particle swarm. $x_{id}^t$ and $v_{id}^t$ are the value of the $dth$ dimension of the $ith$ particle position and speed after $t$ times iteration. $x_{id}^{t+1}$ and $v_{id}^{t+1}$ are the value of the $dth$ dimension of the position and speed of the $ith$ particle after the next iteration.

### 2.4. IPSO-SVM

This paper proposes a dynamic topology to improve the global convergence performance about standard PSO. The standard swarm topology is star-shaped, and the particles learn from the globally optimal particles. As the number of iterations increases, the particle diversity will be greatly reduced, and the probability that the swarm is trapped in the local optimum is greatly enhanced. Kennedy et al. [8] studied the influence of topology on the performance of PSO, and proposed a Ring topology. The Neighborhood of each particle contains two particles before and after it. The social term learning also refers to the case of the two particles. This topology is a local search that greatly increases particle diversity, but the convergence rate is very slow and the global performance is bad.
This paper designs a window that changes with the number of iterations. The neighborhood determines the neighborhood range based on the size of the window. In the Neighborhood, the particles cooperate and learn, and the neighborhood optimal value is used to replace the global optimal value. The equation (13) for calculating the neighborhood optimal value is as follows:

\[
(C,I) = \min\{\text{fitness}(P_{(i-1)\text{best}}),\ldots,\text{fitness}(P_{\text{best}}),\ldots,\text{fitness}(P_{(i+1)\text{best}})\}
\]

\[
P_{\text{best}} = [P_{(i-1)\text{best}},\ldots,P_{\text{best}},\ldots,P_{(i+1)\text{best}}]
\]

\[
L_{\text{best}}(i) = P_{\text{best}}(I)
\]

where \( \text{fitness}(P_{\text{best}}) \) is the historical optimal fitness of the \( i \)th particle; \( P_{\text{best}} \) is the historical best position of the \( i \)th particle; \( P_{\text{best}} \) is the history optimal position set of the particle swarm in the neighborhood; \( L_{\text{best}}(i) \) is the optimal position of the neighborhood of the \( i \)th particle.

The neighborhood size is \( 2\omega \text{in}(n)+1 \). The size of the neighborhood is adjusted according to the number of iterations. When the iteration is started, the neighborhood is equal to the total particle swarm, and the global search ability is the strongest. As the number of iterations changes, the neighborhood decreases gradually into a ring shape, enhancing particle diversity and avoiding falling into locally optimal value. The neighborhood window adjustment equation (14) is as follows:

\[
\omega\text{in}(n) = \left[\text{Win}_{\text{max}}(1 - \exp(-[n-N/2]^2/\omega^2))\right] + 1
\]

where, \( \text{Win}_{\text{max}} \) is the maximum size of the window; \( n \) indicates the current number of iterations, \( N \) is the maximum number of iterations.

The larger the window, the stronger the global search ability, and the smaller the window, the stronger the local search ability. The neighborhood range varies with the number of iterations and satisfies the Gaussian distribution, as shown in the following figure 1. The Gaussian function is used to adjust the size of the window with the change of the number of iterations as figure 1 shows. The idea of normal distribution is used to balance the two kinds of the search abilities to ensure the optimal performance of the PSO. Local search is used in the middle period of the iteration to avoid premature aging. Global search is used in the early and final periods to increase global convergence performance. After using dynamic topology, the particle update equation (15) becomes:

\[
v^{i+1}_d = wv^i_d + C_1 \text{rand} \cdot (P_{\text{best}} - x^i_d) + C_2 \text{rand} \cdot (L_{\text{best}}(i) - x^i_d)
\]

where, \( L_{\text{best}}(i) \) is the value of \( d \)th dimension of the optimal position of the neighborhood of the \( i \)th particle. In addition, considering that the particle swarm has fallen into local optimum, how to increase the probability that the particle jumps out of the local optimum. A new method of particle resetting is proposed under the premise of ensuring the convergence speed after reset. Whitley and others [9] show that when two local optimal solutions are cross-combined, the two descendants obtained are also likely to be locally optimal. Therefore, this paper attempts to obtain some local optimal solutions based on the PSO framework, then uses them to cross-generated descendants as the reset particles, which can help improve the PSO convergence performance.

According to the difference of the rate of change within particle fitness of the three generations, it is judged whether it falls into local optimum.

The conditional equation (16) is as follows:

\[
\text{if} \left[ \partial \text{fitness}(x)^{i+1}/\partial t + \partial \text{fitness}(x)^i/\partial t \leq \varphi \right] \rightarrow P_{\text{num}} = [P_{\text{num},i}]
\]

\[
\text{if} \ (P_{\text{num}} \neq \emptyset) \rightarrow \text{reset}
\]

Create the P matrix of construction is as following equation (17).
where, \( p_{d1}, p_{d2}, p_{d3}, \ldots, p_{nd} \) are the values of the \( d \)th dimension of historical optimal position of each particle; \( f(P_1), f(P_2), \ldots, f(P_n) \) are historical optimal fitness of the \( n \) particles. Taking the particle optimal fitness as the ordinate and the dimension value of the particle history optimal position as the abscissa, Sort \( p_{d1}, p_{d2}, \ldots, p_{nd} \) and corresponding fitness in two-dimensional coordinate system, as shown figure 2.

In this paper, match the values of historical optimal fitness and the dimension values of the historical optimal positions as the figure 2 shows. the local minimum of the dimension is selected and cross-combined to generate the position of the reset particle. The process of achieving partition crossover according to the following pseudo code. A set of local minima for each dimension is generated and then randomly combined to obtain the better positional parameters of the reset particle. Increase the probability of jumping out of local optimum.

Step1: Perform partition crossover of P matrix

For i=1; i≤\( n \); i=i+1
If \( i \neq 1 \)\&\& \( P(i,d)<P(i+1,d)\)\&\&\( P(i,d)<P(i-1,d) \), put \( P(i,d) \) into \( Y_d \) and go to next iter.
If \( i = 1 \)\&\& \( P(i,d)<P(i+1,d) \), put \( P(i,d) \) into \( Y_d \) and go to next iter.
If \( P(i,d)<P(i-1,d) \), put \( P(i,d) \) into \( Y_d \).
End For

Step2: Repeat step 1 until get \[ Y = [Y_1, Y_2, Y_3, \ldots, Y_d, \ldots, Y_D] \]

Step3: Randomly sample from \( Y \) to generate new particles and proceed to the next iteration.

Where \( Y_d \) represents value set of the \( d \)th dimension, after cross combination, \( D \) is the dimension of solution space.

![Figure 1. Dynamic neighborhood topology.](image)
The key of IPSO-SVM is to optimize the parameters of the penalty parameters $C$ and radial basis parameter $\sigma$ in the nonlinear SVM classifier. Find the best match $C$ and $\sigma$, can significantly improve the performance of the classifier as shown below figure 3.

![Figure 2. Local optimum dimension.](image)

**Figure 2.** Local optimum dimension.

2.5. **SVM-WMV**

In this paper, an adaptive weight majority voting decision method fusing Multi-sliding window decision based on training probability of simple classifiers is proposed, which can significantly improve the recognition accuracy of the action.

Since each window is 125ms, when the gesture action is performed, and the time will continuously traverse multiple windows. At the same time, in the book [10], it has been proved that the multi-
window probability fusion is effective by Bayesian reasoning. In the theory, the weighted fusion scheme needs to assume that the entities being merged are statistically independent. In order to comply with the independent conditions in the current EMG classification system, several independent windows occupying disjoint locations on the time axis are used to segment the EMG data into small equal sets. The result of the segmentation process is the time signal in adjacent but non-overlapping windows. On account of the random nature of the EMG signal, the disjoint location of the signal on the time axis, so the statistical in-dependence of the hypothesis is demonstrated.

For the decision of a single window, this paper uses One-to-one Multi-classifier to vote by weight. Considering the misclassification in classification process, the classifier training accuracy is selected as the adaptive weight to vote. Construct the classifier weight matrix $C$ and classifier matrix $F$ as following equation (18).

$$
C = \begin{bmatrix}
0 & C_{12} & C_{13} & \cdots & C_{1n} \\
C_{21} & 0 & C_{23} & \cdots & C_{2n} \\
C_{31} & C_{32} & 0 & \cdots & C_{3n} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
C_{n1} & C_{n2} & C_{n3} & \cdots & 0
\end{bmatrix}
F = \begin{bmatrix}
f_{12} & f_{13} & \cdots & f_{1n} \\
f_{21} & 0 & f_{23} & \cdots & f_{2n} \\
f_{31} & f_{32} & 0 & \cdots & f_{3n} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
f_{n1} & f_{n2} & f_{n3} & \cdots & 0
\end{bmatrix}
$$

(18)

where, $C_{ij}$ is the accuracy of the simple SVM classifier obtained from the training of class $i$ data and class $j$ data. $n$ indicates the number of types of all gestures. $f_{ij}$ is simple classifier function value obtained according to equation (9) when classifying unknown samples between class $i$ and class $j$.

$\bar{C}$ is the Representation classifier weight matrix normalized by column as following equation (19).

$$
\bar{C} = \begin{bmatrix}
C_{11} & C_{12} & C_{13} & \cdots & C_{1n} \\
C_{21} & C_{22} & C_{23} & \cdots & C_{2n} \\
C_{31} & C_{32} & C_{33} & \cdots & C_{3n} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
C_{n1} & C_{n2} & C_{n3} & \cdots & C_{nn}
\end{bmatrix}
$$

(19)

Calculate the result of the weight vote of single window $R$ as following equation (20).

$$
R = [R_1, R_2, \ldots, R_n] = \left[ \bar{C}_1 F_1, \bar{C}_2 F_2, \bar{C}_3 F_3, \ldots, \bar{C}_n F_n \right], \bar{R} = R^T
$$

(20)

Calculate the $m$ window's classifier weight votes as equation (21).

$$
T = [\bar{R}_1, \bar{R}_2, \ldots, \bar{R}_m]
$$

(21)

In addition, considering the decision distribution of the window, the weighting scheme assigns a higher weight to the current decision and gradually reduces the weight of the previous decision. So, adding a probability vector $k_j$ to each window, the equation (22) is as follows.

$$
k_j = \exp(-0.5 \times j / m) / \sum_{i=1}^{m} \exp(-0.5 \times i / m), 1 \leq j \leq m, \ K = [k_1, k_2, k_3, \ldots, k_m]
$$

(22)

Calculate final result of voting is as following equation (23).

$$
A = [A_1, A_2, \ldots, A_n] = K \times T
$$

(23)

where, $A_1, A_2, A_3, \ldots, A_n$ are respectively Number of votes for gestures of $1,2,\ldots,n$ type. $m$ is the number of fused windows in the window group. $j$ is the label of the window in the window group. In the experiment of this paper, $m=5$.

The window group slides on the time domain of the signal, and the fusion voting is performed to optimize the decision result of the current window. The class with the highest number of votes in $A$ is the recognition result.
3. Experiment

3.1. Data Sources
The data were obtained by collecting the EMG signals of the wrist flexor and wrist extensor muscles through the Delsys system. The subjects were 8 subjects, 6 males and 2 females, aged between 20 and 35 years, to perform the required finger movements. Five kinds of pinch gestures((Thumb-Little(TL),Thumb-Middle(TM),Thumb-Ring(TR),Thumb-Index(TI),Hand-Close(HC)) were designed in which each action is repeated 6 times, each duration is 5s, containing 20,000 data points. The EMG collected from the electrode is amplified to a total gain of 1000 using a Delsys Bagnoli-8 amplifier. A 12-bit analog-to-digital converter is used to sample the signal at 4000 Hz, then the EMG signal is bandpass filtered between 20-450 Hz, and the notch filter is used to eliminate the 50 hz power frequency interference. The Algorithm experiments were performed using 5 subject data. The experimental data in this paper is from the Famous scholar Rami N. Khushaba’s paper [11].

3.2. Result Analysis
The two-channel EMG signals of TL, TM, TR, TI, and HC gestures are shown in figure 4 below. The left side of the figure is the first channel EMG signals, and the right side is the second channel EMG signals. In this paper, the idea of non-overlapping adjacent sliding window is used to separate the signal and quickly calculate the sample entropy of the data in the window After EMD decomposition. The window size is 125 ms, as shown in figure 5 below.

![Figure 4. Original EMG signals.](image1)

![Figure 5. Non-overlapping adjacent sliding window.](image2)
In the experiment, five kinds of gestures of HC, TI, TL, TM and TR were collected from different individuals. After decompose the EMG signal of each channel by EMD, quickly calculate sample entropy for each channel. The characteristics of the two channel EMG signals describe by two-dimensional entropy. The feature vector distribution of four different individuals with different gestures is shown in figure 6. It is seen from figure 6 that the feature vectors are clearly separated and the effect is obvious. After using IPSO to optimize the SVM classifier parameters, the classification planes of the 10 classifiers of the five gestures and support vectors are as shown in the following figure 7.

In this paper, EMG data collected from 5 subjects was tested. The EMD decomposition and sample entropy calculation are used to obtain the eigenvectors of the two-channel EMG signals. The recognition rates of five kinds of gestures by SVM, PSO-SVM, PSO-LIBSVM, PSO-SVM-WMV, and IPSO-SVM-WMV are compared. The experimental results are as following figure 8. It can be seen
from figure 8 that IPSO-SVM-WMV has a recognition rate of more than 90% for each gesture compared to the other four methods, and two gestures reach over 97%, and for each gesture. The recognition accuracy is higher than the other four algorithms. It can be seen from figure 9 that using IPSO-SVM-WMV algorithm proposed in this paper, the average recognition rate reaches 94.65% based on double-channel EMG signals, and the recognition rate of the traditional SVM method is 89.7%. After using the classical PSO algorithm to optimize SVM and LIBSVM, the recognition rate is only about 90.8% and 91.1%. Since the recognition accuracy of the above five methods is above 89%, the entropy method used in this paper has achieved good results. in the above five kinds of gesture feature extraction, and the proposed IPSO-SVM-WMV is based on the traditional SVM method. The accuracy is improved by 5%, which is 3.8% higher than the classical PSO-SVM method. Therefore, the method proposed in this paper has certain practical value.

4. Conclusion
This paper studies the gesture recognition based on double-channel EMG signals. The algorithm proposed in this paper improved global convergence of particle swarms and reduced the possibility of local optimum. And the generalization ability of the algorithm is also greatly improved by fusion decision of multi-window. Sample entropy is a good representation of the characteristics of EMG signals. Combination of sample entropy and IPSO-SVM-SVM algorithm have a good application effect in the field of gesture recognition of surface EMG signals. It significantly improves the accuracy of gesture recognition under low cost and comfort conditions about Wearable device. This paper
provides some ideas and recommendations for the application of EMG signals in remote operation, rehabilitation and repair applications.

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