Fine Movement Classification for Finger and Arm Movements

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Abstract- The existing research on gesture classification has mainly focused on larger amplitudes. However, studying subtle movements is essential to achieving precise control of prosthetics or manipulators. This paper proposes a refined recognition method for finger and arm movements. Ten-finger and ten-arm movements were designed for subtle classification, respectively. Features extracted from the time domain, frequency domain, and time-frequency domain included Mean Absolute Value (MAV), Fast Fourier Transform (FFT), and Hilbert-Huang Transform (HHT). The study compares the effects of seven types of feature combinations and uses five classification algorithms to predict results. The combination of "FFT+HHT" yielded better results, and the linear discriminant analysis algorithm achieved better prediction accuracy. This research has significant implications for the precise control of robots or prosthetics and proper rehabilitation in later stages.

Index Terms **— sEMG, classification, features, movement**

I. INTRODUCTION

The application of EMG has extended beyond traditional areas such as medical diagnosis and rehabilitation engineering to prosthetic control and human-robot interaction. Surface electromyography (sEMG) is a bioelectrical signal that contains various muscle activities, including deep layer EMG signals extracted from needle electrodes and surface EMG signals extracted from surface electrodes. While needle-type sensors perform well in receiving clear EMG signals, the trauma caused to the human body by the insertion of the needle deeply into muscles seems unavoidable. Conversely, the non-invasive nature of surface electrodes extracting movements makes them widely used as control signals for intelligent robotic arms and other devices. To achieve precise control of the intelligent robotic arm, it is necessary to improve the classification accuracy of movements. In the existing research, emphasis has been placed on the classification of sEMG signals with larger amplitudes, which are easier to distinguish and typically yield higher accuracy. Chu *et al*. [1] employed a Wavelet Packet Transform (WPT) to extract features. They classified eigenvalues with the Linear Discriminant Analysis (LDA) to recognize eight hand actions, and the precision could reach 97.4%. Kevin *et al*. [2] placed a four-channel Ag-Cl sensor on the arm, extracted four features for the hand's six movements, and classified them with LDA. The classification conclusion could reach 98%. Michael *et al*. [3] combined accelerometers and gyroscopes with myoelectric sensors to organize 17 activities in everyday life. The angular acceleration and the angular velocity were respectively averaged, and the averages were separately integrated as two sets of features. Root Mean Square (RMS) was used as an additional feature for the sEMG, and the accuracy was 89.2%. Despite the high accuracy attained in previous studies by focusing on larger amplitude movements, little research has been conducted on movements with smaller amplitudes. This paper focuses on fine movements, which refer to upper limb actions with subtle differentiation, such as the combination of finger extension and closure depicted in FIGURE 1(a).

Surface Electromyography (sEMG) is a non-stationary bioelectrical signal that arises in a muscle when it contracts. The primary focus of sEMG research has been on feature extraction and classification. Various feature extraction methods have been employed by researchers to enhance the classification performance of sEMG. For instance, Dori et al. [4] employed the discrete Fourier transform to process the signals, achieving a percent correct of 65%. Sebastian et al. [5] used Root Mean Square (RMS) to obtain the eigenvalues, which yielded an accuracy of 77.4%. Yang et al. [6] employed Maximum Absolute Value (MAV) and obtained a 96% accuracy while testing 11 subjects. In addition to these methods [4-6], others such as Wavelet Transform (WT), Fast Fourier Transform (FFT), and Hilbert-Huang Transform (HHT) have also been used. Nagineni et al. [7] applied Hilbert-Huang Transform to the EMG signal to classify

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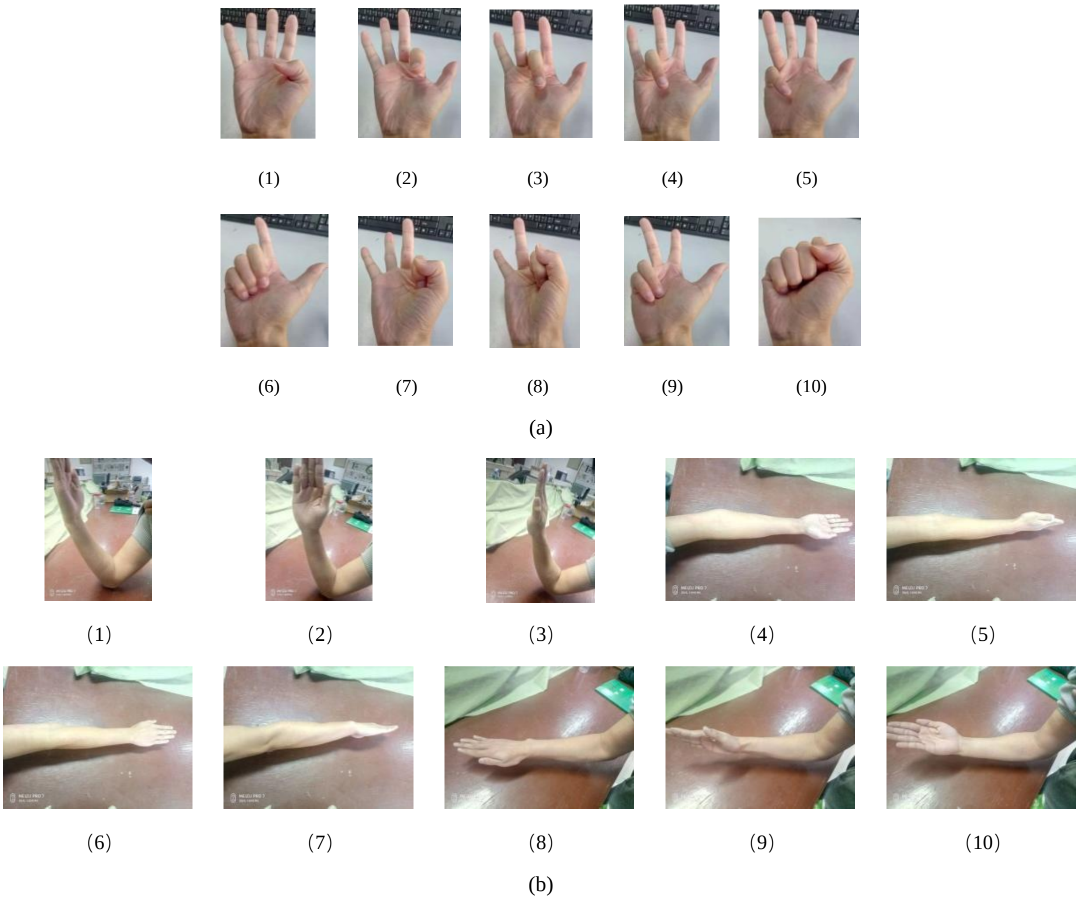


FIGURE 1. The movements for subjects to complete. (a) Ten finger movements. (1)~(5) Five fingers bend separately, and other fingers stretch out; (6) (7) respectively stretch and bend two fingers; (8) (9) respectively stretch and bend three fingers. (b) 10 arm movements. (1)~(3), (4)~(7), (8)~(10) are three groups, and the difference is the direction of the palm.

forearm movements and obtained good results. In this study, the "MAV+FFT" technique was used to distinguish the sEMG, inspired by [7].

This paper presents a classification method for fine movements of fingers and arms. While previous studies focused on larger movements that are easier to distinguish and hence produced higher accuracy, the study of slight movements is crucial for improving prosthetic or robot control precision in the future. The feature extraction methods utilized in this study include HHT, FFT, and MAV. Subsequently, five algorithms are compared, and the results show that LDA has a better recognition effect [8-10].

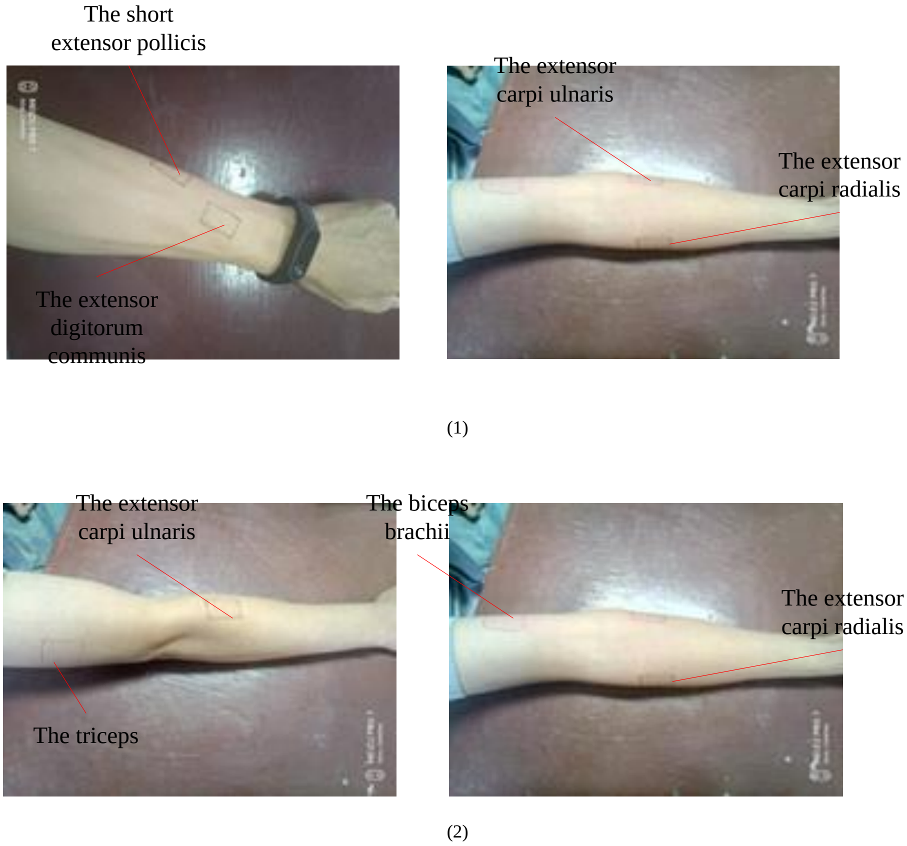
II. BACKGROUND AND METHODS

A. USER TRAINING

Twelve participants were recruited for this study, comprising of 11 males and 1 female, with ages ranging from 23 to 32 years. Ten of the participants were right-handed, while the remaining 2 were left-handed. Prior to the experiment, the subjects were provided with detailed information about the study. They were trained to perform the movements presented in FIGURE 1 to ensure consistent performance of the movements with the same intensity and amplitude during testing. The subjects were required to complete the movements depicted in FIGURE 1 (a) and (b), respectively. In FIGURE 1 (a), the finger movements were relatively small, resulting in a minor variation in the myoelectric signals extracted. In (b), the arm movements could be divided into three groups, each consisting of movements that differed only in the rotation of the palm. For the movements in FIGURE 1(a), the sEMG sensors were placed on the extensor carpi radialis, the extensor carpi ulnaris, the short extensor pollicis, and the extensor digitorum communis. For the movements in FIGURE 1(b), the sensors were placed on the extensor carpi radialis, the extensor carpi ulnaris, the biceps brachii, and the triceps. The position of the sEMG sensors is depicted in FIGURE 2. A tester placed the sensors, and the participants followed the tester's instructions to complete the movements. Prior to the test, the subjects were asked to familiarize themselves with the selected movements. The process is illustrated in FIGURE 3.

B. DATA COLLECTION

Four sEMG sensors were used with an acquisition frequency 1000 Hz, as shown in FIGURE 4. The data acquisition card was the Advantech USB-4704. The feature extraction and classification program runs on a Lenovo PC (CPU: Intel i5-6500, RAM: 20G, SSD: 128G, Windows 7) and MATLAB2017B. FIGURE 5 shows the acquired myoelectric signals. Every movement lasted for 5 seconds with an interval of 5 seconds, so a group of 5 activities lasted for 25 seconds in total. The break is added; it's 50 seconds.



IGURE 2. sEMG sensors' position. (1) corresponding to the movements in FIGURE 1(a); (2) corresponding to movements in FIGURE 1(b).

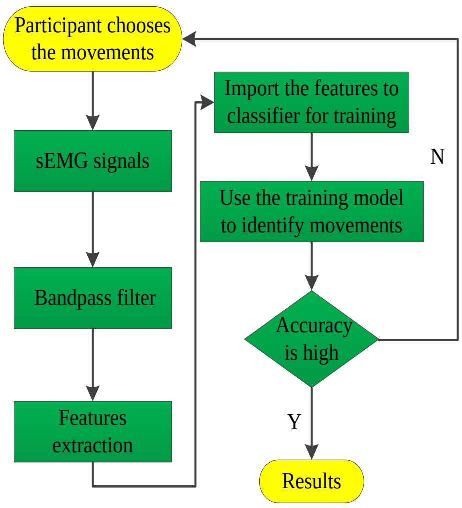


FIGURE 3. The recognition process

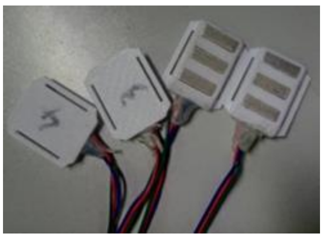


FIGURE 4. sEMG sensors

C. FEATURES EXTRACTION AND CLASSIFICATION ALGORITHMS

The collected data required pre-processing before feature extraction. According to previous studies [11-17], the data was bandpass filtered from 20-200 Hz, and Kalman filtering was applied. To ensure minimal perceptible delay, a data set of 250 milliseconds was selected to obtain features. Selecting appropriate features is crucial to ensure classification accuracy, as highlighted in [18]. Time-domain methods, such as Mean Absolute Value (MAV) [15], the number of Zero-Crossings (ZC) [15, 19, 20], Waveform Length (WL) [14], and Slope Sign Changes (SSC) can be used for feature extraction. Frequency-domain methods, such as Fast Fourier Transform (FFT), Mean Square Frequency (MSF), and Root Mean Square Frequency (RMSF), can also be employed. Time-frequency domain methods include Short-time Fourier transform (STFT) [11], Wavelet Transform (WT) [11], and wavelet transform coefficients. For this study, MAV, FFT, and HHT were used for feature extraction [21, 22].

1) Mean Absolute Value (MAV)

$$\mathrm{MAV} = \frac{1}{N}\sum_{n=1}^{N}\left|x(n)\right| \tag{1}$$

where, N is the number of the sample; $x(n)$ is the signal value.

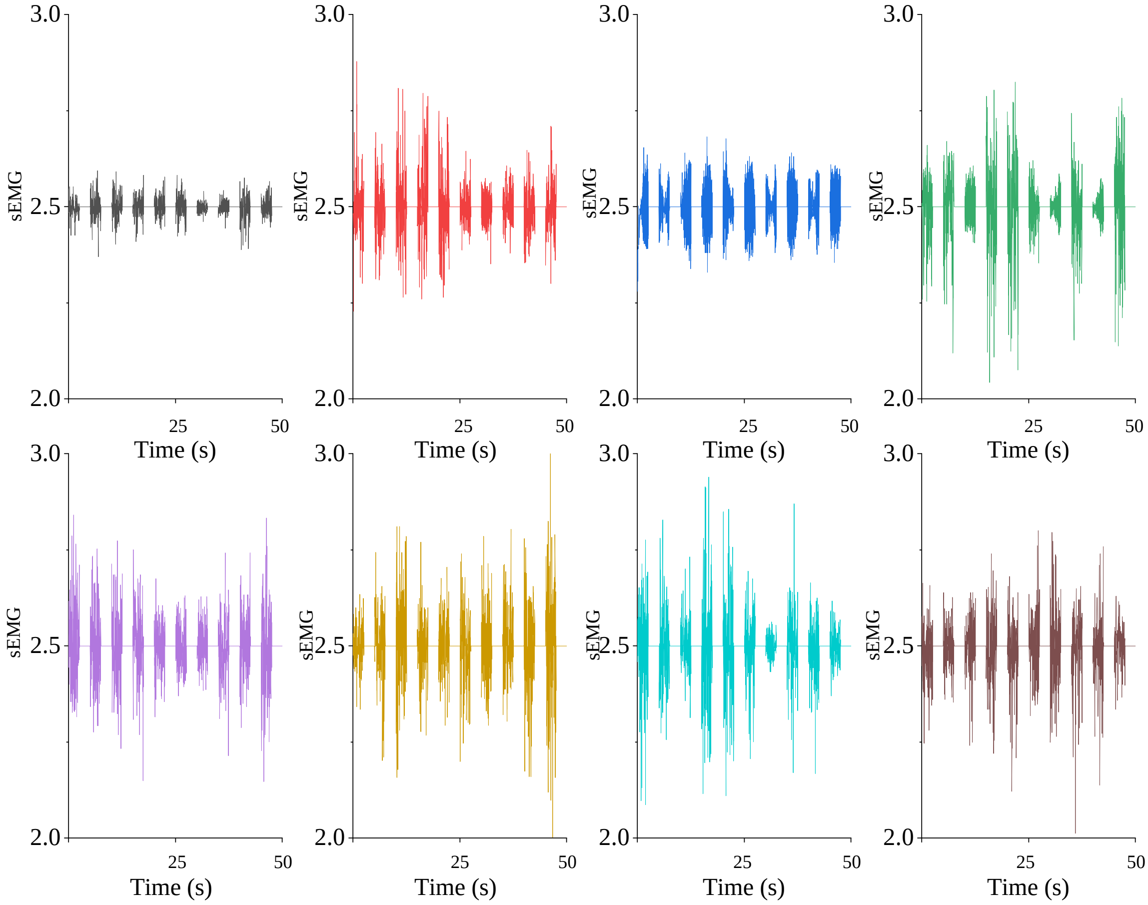


FIGURE 5. The following signals were acquired during the experiment: (1) sEMG of extensor carpi radialis, (2) sEMG of extensor carpi ulnaris, (3) sEMG of short extensor pollicis, and (4) sEMG of extensor digitorum communis for finger movements; (5) sEMG of carpi radialis, (6) sEMG of extensor carpi ulnaris, (7) sEMG of biceps brachii, and (8) sEMG of triceps for arm movements.

2) Fast Fourier Transformation (FFT)

The Fourier transform converts the signals from the time domain to the frequency domain; thus, researchers could observe information that can't be kept in the time domain. In the frequency domain, it was possible to follow each frequency component's amplitude and the primary frequency distribution of the sEMG. The Fourier transform of the signal $x(n)$ is

$$H\left(\mathrm{e}^{\mathrm{j}\omega}\right)=\sum_{n=0}^{\infty}x(n)\mathrm{e}^{-\mathrm{j}\omega n} \tag{2}$$

where, ω is the frequency.

3) Hilbert-Huang Transform (HHT)

$$x(t)=\sum_{i=1}^{n}c_i(t)+r(t) \tag{3}$$

where, $x(t)$ is the original signal; $c_i(t)$ is the decomposition of each IMF component, and $r(t)$ is the remainder. The Hilbert transform is

$$H[c_i(t)]=\frac{1}{\pi}\int_{-\infty}^{\infty}\frac{c_i(\tau)}{t-\tau}\mathrm{d}\tau \tag{4}$$

The instantaneous frequency $w_i(t)$ can be obtained as

Most signals do not have linear stability in real life, but the Hilbert algorithm requires that the input signals be linearly stable. Thus, Huang *et al.* [23] introduced the Empirical Mode Decomposition (EMD) to convert them into linearly stable signals. EMD mainly adaptively decomposes them into a series of Intrinsic Mode Functions (IFM) based on their characteristics [24, 25]. Any function that satisfies the following two conditions is called an intrinsic modal part. ① A zero-crossing point must immediately follow a local maximum or minimum point. ② At any moment, the average of the upper envelope defined by the local maximum and the lower envelope defined by the local minimum should be close to zero. $x(t)$ is decomposed by EMD as follows. The signal decomposed by EMD can be expressed

$$w_i(t)=\frac{\mathrm{d}\arctan\dfrac{H[c_i(t)]}{c_i(t)}}{\mathrm{d}t} \tag{5}$$

$x(t)$ can be expressed as

$$x(t)=\mathrm{Re}\left\{\begin{array}{l}\sum_{i=1}^{n}\sqrt{c_i(t)^2+\{H[c_i(t)]\}^2}\\ \times\exp[\mathrm{j}\int w_i(t)\mathrm{d}t]\end{array}\right\} \tag{6}$$

$r(t)$ is omitted and Equation (9) is called the Hilbert spectrum, and (9)'s Hilbert can be transformed as

$$H(w,t) = \mathrm{Re}\left\{ \begin{array}{l} \sum_{i=1}^{n} \sqrt{c_i(t)^2 + \{H[c_i(t)]\}^2} \times \\ \exp[\mathrm{j}\int w_i(t)\mathrm{d}t] \end{array} \right\} \tag{7}$$

The marginal spectrum is obtained by integrating

$$h(w) = \int_0^T H(w,t)\mathrm{d}t \tag{8}$$

This paper calculates the mean value of the obtained marginal spectrum to get the time-frequency domain features.

In recent years, pattern recognition and classification algorithms have been continuously explored, including Neural Networks [26-29], Bayesian [30, 31], Fuzzy [28, 32], Support vector machine (SVM) [16], and so on. This research chose LDA, K-Nearest Neighbor (KNN), SVM, Decision Tree (DT), and Ensembles (En) [33] as the classification means and found the most suitable from the five algorithms. The algorithms were generated using the Classification Learner app in MATLAB 2017b. LDA's covariance structure and preset were set to full and linear discriminant, respectively. KNN's parameters, including the number of neighbors, distance metric, distance weight, and standardized data, were set to 3, Euclidean, equal, and false, respectively. SVM's parameters, such as the kernel function, box constraint level, kernel scale model, multiclass method, and standardized data, were set to quadratic, quadratic, 1, auto, one-vs-one, and false, respectively. DT's parameters, such as the maximum number of splits, splits criterion, and surrogate decision splits, were set to 100, Gini's diversity index, and off, respectively. Finally, En's parameters, such as the ensemble method, learner type, maximum number of splits, learners, and learning rate, were set to boosted, AdaBoost, decision tree, 20, 30, and 0.1, respectively.

D. EVALUATION INDICATORS

In this thesis, the classification effect was evaluated by recognition accuracy. Besides, to assess the performance of different feature extraction methods, the ANOVA method was employed for statistical analysis of the data in SPSS, and $p<0.05$ indicated significant differences between other techniques.

III. DISCUSSION

A. EXPERIMENTAL RESULTS OF FINGERS AND ARM

The finger recognition results obtained from 12 subjects are presented in Figure 6. As observed in Figure 6, the LDA approach achieved the highest accuracy among all the methods tested. The average accuracy of all experiments is summarized in TABLE 1, where SD represents the Standard Deviation of each algorithm. In comparison with other classification methods, LDA yielded a significantly higher percent correct and a more consistent outcome. The mean accuracy of the LDA method was 75.9% (±5.7), which was superior to the other five approaches (TABLE 1). Furthermore, the LDA method's results were the most stable, thereby minimizing the possibility of extremely low accuracy among some subjects.The results of arm recognition obtained from 12 independent subjects are shown in FIGURE 7. As can be seen from FIGURE 7, LDA had an excellent result. Compared with other algorithms, LDA could receive higher and more stable results. The average accuracy of the LDA was 86.4% (±4.0), which was higher than the other five algorithms (TABLE 1), and the results were more stable. The basic idea of LDA is to project the high-dimensional pattern samples into the optimal discriminant vector space to extract the classified information.After projection, the maximum and the minimum inter-class distance of the new subspace pattern samples are guaranteed. This algorithm performs best in this essay.

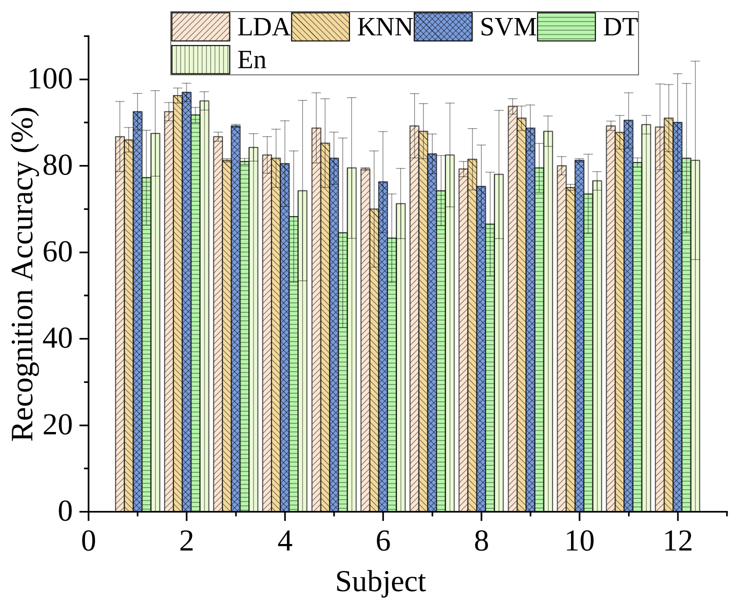


FIGURE 6. Fingers recognition results. The x-axis corresponds to the different subjects (a total of 12 subjects). For each subject, the recognition accuracy was obtained using five algorithms. The y-axis represents the accuracy of FIGURE 1(a) after training, and the error bars represent the standard deviation (SD). the LDA algorithm performed better than the other algorithms. The "percent correct" mentioned refers to the average accuracy.

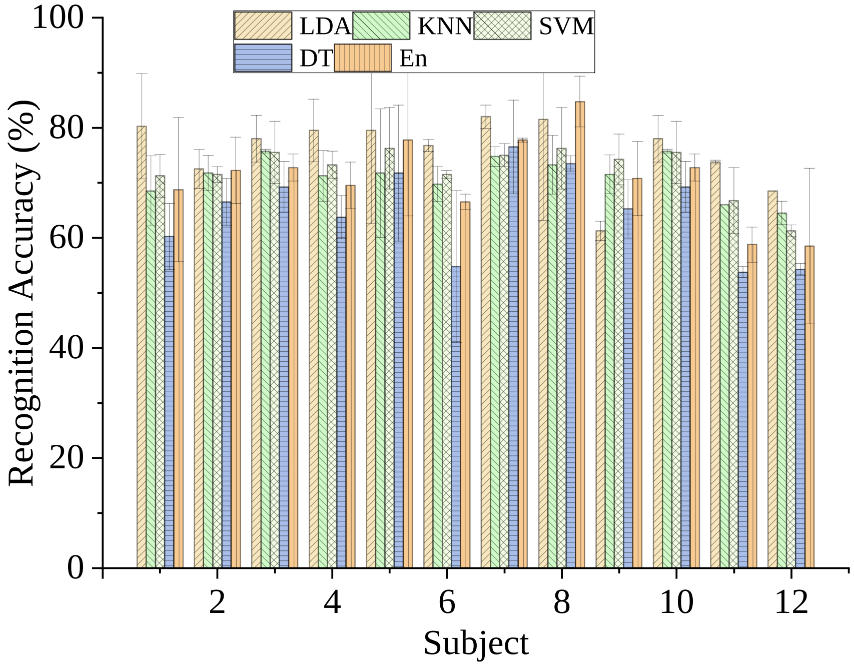


FIGURE 7. Results of arm recognition. The x-axis represents different subjects (a total of 12 subjects), and for each subject, the accuracy obtained by the five algorithms is plotted. The y-axis represents the accuracy after training as shown in FIGURE 1 (b), with error bars indicating the standard deviation. LDA outperformed the other algorithms. For subject 2, the average accuracy for finger recognition using MAV was 58.1%, while for FFT it was 59.9%, and for HHT it was 62.6%. For "MAV+FFT" it was 59.1%, for "MAV+HHT" it was 62.5%, for "FFT+HHT" it was 74.7%, and for "MAV+FFT+HHT" it was 74.3%. The highest accuracy of 91% was achieved using LDA for all three methods ("MAV+FFT+HHT"), followed by 68% for "FFT+HHT" as shown in TABLE 3

TABLE 1
RECOGNITION ACCURACY AVERAGE OF THE SUBJECTS

	LDA (%)	SD. (%)	KNN (%)	SD. (%)	SVM (%)	SD. (%)	D.T. (%)	SD. (%)	En (%)	SD. (%)
Finger	75.9	5.7	71.2	3.5	72.3	4	64.9	5.6	70.9	6
Arm	86.4	4	84.6	5.3	85.5	6	75.2	9.5	82.3	9.8

TABLE 2
FINGERS ACCURACY FOR THE SUBJECT 1

	MAV (%)	FFT (%)	HHT (%)	MAV+FFT (%)	MAV+HHT (%)	FFT+HHT (%)	MAV+FFT+HHT (%)
LDA	9.5	79	74	10	74.5	75	74.5
KNN	15	75.5	70	78	62.5	76	77
SVM	10.5	77	73	76.5	71.5	79.5	77.5
DT	12	68.5	57.5	67.5	54.5	66	67
En	8.5	71	69.5	72	10	71.5	73
Average	11.1	74.2	68.8	60.8	54.6	73.6	73.8

B. COMPARISON OF RESULTS USING DIFFERENT COMBINATIONS OF FEATURES

For subject1, the average accuracy for finger recognition using MAV was 11.1%, while FFT achieved 74.8%, and HHT achieved 68.8%. Combining MAV with FFT resulted in an accuracy of 60.8%, while combining MAV with HHT resulted in 54.6%. The combination of FFT and HHT achieved an accuracy of 73.6%, and using all three methods together ("MAV+FFT+HHT") resulted in an accuracy of 73.8%. The highest accuracy of 79% was achieved with FFT using the LDA, followed by "FFT+HHT" with an accuracy of 75%, as shown in TABLE 2.

For subject 3, when the MAV was used, average accuracy for arm recognition was 11.5%; FFT was 70.7%; HHT was 59.3; "MAV+FFT" were 70.8%; "MAV+HHT" was 59.4%; "FFT+HHT" was 72.6%; "MAV+FFT +HHT" was 72.4%. The maximum accuracy of "FFT+HHT" using the LDA algorithm was 87% in TABLE 3.

TABLE 3
FINGERS ACCURACY FOR THE SUBJECT 2

	MAV (%)	FFT (%)	HHT (%)	MAV+FFT (%)	MAV+HHT (%)	FFT+HHT (%)	MAV+FFT+HHT (%)
LDA	11	16.5	17.5	15.5	14.5	68	91
KNN	67.5	80.5	59	74.5	83.5	75	77.5
SVM	48	69.5	91	67	76	59	73.5
DT	83.5	74	77	48	68.5	90.5	70.5
En	80.5	59	68.5	90.5	70	81	59
Average	58.1	59.9	62.6	59.1	62.5	74.7	74.3

For Subject 4, when MAV was used, average accuracy was 18.2% for arm movements recognition; FFT was 61%; HHT was 25.8%; "MAV+FFT" was 61.9%; "MAV+HHT" was 25.9%; "FFT+HHT" was 60%; "MAV+FFT+HHT" was 59.9%. The maximum accuracy of "FFT+HHT" using the LDA algorithm was 64.5%, followed by FFT's 62% in TABLE 5. The data was selected from every subject for averaging, and the results are shown in TABLE 6. Every accuracy came from an average of 12 subjects. The standard was obtained by averaging the data of all the algorithms. Single-factor repeated detection analysis of different features was conducted by SPSS, and the results showed significant differences ($p<0.001$). It can be seen from Table 6 that the averages of FFT, "FFT+HHT" and "MAV+FFT+HHT" had not much difference, which was all close to 71%; the maximum value which appears in the LDA algorithm for the three methods (FFT, "FFT+HHT", "MAV+FFT+HHT") ranges from 75% to 76%. Thus, this essay decided to employ the LDA to identify the movement of fingers. Therefore, the combination of the three was not much distinction. Still, to avoid the case where some individual's accuracy was too small. For example, in subject 3, the application of the FFT had a high error rate. Simultaneously, considering that the MAV was not high overall, the average and some subjects it was given up. So, combining the general and individual, this paper determined to use the group of "FFT+HHT".

The data were averaged from each subject's data; the results are shown in TABLE 7. SPSS conducted a one-way ANOVA analysis of different features combination, and the results showed significant differences ($p<0.001$).The averages of FFT and "FFT+HHT" had little difference, both close to 83%, so there was little difference between them. The combination of the above two features was not much different. However, considering the individual case, TABLE 4 and 5, the "FFT+HHT" combination using the LDA algorithm was better than the FFT,so "FFT+HHT" was selected. It is seen from TABLE 6 that the maximum value appears in the LDA algorithm. Therefore, the LDA algorithm was used for the recognition of arm movements.

TABLE 4
ARM ACCURACY FOR THE SUBJECT 3

	MAV (%)	FFT (%)	HHT (%)	MAV+FFT (%)	MAV+HHT (%)	FFT+HHT (%)	MAV+FFT+HHT (%)
LDA	9	86	69	86.5	69.5	87	87
KNN	10	76.5	65.5	76.5	64.5	78	78
SVM	13.5	67.5	62	66.5	63.5	72.5	71
DT	15.5	75.5	67	76.5	66.5	77.5	78
En	9.5	48	33	48	33	48	48
Average	11.5	70.7	59.3	70.8	59.4	72.6	72.4

TABLE 5
ARM ACCURACY FOR THE SUBJECT 4

	MAV (%)	FFT (%)	HHT (%)	MAV+FFT (%)	MAV+HHT (%)	FFT+HHT (%)	MAV+FFT+HHT (%)
LDA	15.5	62	23	62.5	23	64.5	64.5
KNN	17	76	26	76	25.5	76	76
SVM	18.5	53.5	28.5	54	29.5	49.5	49.5
DT.	21	66.5	26	70	26	63	62.5
En	19	47	25.5	47	25.5	47	47
Average	18.2	61	25.8	61.9	25.9	60	59.9

TABLE 6
FINGERS RECOGNITION RESULTS WITH DIFFERENT COMBINATIONS OF FEATURES

	MAV (%)	FFT (%)	HHT (%)	MAV+FFT (%)	MAV+HHT (%)	FFT+HHT (%)	MAV+FFT+HHT (%)
LDA	10.5	76	67.3	10.3	67.1	76	75.5
KNN	13.1	73.4	63	61.7	51.9	71.2	63.3
SVM	11.1	72.9	66.6	71.9	64.5	72.4	71.8
DT	13	65.6	57.3	64.4	55.9	64.9	64.4
En	14	70.5	64	70.5	12.8	70.7	71.7
Average	12.3	71.7	63.6	55.8	50.4	71	69.3

IV. CONCLUSION

A. THE IMPORTANCE OF FINE MOVEMENTS

Existing classification algorithms have achieved higher precision for movements with large amplitude [34-36]. However, limited literature exists on the study of specialized fine movements, which is the main focus of this study. The recognition accuracy achieved for the ten-finger movements was 75.9%, while for the ten-arm movements, it was 86.4%. It is imperative to achieve correct recognition of myoelectric signals for clinical application in the future [37]. The precise recognition of slight movements can significantly help in controlling prosthetic hands or robots [4, 34] and in facilitating patients' rehabilitation training [38, 39].

Existing classification algorithms have achieved higher precision for movements with large amplitude. However, there is very little literature on the study of specialized fine movements, which is the main focus of this study. The recognition accuracy for ten-finger movements reached 75.9%, and the accuracy for ten-arm movements reached 86.4%. The correct recognition of myoelectric signals is a guarantee for clinical application in the future. These slight movements help control prosthetic hands or robots and patients' rehabilitation training .

B. ADVANTAGES OF HHT

TABLE 6-7 reveal that the Mean Absolute Value (MAV) was the least effective among the three feature extraction methods. The mean accuracy of the five classification algorithms is as follows: the Fast Fourier Transform (FFT) achieved an accuracy of 71.7% and 82.6%, while the Hilbert-Huang Transform (HHT) achieved 63.6% and 74.6%; for Linear Discriminant Analysis (LDA), the accuracy of FFT was 76% and 85.2%, which is superior to the 67.3% and 77.4% achieved by HHT. Regardless of the average or individual algorithms, FFT outperformed HHT significantly. Using the "FFT+HHT" combination for LDA, the percent correct reached up to 76% and 85.8%, as demonstrated in Table 6 and Table 7, which is equivalent to the accuracy achieved by FFT alone. Furthermore, TABLE 3 indicates that the percent correct is more consistent across various algorithms for a single individual when using the "FFT+HHT" combination. TABLES 2, 4, and 5 also indicate that the "FFT+HHT" combination outperforms FFT alone. Therefore, adding HHT provided certain advantages for a single individual and did not negatively impact the accuracy of LDA.

C. THE REASON FOR LOW RECOGNITION ACCURACY BUT HIGH CLASSIFICATION ACCURACY

The confusion matrix of some subjects' classification is presented in FIGURE 8, revealing that movements 8 and 9, as well as movements 1 and 2, exhibit high similarity, which indicates the necessity of distinguishing these similar movements in the following training. Accordingly, during the training, the similarities between the activities should be carefully observed to improve classification accuracy and expedite the practice.

TABLE 7
ARM RECOGNITION RESULTS WITH DIFFERENT COMBINATIONS OF FEATURES

	MAV (%)	FFT (%)	HHT (%)	MAV+FFT (%)	MAV+HHT (%)	FFT+HHT (%)	MAV+FFT+HHT (%)
LDA	10.7	85.2	77.4	11.7	77.2	85.8	85.5
KNN	16	84.8	75.4	73.7	64.2	83.9	75.8
SVM	10.1	86	77.1	85.1	76.3	85	83.9
DT	14.4	74.6	67.9	74.9	68.1	74.2	74.6
En	16	82.2	75.4	81.6	24.2	81.4	81.5
Average	13.5	82.6	74.6	65.4	62	82.1	80.3

TABLE 8
FINGERS CLASSIFICATION RESULTS WITH DIFFERENT COMBINATIONS OF FEATURES

	MAV (%)	FFT (%)	HHT (%)	MAV+FFT (%)	MAV+HHT (%)	FFT+HHT (%)	MAV+FFT+HHT (%)
LDA	4.2	88.4	78.1	74.6	74.7	87.5	85.9
KNN	12.3	89.7	73.9	71.3	60	86.7	74.7
SVM	4.1	91.3	79.2	87.7	73.4	89.3	86.5
DT	12	84.2	70.7	83.7	68	83.5	83.9
En	12.3	89.9	76.4	88.6	89.2	89.5	87.8
Average	9	88.7	75.7	81.2	73.1	87.3	83.8

The comparison between TABLE 6 and 8, 7 and 9 revealed that the classification accuracy was ten percentage points higher than the recognition accuracy. The reason behind this phenomenon remains unclear. The features were extracted from some subjects whose classification accuracy was 92%. For LDA classification, the accuracy could reach 92%; however, the recognition accuracy was 86% for FIGURE 9 (1) and only 62.5% for FIGURE 9 (2). Notably, the difference in the feature values of FIGURE 9 (1) was significantly smaller than that of FIGURE 9 (2), suggesting the possibility of achieving higher recognition accuracy. Moreover, FIGURE 9 (3) demonstrated that the group with low recognition accuracy was more volatile, emphasizing the need to reinforce the training process and decrease volatility in experiments with low recognition accuracy.

D. RELATIONSHIP BETWEEN TRAINING TIMES AND ACCURACY

As can be seen from FIGURE 10, the classification accuracy was easier to improve, but the recognition accuracy was more challenging to increase. The classification accuracy could be stabilized above 95% by using the LDA, but the recognition percent correct could only be maintained at 85.9%.Sometimes, the classification accuracy could reach more than 95%, but the recognition accuracy was only 30%-40%. In the experiment, training was to reduce the feature difference of the same movement, so multiple training is needed to improve the recognition result. FIGURE 10 resulted from training subjects with a low classification and recognition accuracy. It could be seen from FIGURE 10 that the classification and recognition percent correct were significantly increased after training. But limited to the subjects' training time, they were only trained 5 times in TABLE 2-5. If the training increases, the recognition consequence will be better.

E. LIMITATIONS

Five single-finger bendings, two-finger bending and stretchings, three-finger extension and bendings, and fist were selected. These movements were chosen randomly, and there was no deliberate observation of which actions could obtain more considerable classification accuracy, so the percent correct was relatively lower than the traditional conclusion [40, 41]. But these activities represent four types of signs: single-finger, two-finger, three-finger, and five-finger movements. There are a total of 25 trends in hand movements. If researchers want to get all fingers' recognition, the sensors' number and quality must be improved, and the data processing method must be optimized.

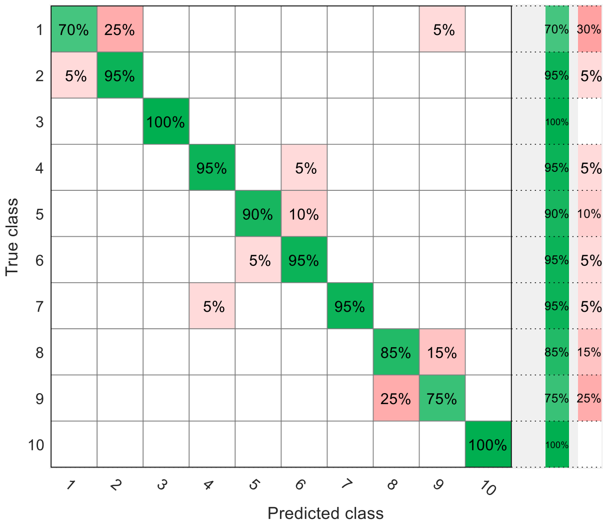
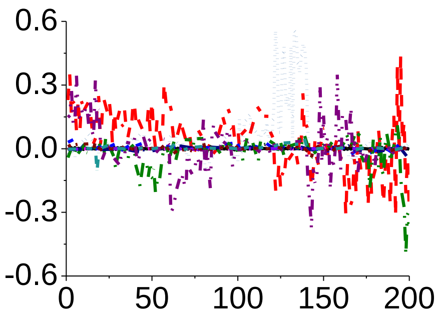


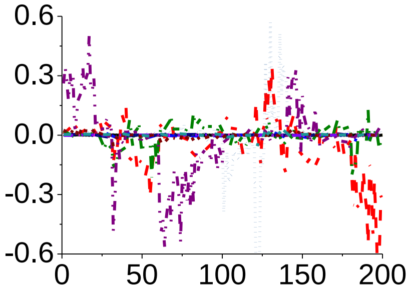
FIGURE 8. Classification of features. The figure used 2 dimensions to represent 12 dimensions. Each number represents a type of movement. For example, number 1 represents movement 1 of Figure 1 (a).

TABLE 9
ARM CLASSIFICATION RESULTS WITH DIFFERENT COMBINATIONS OF FEATURES

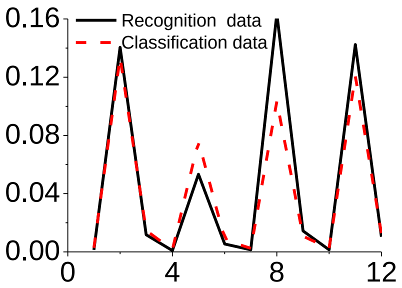
	MAV (%)	FFT (%)	HHT (%)	MAV+FFT (%)	MAV+HHT (%)	FFT+HHT (%)	MAV+FFT+HHT (%)
LDA	4.8	94.8	88.8	87.3	86.7	94.7	94.3
KNN	13.9	95.7	86.5	78.6	69.7	94.4	84.4
SVM	4.7	96.9	89.1	95.7	86.4	96.2	94.9
DT	13.4	92.9	84.8	92.5	83.5	93	92.8
En	12.6	96.1	88.8	95.9	96	96.5	96.3
Average	9.9	95.3	87.6	90	84.4	95	92.5



(1)

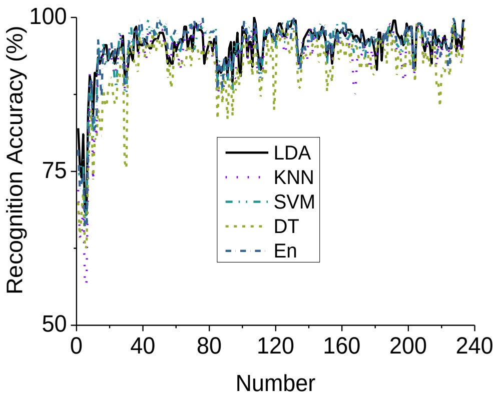


(2)

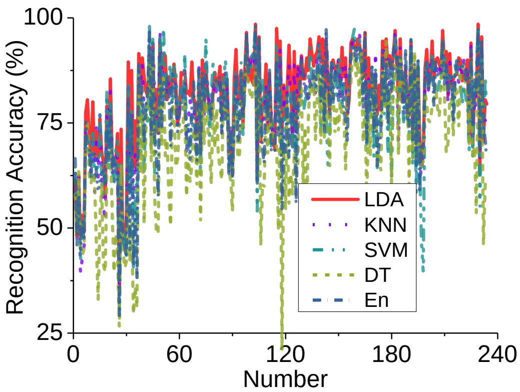


(3)

FIGURE 9. Features differences for classification and recognition. The x-axis of (1) and (2) represents the number of data points, while the y-axis represents the difference value between five movements. The x-axis of (3) represents the number of feature columns, and the y-axis represents the standard deviation of the difference in recognition and classification features. (1) The classification accuracy is 92%, and the recognition accuracy is 86%. (2) The classification accuracy is 92%, and the recognition accuracy is 62.5%. (3) The standard deviation of the difference in recognition and classification features is presented.



(1)



(2)

FIGURE 10. Relationship between the number of training and the accuracy of arms. (1) relationship between classification accuracy and training times (2) relationship between recognition accuracy and practice times.

F. CONCLUSION

The classification confusion matrices of some subjects are shown in Figure 8, which demonstrates that movements 8 and 9 were very similar, and movements 1 and 2 were very similar, making it challenging to distinguish these similar movements. Therefore, the next training will focus on improving classification accuracy by observing the similarities among these activities and speeding up the practice. TABLES 6 and 8, 7 and 9 were compared, and the classification accuracy was ten percentage points higher than the recognition accuracy. To explain this phenomenon, we examined the feature differences obtained from some subjects whose classification accuracy was 92%. Using LDA classification, the accuracy could reach 92%. However, for Figure 9 (1), the recognition accuracy was only 86%, and for Figure 9 (2), it was only 62.5%. The difference value in the features of Figure 9 (1) was significantly smaller than that of Figure 9 (2), indicating that higher recognition accuracy could be achieved with a smaller difference in features. Figure 9 (3) showed that the group with low recognition accuracy was more volatile, suggesting the need to strengthen training and reduce volatility in the experiments with low recognition accuracy.

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