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Classification of surface electromyogram signals based on directed acyclic graphs and support vector machines

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Abstract: This paper presents a novel classification approach for surface electromyogram (sEMG) signals. The proposed classification approach involves two steps: (1) feature extraction from an sEMG, in which a 7-dimensional feature vector is extracted from 27 types of features of the sEMG by linear discriminant analysis (LDA), and (2) a novel classifier, DAGSVMerr, based on a directed acyclic graph (DAG) and support vector machine (SVM), in which a separability measure function based on erroneous recognition rates (ERRs) is defined to determine the initial operation list. The proposed approach takes advantage of the feedback idea to improve the performance of the classification. The experimental results show that the proposed approach has a better performance than traditional methods, and it achieves an average classification accuracy rate of 99.4% ± 1.3% with an error rate of 0.6%. Correct classification rates of the proposed approach are very high, and the approach can be utilized to recognize gesture instructions by analyzing sEMG signals in gesture equipment control studies.

Key words: Surface electromyogram, classification, directed acyclic graph, support vector machine

1. Introduction

A surface electromyogram (sEMG) signal reflects the electrical activity of skeletal muscles that manifest different parts of body movements, thus providing information about the structure and function of muscles [1]. Due to the complex nature of the signal and its nonstationary characteristics, detailed analysis and classification of movements are very difficult [2] and, therefore, it is crucial to build an effective recognition model to accurately classify body language. The sEMG classification/analysis steps are shown in Figure 1.

Figure 1. Basic diagram of the recognition procedure.

The classification stage can be briefly defined as the process of recognizing one out of all specific classes for a given input vector [3]. Many empirical studies have been conducted that investigate different types of classifiers using various features computed from sEMG signals. For real-time, close-range, and convenient controlling, a variety of classification approaches, such as the support vector machine (SVM), neural networks (NNs), and quadratic discriminant analysis (QDA), have been applied to estimate the motion intent from the sEMG signals

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[4–6]. Among the various types of classifiers, however, the SVM is considered to have a better performance than other approaches such as decision trees, neural networks, and model-based reasoning approaches [7]. For example, the research in [8] showed that compared to multilayer perceptron neural networks and classification and regression trees (CARTs) SVMs had a superior generalization capability in their classification performance with respect to the training sample size, sample variability, and landscape homogeneity. In addition, modified algorithms based on SVMs have resulted in excellent performances. In [9], a multiple-kernel learning SVM (MKL-SVM) is proposed as a novel technique for the efficient recognition of hand gestures, and the experimental results showed promising performance results in offline recognition, with an average recognition accuracy rate of above 91% and a highest accuracy rate of 97.93%.

However, when performing one-time recognition of all classes, there is a serious problem: one or two classes are predicted wrongly as belonging to other classes, which severely decreases recognition accuracy. For example, in [10], the recognition rate of the wrist extension movement was able to reach 99.59%, while the pinch grip movement obtained only an 84.69% recognition rate, with an 8.68% chance of predicting it inaccurately as a power grip movement.

Current multiple classifiers based on SVMs are mainly achieved through a series of binary classifiers, in which there are two common algorithms: one-against-the-rest (one-vs-rest) and one-against-one (one-vs-one). The one-vs-rest algorithm takes samples from one class as a class and samples from the other classes as another class and trains the classifiers in turn. The one-vs-one algorithm combines all of the possible classifiers and trains the classifiers with two of these classes at a time. However, these two algorithms have limitations in their practical application. For example, any classifier's errors could lead to the existence of nonseparable regions or, even worse, the training speed of these multiple classifiers will be slow when there is an increase in the number of training samples or in the number of categories [11].

In this work, a novel classifier is proposed to solve the confusion problem. This approach combines the advantages of the directed acyclic graph (DAG) and the SVM and defines an initial operation list function. The DAG utilizes a coarse-to-fine strategy for classification that includes several binary classifiers. The SVM is superior in the nonlinearly separable problem because it transforms the problem into a linearly separable one in a high-dimensional space to find the optimal hyperplane between two classes. The proposed method uses the SVM as the binary classifier at each node in the DAG. To obtain the initial operation list of the DAG, we apply the feedback ideas with the erroneous recognition rates (ERRs) and define a new separability measure function, which means that we obtain feedback information by preclassification. As a result, we can determine the order of the classes in the list.

2. Methodology

2.1. Data collection

In this study, fifteen subjects from Beijing Forestry University in China with no neurological or muscular disorders volunteered to participate in the experiments. The average age of the subjects was 23 years (range: 20–27).

The six hand gestures [12] included fist, finger spread, palm supination, palm pronation, palm lateral supination, and palm lateral pronation, as presented in Figure 2. These four selected muscles were the palmaris longus, brachioradialis, extensor digitorum, and extensor carpi ulnaris. The placement positions of surface electrodes are shown in Figure 3.

A 4-channel sEMG system (Life Science Instrument, Chengdu Instrument Factory, Chengdu, China)

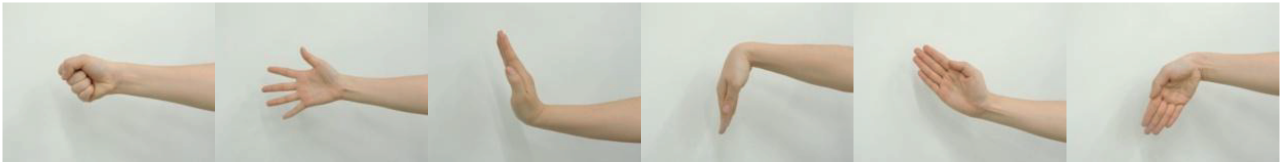
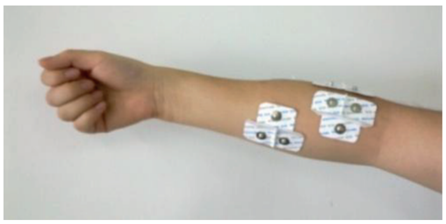
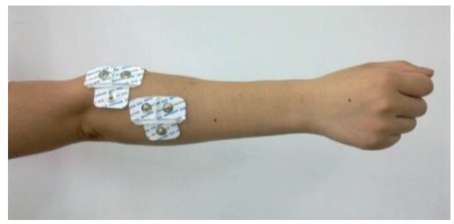


Figure 2. Six classes of hand gestures: fist, finger spread, palm supination, palm pronation, palm lateral supination, and palm lateral pronation.



(a) Abdominal positions of palmaris



(b) Abdominal positions of extensor digitorum

Figure 3. Photo of placement positions of surface electrodes: a) abdominal positions of palmaris longus muscle and brachioradialis muscle; b) abdominal positions of extensor digitorum muscle and extensor carpi ulnaris muscle.

was used to collect the sEMG signals from each subject using disposable AgCl electrodes (Junkang Medical Equipment Inc., Shanghai, China) placed on the surface of four muscles as mentioned above. The sampling frequency of the acquisition system was 1000 Hz.

Fifteen subjects with no neurological or muscular disorders volunteered to participate in the experiments. All of the subjects signed informed consent documents. Every gesture was repeated 10 times, and the interval between two adjacent movements was approximately 5 s.

2.2. Feature set computation and reduction

To comprehensively reflect the information of the sEMG signals, features that were used in previous research studies were collected in this study. Twenty-seven features of four types (time-domain, frequency-domain, time- and frequency-domain, and nonlinear dynamic features) were calculated. The ten time-domain features included mean absolute value, mean absolute value slope, Willison amplitude, variance (VAR), zero crossing, slope sign change, waveform length (WL), root mean square, autoregressive coefficients (AR), and autoregressive coefficients from the first difference of EMG (FDAR) [6,13–15]. The two frequency-domain features were median frequency and mean power frequency [16–18]. The twelve time- and frequency-domain features included maximum, singular value, average energy, VAR, standard deviation, and WL of wavelet coefficients and wavelet packet coefficients [19–26]. The three nonlinear dynamic features were entropy of wavelet coefficients, entropy of wavelet packet coefficients, and maximum of Lyapunov exponent [27–29]. We made use of wavelet base sym3 to decompose the sEMG signal into three layers by wavelet decomposition and wavelet packet decomposition. Therefore, we obtained 252-dimensional vectors for the final feature set.

In this study, linear discriminant analysis (LDA) [30] was employed to reduce the feature dimensionality. The basic idea of LDA is to attempt to project the class samples onto a finely orientated line in such a way that the scatter within the class is as small as possible and the scatter between classes is as large as possible. Therefore, to separate the classes, the LDA algorithm must seek a projection matrix that projects the original

p-dimensional observation space into a c-dimensional feature space. The linear transformation matrix T can be obtained by

$$J(T) = \frac{\left|T^T S_B T\right|}{\left|T^T S_w T\right|}, \tag{1}$$

where S_B is the between-class scatter and S_W is the within-class scatter.

2.3. Recognition algorithms

2.3.1. Directed acyclic graph

Platt et al. [31] proposed a DAG that was a new learning architecture used to combine several binary classifiers into a multiclass classifier based on the one-vs-one algorithm. With regard to the m-motion classification, there are $m(m-1)/2$ decision nodes in the DAG method corresponding to $m(m-1)/2$ binary classifiers that are distributed in the m-layer structure. As in Figure 4, there is only one node called the root node in the top layer, two nodes in the second layer and, similarly, j nodes in the jth layer and m nodes in the bottom layer, with the ith node in the jth layer pointing to the ith node and $(i{+}1)$th node in the $(j+1)$th layer.

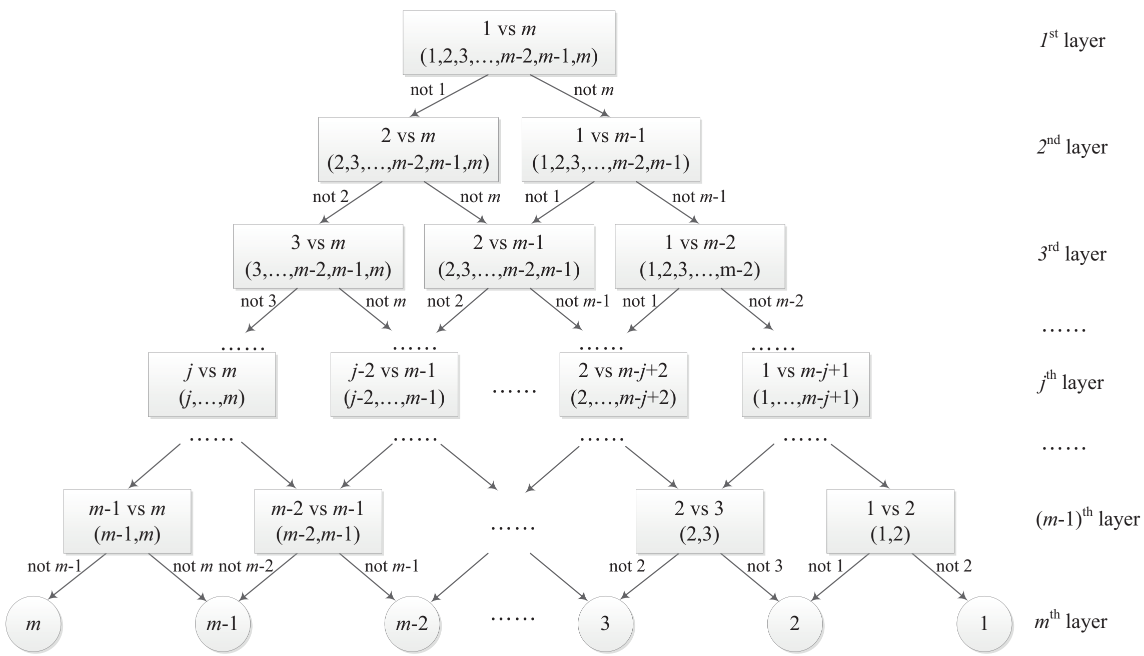


Figure 4. Structure chart of a DAG.

For a given input sample, the corresponding decision function value of each node will be calculated from the root node. If the value is 1, which indicates that this sample does not belong to the first class in the class ordering for this node, we enter the next node from the left. If it is -1, which indicates that this sample does not belong to the last class in the order, we enter the next node from the right. We then calculate the decision function value of the next node and so on. The output of the nodes in the bottom layer represents the class of this sample.

The procedure of a DAG is equivalent to operating on a list, and each node eliminates one class from the list. In the initial state, all of the classes are included in the table, and during the classification, a test sample is evaluated at the decision node that corresponds to the first and last elements of the list. If the node prefers one of the two classes, this means that there is a higher possibility that the sample belongs to this class, and the other class is eliminated from the list.

Different decisions on the nodes could contribute to different paths of several samples, which could directly impact classification performance. In other words, the classification results of the DAG are highly dependent on class ordering.

2.3.2. Support vector machine

The SVM was originally designed for two-class classification. It aims to find the optimal hyperplane between two classes by mapping the sample space into a high-dimensional feature space, called the Hilbert space, to change the nonlinearly separable problem in the primary space to a linearly separable problem in the feature space. The classification problem in this paper is specifically a nonlinearly separable problem for which the SVM has a great advantage. The SVM can be extended to multiclass classification [32]. The nonlinear transformation that transforms the input space into a high-dimensional space is realized by defining an appropriate inner product function.

In the SVM, a kernel function K maps a sample x to a feature space ϕ given by a feature map $K(x_i, x_j)\,\langle\phi(x_i), \phi(x_j)\rangle$. Currently, the most commonly used inner product functions are the polynomial kernel function, the radial basis function, and the linear kernel function. In this paper, the radial basis function was selected. Except for types of inner product functions, the most important parameters that influence the properties of the SVM are the error penalty factor c and the kernel function parameter g. The major influence of the kernel function parameter g on the SVM performance is through the complexity distribution of the sample data in the high-dimensional feature space, while the role of the error penalty factor c is exploited through the ratio of the fiducial range and empirical risk in the determined feature space. This study utilizes the grid search method [33] to acquire the best combination for (c, g).

2.3.3. Modified classifier based on a DAG and SVM

To determine the initial operation list, the separability measure (SM) is computed, usually by the Euclidean distance [34] called DAGSVMeuc1. The authors in [35] proposed a classification measure based on the distribution of multiclass data and the Euclidean distance called DAGSVMeuc2. However, with regard to gesture classification based on a sEMG signal, the feature set is multidimensional, which gives the SM based on the Euclidean distance no practical significance. In this study, the ERRs were provided from the preclassification that was done through cross-validation (CV) methods, from which we can get the ERRs through training data. The classification of each fold in CV was done through a one-vs-one SVM. ERRs are utilized to calculate the SM to determine the initial operation list, which means that the higher the number of times that class i is misrecognized as class j and that class j is misrecognized as class i, the larger the value of the SM between class i and class j.

Consider the training data $X = \{X_1, X_2, \cdots, X_m\}$, which has m classes; the SM value $sm_{ij}(ij = 1, 2, \cdots, m)$ is defined as

$$sm_{ij} = \frac{ERR(i,j) + ERR(j,i)}{\sum_{p=1}^{m}\sum_{q=1}^{m} ERR(p,q)}, \tag{2}$$

where $ERR(i,j)$ is the number of erroneous recognition times in which class i is misrecognized as class j.

A between-class SM matrix can be obtained by calculating $sm_{ij}(ij = 1, 2, \cdots, m)$. Thus, the initial operation list can be constructed with the following steps: the first step is to seek the maximum of the SM values among class k and other classes, $k = 1, \ldots, m$, the second step is to compare the maximum values that indicate the similarity between this class and other categories and sort these classes, and the last step is to construct the initial operation list.

First, for every class, there are $(m-1)$ SM values with other classes. These values are first arranged in a large-to-small order and they are renumbered. For example, the renumbered order of the SM values between class k and the other classes is $re\_sm_{k1} \gg re\_sm_{k2} \gg \cdots re\_sm_{kt} \cdots \gg re\_sm_{k(m-1)}$, $t = 1, 2, \cdots, m-1$.

Second, according to the large-to-small order of $re\_sm_{k1}(k = 1, 2, \cdots, m)$, sort the corresponding classes. When there are two or more classes that have the same value for re_sm_{k1}, compare their values for re_sm_{k2} and continue in the same manner; in addition, if the values of re_sm_{k1}, re_sm_{k2}, $\cdots$, $re\_sm_{k(m-1)}$ are equal, then put the class that has the smaller label in front. For example, while comparing class i and class j, if $re\_sm_{i1} < re\_sm_{j1}$, then place class i in front of class j and, conversely, if $re\_sm_{i1} > re\_sm_{j1}$, then place class j in front of class i. If $re\_sm_{i1} = re\_sm_{j1}$, then re_sm_{i2} and re_sm_{j2} will be compared and, successively, if $re\_sm_{it} = re\_sm_{jt}$ $(t = 1, 2, \cdots, m-1)$, then place the one that has the smaller label of i and j in front of the other.

Finally, according to the orderings of all of the classes obtained from step 2, construct the initial operation list, which is $[s_1 s_2, \cdots, s_m]$, $s_k \in \{1, 2, \cdots, m\}$, $k = 1, 2, \cdots m$, in which k indicates the class labels. Accordingly, the two classes of the leading and trailing order are the least likely to be confused and, hence, by arranging the ordering of the nodes, DAG topology is generated.

3. Results

There were fifteen subjects in total, and each subject performed 10 experimental trials for each of the six designed hand gestures; thus, there were a total of 900 active segments. Then 90% of the feature data were considered as training data based on the separate individual trials, which were the training data of the classifiers, and the others were considered to be testing data. For the characteristic data for each subject, ten sets of training and test data were randomly obtained, such that each set formed different initial operation lists for the three algorithms based on the DAG. The final recognition rates were the average of the ten tests' results.

Table 1 shows the ten tests' results of five different classifiers, including one-vs-rest, one-vs-one, DAGSVMeuc1, DAGSVMeuc2, and the proposed DAGSVMerr method. The recognition accuracies are as follows: one-vs-one 95.5% $\pm$ 4.2%, one-vs-rest 97.3% $\pm$ 2.8%, DAGSVMeuc1 98.1% $\pm$ 2.8%, DAGSVMeuc2 98.7% $\pm$ 2.2%, and DAGSVMerr 99.4% $\pm$ 1.7%. It is clear that DAGSVMerr has the highest accuracies, with a rate of 100% for the twelve subjects.

From the confusion matrices in Figure 5, we can see that, comparatively, the recognition accuracies for the six gestures and the overall average accuracies of DAGSVMerr are quite satisfying, except that class 1 was misrecognized as class 2 three times.

The execution time, which was computed as the average of ten sets, is presented in Table 2. Since the classifiers based on a DAG must form the initial operation list, their execution time consists of two parts, the time for forming the initial operation list and the time for classification. Although the total time of a DAG method could be longer than that of one-vs-rest or one-vs-one, the time of the second part is more significant in a practical application because the step of forming the initial operation list is completed when training the classifiers.

Compared with one-vs-rest and one-vs-one, DAG methods can solve the unclassifiable region problems and achieve higher prediction accuracies and, because they use fewer binary sub-classifiers, DAG methods execute

Table 1. Overall classification accuracies (%) for each subject when employing different classifiers.

Subject no.	One-vs-rest	One-vs-one	DAGSVMeuc1	DAGSVMeuc2	DAGSVMerr
1	100.0	100.0	100.0	100.0	100.0
2	93.3	100.0	100.0	100.0	100.0
3	95.0	95.0	100.0	95.0	95.0
4	96.7	96.7	100.0	100.0	100.0
5	90.0	90.0	93.3	93.3	100.0
6	83.3	95.0	100.0	100.0	100.0
7	100.0	98.3	98.3	98.3	98.3
8	98.3	100.0	96.7	100.0	100.0
9	98.3	100.0	100.0	100.0	100.0
10	95.0	95.0	93.3	100.0	100.0
11	98.3	98.3	98.3	98.3	98.3
12	95.0	100.0	91.7	100.0	100.0
13	98.3	98.3	100.0	100.0	100.0
14	93.3	95.0	100.0	95.0	100.0
15	98.3	98.3	100.0	100.0	100.0
Average (mean $\pm$ SD)	95.5 ± 4.2	97.3 ± 2.8	98.1 ± 2.8	98.7 ± 2.2	99.4 ± 1.3

Table 2. Execution time of the five algorithms.

Algorithm based on SVM	Time for forming the initial operation list/(s)	Time for classification/(s)
One-vs-rest	-	0.2934
One-vs-one	-	0.1508
DAGSVMeuc1	0.0087	0.1249
DAGSVMeuc2	0.4947	0.1278
DAGSVMerr	0.2529	0.1187

the classification faster. When applied to the analysis of the sEMG data obtained in this study, the proposed DAGSVMerr method, which initializes the operation lists by introducing the SM based on ERRs, rearranges the node sequence and constructs the topology structure, improving the effectiveness of the prediction for the six gestures.

4. Discussion and conclusions

In this paper, we introduced and evaluated the proposed classifier DAGSVMerr for sEMG classification. The performance of this novel classifier was discussed with regard to three aspects. First, the classification accuracies for each subject show that DAGSVMerr has a better generalization ability than other classifiers (one-vs-rest, one-vs-one, DAGSVMeuc1, and DAGSVMeuc2). Second, the confusion matrices suggest that for each gesture motion, the accuracies of DAGSVMerr are satisfactory. Through comprehensive consideration of Table 1 and Figure 5, the order of the classification performances in terms of their accuracies is the following: DAGSVMerr > DAGSVMeuc2 > DAGSVMeuc1 > one-vs-one > one-vs-rest. Third, the execution time for the classification

One-vs-rest

	1	2	3	4	5	6	Acc/%
1	140	5	0	1	1	3	93.33
2	3	141	1	2	1	2	94.00
3	0	2	144	0	1	3	96.00
4	0	0	0	148	0	2	98.67
5	0	5	0	1	144	0	96.00
6	2	2	0	3	0	143	95.33

Overall accuracy (Mean ± SD): (95.56± 1.7087)%

(a)

One-vs-one

	1	2	3	4	5	6	Acc/%
1	142	4	0	0	4	0	94.67
2	3	143	3	0	1	0	95.33
3	0	2	148	0	0	0	98.67
4	0	0	0	147	0	3	98.00
5	0	0	0	0	150	0	100.00
6	3	0	0	1	0	146	97.33

Overall accuracy (Mean ± SD): (97.33± 1.8461)%

(b)

DAGSVMeuc1

	1	2	3	4	5	6	Acc/%
1	147	2	0	0	1	0	98.00
2	0	145	3	0	2	0	96.67
3	0	3	147	0	0	0	98.00
4	0	0	0	150	0	0	100.00
5	0	0	3	0	147	0	98.00
6	2	0	0	1	0	147	98.00

Overall accuracy (Mean ± SD): (98.11± 0.9742)%

(c)

DAGSVMeuc2

	1	2	3	4	5	6	Acc/%
1	147	2	0	0	1	0	98.00
2	3	147	0	0	0	0	98.00
3	0	2	148	0	0	0	98.67
4	0	0	0	147	0	3	98.00
5	0	0	0	0	150	0	100.00
6	0	0	0	1	0	149	99.33

Overall accuracy (Mean ± SD): (98.67± 0.7693)%

(d)

DAGSVMerr

	1	2	3	4	5	6	Acc/%
1	149	0	0	0	1	0	99.33
2	3	147	0	0	0	0	98.00
3	0	0	150	0	0	0	100.00
4	0	0	0	150	0	0	100.00
5	0	0	0	0	150	0	100.00
6	0	0	0	1	0	149	99.33

Overall accuracy (Mean ± SD): (99.44± 0.7116)%

(e)

Figure 5. Confusion matrices of the five algorithms: a) One-vs-rest; b) One-vs-one; c) DAGSVMeuc1; d) DAGSVMeuc2; e) DAGSVMerr.

of the modified method is shorter than that of the others. Moreover, the difference between the three classifiers based on DAGs is the initial operation list. This finding suggests that the initial operation list plays an important role in classification performance.

By studying the existing literature, we also noted that the recognition results in our case are comparable to, or even better than, the rates in similar-gesture cases. Chen et al. [36] utilized a discriminant bispectrum feature extraction approach and AR model to attain features from the collected six-channel sEMG signals and classifying gestures by using SVM, with an average classification accuracy rate of 98.46%. They claim that the recognition rate was as high as 99.4%, but this was only for a particular subject. Second, in [21], for eight sEMG channels, the discrete wavelet transform and SVM were used to classify the same gestures as those in this study, and the reported misclassification rate was 4.7% ± 3.7%. Third, Liu [37] employed a combination of AR model coefficients and the time domain feature set from the eight-channel sEMG signals as features, and the average recognition rate of the adaptive unsupervised classifier based on SVM was 96.6% ± 1.5%. In terms of classification accuracy, the recognition method of this paper is superior to those in the above-mentioned articles, and this paper only collected the signals of the four channels, indicating that our gesture recognition system extracted effective features from the original signals with less information. Furthermore, the DAGSVMerr method made full use of these features, successfully solved the confusion problem, and eventually made a significant recognition performance.

In conclusion, our experiment demonstrates that DAGSVMerr, which considers ERRs as feedback information, is superior to other traditional SVM classifiers. This study has established a proper basis for further research, and the findings can be applied in many EMG applications, including myoelectric control; thus, they can be applied in practical applications such as human–computer interaction.

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