Recognition of Subtle Gestures by 2-Channel sEMG Using Parameter Estimation Classifiers Based on Probability Density

SHILI LIANG, JIANFEI CHEN, YANSHEW WU, SHIFENG YAN, AND JIPENG HUANG
School of Physics, Northeast Normal University, Changchun 130022, China
Corresponding author: Jipeng Huang (huangjp848@nenu.edu.cn)

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ABSTRACT The abundant movement information carried by the surface electromyography (sEMG) signal can comprehensively reflect the muscle movement patterns on the surface of the human body, and the characteristics of physiological signals involving movement information have promoted the vigorous development in the field of human-computer interaction in machine learning. This paper takes subtle gestures as the research objects, and proposes a subtle gestures recognition system that uses two-channel sEMG signal and utilizes Quadratic Discriminant Analysis (QDA) and Linear Discriminant Analysis (LDA) which are parameter estimation classifiers based on probability density. First, combining the raw sEMG signal and the envelope sEMG signal, the number of channels for sensors and corresponding position of the muscle groups are preferably selected. Then, we propose to use the Pearson correlation coefficient to optimize the four types of features extracted in the time domain, frequency domain, time-frequency domain and AR model parameters, which effectively ensures the uniqueness of each gesture and eliminates individual differences. Finally, this paper compares four classifiers of QDA, LDA, Support Vector Machine (SVM), and K-Nearest Neighbor (KNN), and explores the pattern recognition classifier suitable for subtle actions. The experiment collects 9 kinds of subtle gestures from 8 subjects. The results show that the system can use only two channels of sEMG signal to recognize 9 kinds of subtle gestures which include multi-finger clicking or pinching or holding objects, and the most suitable classifiers QDA and LDA have the average recognition rates of 95.79% and 95.01%, respectively.

INDEX TERMS Gesture recognition, Pearson correlation coefficient, parameter estimation classifiers based on probability density, surface electromyography signal.

I. INTRODUCTION Surface electromyography (sEMG) signal comprehensively reflects the muscle movement patterns on the surface of the human body through the velocity information conducted by the activated nerve potential of motor nerves [1], which can not only characterize the ongoing limb movement, but also reflect the movement intention that has not been converted into the actual movement, such as the extending and flexing conditions of the joints, and the shape and position of the limbs for the human body, and then transmits the movement intention of the limbs to the brain. This characteristic that physiological signals could carry motion information has promoted the vigorous development in the field of human-computer interaction in machine learning. Gesture is an important means of communication in human daily life, and also one of the research topics that has received much attention in the field of machine learning. Gesture recognition is considered to be an important part of human-computer interaction. It enables computers to capture, interpret, and execute instructions. This makes more researchers devote to explore and develop the field of gesture recognition based on sEMG signals [2]. Gesture recognition research based on sEMG signal is relatively abundant, and the methods are relatively mature. According to the process of sEMG signal collection and
processing, researchers at home and abroad have conducted in-depth research on data collection, recognized gesture types, effective active segments extraction, feature extraction, classification methods, and practical applications:

In terms of sEMG signal data collection, some researchers have chosen wireless sEMG acquisition devices to achieve sEMG signal data collection on the skin surface of the muscle groups of the forearm when the subject makes different gestures, such as MYO armband produced by Thalmic Labs in Canada. The armband can recognize five kinds of hand movements, including palm extension, making a fist, turning wrist outwards, turning wrist inwards, thumb and middle finger two consecutive clicking. This sEMG sensor is equipped with eight medical grade stainless steel dry electrodes that can achieve eight-channel sEMG data acquisition [3], [4]. This device is easy to use. At the beginning of the using, users only need to complete a small number of training samples for five types of gestures. However, the types of gestures recognized are single, so if we want to add or change gestures, we need to make secondary development and utilization of armband.

At the same time, in order to reduce the environmental interference of the experiment and improve the accuracy of effective motion extraction, some researchers prefer to use the developed wired equipment to collect sEMG signal data. Most of these wired sEMG acquisition equipments are attached to the skin by silver chloride electrodes which could directly acquire the raw sEMG signal [5]. In addition, some researchers also have introduced streaming media for video monitoring or subsequent formation of signal images [6], [7], or use sensors to rectify, filter, and amplify the collected raw sEMG signal, so as to obtain the envelope sEMG signal simultaneously [8]. These studies have opened up new ideas for the exploration of gesture recognition based on the sEMG signal.

Due to the high degree of freedom of the human hand and the complexity and diversity of gesture movements, the content and the number of gesture recognition based on sEMG are various. Some researchers mainly have used sEMG signal to identify sign language gestures used in different countries for the deaf and mute [9]; some researchers have performed gestures recognition in real working situations such as hammer striking [7]. Although the target groups or application scenarios are different, from the perspective of the types of gestures studied by researchers, it generally takes two types of gestures as research objects: one is the type of general gesture with larger signal amplitude, such as five fingers stretching, making a fist, turning wrist outwards, turning wrist inwards, fingers bending in varying degrees and so on, which are often used in daily life; and another is the subtle gesture that correspond to change in the pressure on the fingers, such as clicking or pinching or holding objects of different shapes between the fingers [6], [10]–[13]. Of course, as the number and complexity of gestures increase, the number of sEMG channels used by researchers will change accordingly.

As for the classification model construction of sENG signal, parameter estimation classifiers based on probability density Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis(QDA), parameterless estimation classifier K-Nearest Neighbors (KNN), and classifier based on discriminant function Support Vector Machines (SVM) and other classifiers are commonly used [6], [14]. Hard classifiers, output the exacting classification results directly, but cannot judge the correctness of the classification online, while soft classifiers, such as Bayes classifier and Gaussian mixture model (GMM), output the probability that the sample belongs to a certain class [15]. In recent years, with the rapid development of artificial intelligence technology, the theory of artificial neural network technology has gradually matured. Deep learning networks such as Convolutional Neural Networks(CNN) have been used to train sEMG signal data, it can be used for unsupervised or supervised feature extraction, neural network can also be used for gesture recognition directly, so as to avoid feature extraction and realize gesture pattern recognition or gesture prediction [4], [16]–[18]. Besides, Duan et al. use Wavelet Neural Network(WNN) combined with Discrete Wavelet Transform(DWT) to recognize six kinds of gestures, and then utilize incremental learning to adapt to the gradual changes in sEMG characteristics. However, with the increase of the recognition accuracy of the system, the sample data required for training and processing by the system also increase.

It can be seen from the above analysis that the efficiency and accuracy of the gesture recognition system based on sEMG signals are mutually restrictive. As the number of gesture recognition types increases and the complexity of actions enlarges, researchers usually increase the number of sensors to ensure the recognition accuracy of the entire system, which will undoubtedly bring the complex data processing and prolong data analysis processing time at the same time, and the transmission interference between multiple sensors is also a problem that cannot be ignored. These factors ultimately can reduce the efficiency of the entire recognition system.

In response to the above contradictions, this paper optimize the positions of the muscle groups where sMEG sensors are placed in order to complete the recognition of as many subtle gestures as possible with a small number of sensor channels, and the recognized actions are changed from the conventional gestures such as finger bending and stretching into more subtle gestures such as fingers pinching and clicking. Finally, the classifiers QDA and LDA based on the two-channel sEMG signal data are used to realize the recognition of 9 kinds of subtle gestures, including multi-finger pinching modes such as clicking between fingers and pinching objects. The 9 kinds of specific subtle gestures are as follows: thumb and index finger clicking, thumb and middle finger clicking, thumb and little finger clicking, pinch thumb and index finger together, pinch thumb with index and middle fingers, pinch five fingers together, hold a baseball with five fingers, hold a baseball with the first knuckle of the five fingers, pinch the credit card between thumb and forefinger, etc. Then 8 subjects are
tested, and the average recognition rate reaches 95.79% and 95.01%, which proves the accuracy of the whole system. Finally, a new subtle gestures recognition system based on sEMG signal is proposed, which includes data acquisition, effective activity segment extraction, feature extraction and pattern recognition.

The advantages of the subtle gestures recognition system based on sEMG signal proposed in this paper are as follows:

1) Fewer channels identify more subtle types of gestures. With only two channels of sEMG signal, 9 kinds of subtle gestures including multi-finger pinching are recognized accurately. With the number of recognized gestures types and the complexity of actions increase, the amount of processing data is successfully decreased, and the efficiency and accuracy of the recognition system are effectively guaranteed to be improved synchronously and stably. 2) Parameterized estimation classifiers based on probability density recognize more subtle gestures. LDA and QDA of parameter estimation classifiers based on probability density are used to realize the recognition of subtle gestures of small amplitude signals. It shows that after processing, subtle gestures are no longer limited to use deep algorithms such as neural networks for classification and recognition, which opens up new ideas for pattern recognition of subtle gestures. At the same time, due to the superior efficiency and accuracy of the whole subtle gesture recognition system, it provides reference value for the practical application fields of gesture recognition when it turns to the direction of more real-time and accurate development, such as bionics and intelligent artificial limbs.

II. sEMG SIGNAL DATA ACQUISITION

A. EXPERIMENTAL PROCESS

This paper proposes a recognition system for subtle gestures based on two-channel sEMG signals using the parameter estimation classifiers based on probability density. Firstly, corresponding position of the muscle groups for sensors is determined, and two channels of the raw sEMG signal and the envelope sEMG signal are acquired by sEMG sensors. Secondly, the sliding window absolute average algorithm is used to extract the collected data from the effective active segment so as to extract the effective action data. Then, signal denoising and preprocessing are carried out on the extracted active segment data to reduce the noise interference effect caused by the environment and equipment during the acquisition process. Next, a total of 76 features are extracted from time domain features (such as average absolute value, waveform length, etc.), frequency features (such as median frequency, mean frequency, etc.), time-frequency features (such as wavelet transform coefficient, etc.) and AR model parameters features. Finally, four classifiers are used for algorithm comparison. The overall process of the identification system is shown as Fig. 1.

B. RECOGNIZING GESTURES AND ELECTRODE POSITION

This system recognizes 9 kinds of subtle gestures [19], the specific subtle gestures are as follows: thumb and index finger clicking (IC), thumb and middle finger clicking (MC), thumb and little finger clicking (LC), pinch thumb and index finger together (IP), pinch thumb with index and middle fingers (MP), pinch five fingers together (FP), hold a baseball
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FIGURE 2. Nine subtle gestures and idle gesture.

with five fingers (BF), hold a baseball with the first knuckle of the five fingers (BK), pinch the credit card between thumb and forefinger (PC), as shown in Fig. 2.

There are many types of muscles in the forearm of the hand, 14 muscles coordinate the movement of fingers, wrists and forearms. At the same time, the movement intensity of the subtle gestures recognized is relatively small, which makes the amplitude of the motion signal relatively weak. Obviously, reasonable electrode position and an appropriate number of signal channels can not only help researchers extract the low-noise sEMG signal, but also serve as an important basis for multi-gesture recognition [20], so as to ensure the accuracy and efficiency of the whole sEMG system.

In this study, 8 college students are selected as subjects for data collection, 4 males and 4 females, aged 25 ± 2 years. All the subjects are healthy and free from diseases. The sampling frequency is set at 2000Hz, and 10 sets of experimental data are collected for each subject within three weeks, so that to reduce the impact of muscle fatigue on the collected data.

In the single set of data, each subject repeats every gesture 12 times. 60% samples are select randomly from all data as the training set, 20% as the cross-validation set, and 20% as the testing set. A total of 1080 sets of experimental data are collected, as shown in Table 1. Before each experiment, the subjects’ right forearm should be cleaned with a sterile tissue. Before collecting data, the subjects receive gesture guidance from the relevant personnel. The hardware part of the data acquisition device uses STM32F103ZET6 microcontroller as the main control chip which performs analog-to-digital conversion on the analog signal collected by the sensors (the third-generation sEMG sensor developed by Myo Company in 2015) so that to obtain the two kinds of sEMG digital signals, and then the digital signals are displayed in the form of waveforms on the LabVIEW interface which is independently developed by our research team, and are saved as csv file. Instructions to start and stop the recording of each acquisition experiment are controlled by the external trigger, as shown in Fig.4. When collecting data, the fingers return to the idle state after the action is completed, as shown in Fig. 2.

The typical waveforms corresponding to the first gesture are shown in Fig.5.

TABLE 1. Sample distribution in each classifier.

| Data Classification | Training set | Cross-validation set | Testing set | Total |
|---------------------|--------------|----------------------|-------------|-------|
| IC                  | 72           | 24                   | 24          | 120   |
| MC                  | 72           | 24                   | 24          | 120   |
| LC                  | 72           | 24                   | 24          | 120   |
| IP                  | 72           | 24                   | 24          | 120   |
| MP                  | 72           | 24                   | 24          | 120   |
| FP                  | 72           | 24                   | 24          | 120   |
| BF                  | 72           | 24                   | 24          | 120   |
| BK                  | 72           | 24                   | 24          | 120   |
| PC                  | 72           | 24                   | 24          | 120   |
| Total               | 648          | 216                  | 216         | 1080  |

III. EXPERIMENTAL ALGORITHMS

A. EXTRACTION OF EFFECTIVE ACTIVE SEGMENTS

During the data collection, there is an idle state between each action. This data belongs to the inactive segment. If it is not processed, the amount of data processing will be increased. Therefore, it is necessary to extract effective active segments by determining the start sampling point and end sampling point of each active waveform, so as to reduce the influence of interference noise and the amount of data processed, and also to ensure that the information in the active segment is maximized [21]. The envelope sEMG signal is the envelope track of the raw sEMG signal. Comparing with the
disadvantages of smaller amplitude and greater randomness of the raw sEMG signal, the envelope sENG signal has the relatively higher amplitude and is not easy to be drowned by the noise. It is easier to find the start sampling points and the end sampling points when extracting the active segments, which has the obvious advantages [8]. In this paper, based on the sliding window absolute average algorithm, the effective active segments extraction of the envelope sEMG signal is achieved [7], [10], [22]. The specific process is as follows:

1) Calculate the absolute sliding average of the sampling points in the sliding window. For each channel, a sliding window with a specification of 32 milliseconds is selected. Since the sampling frequency is 2000 Hz, the corresponding number of sampling points is 64, and the moving absolute value (MAA) of the sampling point data is calculated:

\[
\alpha = \frac{1}{64} \sum_{m=1}^{j} \sum_{n=0}^{i} |x_n| \quad (1)
\]

where m represents the mth sampling channel, j represents the total number of sampling channels, n represents the nth sampling point, i represents the total number of sampling points, and \(x_n\) represents the nth sampling point. In this study, \(i = 63\) and \(j = 2\). Calculate the \(\alpha\) value corresponding to each sampling point \(x_n\).

2) Determine the start threshold TH1 and the end threshold TH2. The threshold TH2 is slightly larger than TH1 to improve the anti-interference ability. Assume that the absolute sliding average value corresponding to the sth sliding window with \(x_0\) as the first sampling point is \(\alpha_{sv}\), which satisfies \(\alpha_{sv} > TH1\). Then in the next sampling point, there must be an absolute sliding average value \(\alpha_{ev}\) of the eth sliding window where a certain sampling point is located, which satisfies \(\alpha_{ev} > TH2\). And the 63rd sampling point \(x_{es}\) in the eth sliding window is used as the end sampling point.

3) Determine the effective active segments. It can be known from step 2 that the effective active segment data of sEMG signal are all sampling points \(x_w\) (\(s \leq w \leq e\)) which are from the sth sliding window to the eth sliding window. The sampling points of the rest can be regarded as data or fluctuating noise corresponding to the idle state.

The specific extraction process of the effective active end is shown in Fig.6. Since the envelope signals and the raw signals are synchronized, finding the start sampling points and the end sampling points of the envelope signals means finding the start sampling points and the end sampling points of the raw signals at the same time [8].

**B. DATA DE NOISING PREPROCESSING**

sEMG signal is the weak physical non-stationary signal, whose amplitude is less than 5mV, which makes it highly sensitive to noise. Even if non-invasive technology is used for data acquisition, it cannot completely remove the interference of environmental noise, motion artifact, inherent noise of electronic equipment and other noise. Therefore, it is necessary to filter the noise to achieve a better gesture recognition effect [23].

This paper analyzes two denoising methods of Butterworth band-pass filter and the wavelet denoising, and achieves the
noise reduction processing of the raw sEMG signal and the envelope sEMG signal [24].

The useful frequency of the raw sEMG signal is mainly concentrated in the range below 500Hz [22]. For 50Hz power frequency interference noise, we use a fifth-order Butterworth filter with a passband frequency of 49-51Hz to eliminate it. In order to filter out baseline drift, electrode shift, motion artifacts and system-induced noise, frequency components below 20 Hz need to be discarded. Since the frequency components above 500 Hz contain less information, the frequency components above 500 Hz also need to be filtered out. In this paper, an eighth-order Butterworth filter with a passband frequency of 20-500 Hz is used to reduce the noise of the raw sEMG signal.
### TABLE 2. Features extracted from the raw sEMG signal.

| Acronym | Full name | Formula |
|---------|-----------|---------|
| MAV     | Mean absolute value | $\text{MAV} = \frac{1}{N} \sum_{i=1}^{N} |x_i|$ |
| MAV1    | Modified mean absolute value | $\text{MAV1} = \frac{1}{N} \sum_{i=1}^{N} w_i |x_i|$, $w_i = \begin{cases} 1, & \text{if } 0.25N \leq i \leq 0.75N \\ 0.5, & \text{otherwise} \end{cases}$ |
| MAV2    | Modified mean absolute value | $\text{MAV2} = \frac{1}{N} \sum_{i=1}^{N} w_i |x_i|$, $w_i = \begin{cases} 1, & \text{if } 0.25N \leq i \leq 0.75N \\ \frac{4i}{N(N-1)}, & \text{else if } i < 0.25N \\ \frac{4N-4i}{N(N-1)}, & \text{otherwise} \end{cases}$ |
| VAR     | Variance | $\text{VAR} = \frac{1}{N-1} \sum_{i=1}^{N} x_i^2$ |
| RMS     | Root mean square | $\text{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} x_i^2}$ |
| SSI     | Simple square integral | $\text{SSI} = \frac{1}{N} \sum_{i=1}^{N} x_i^2$ |
| V       | V-order | $V = \left(\frac{2}{N} \sum_{i=1}^{N} x_i^2\right)^{1/2}$, in our work, $v = 3$ |
| IEMG    | Integrated EMG | $\text{IEMG} = \frac{1}{N} \sum_{i=1}^{N} x_i$ |
| DASDV   | Difference absolute standard Deviation value | $\text{DASDV} = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (x_{i+1} - x_i)^2}$ |
| AAC     | Average amplitude change | $\text{AAC} = \frac{1}{N-1} \sum_{i=1}^{N} |x_{i+1} - x_i|$ |
| ZC      | Zero crossing | $\text{ZC} = \sum_{i=1}^{N} f(\Delta_i)$, $f(\Delta_i) = \begin{cases} 1, & \text{if } x_{i+1} < 0 \text{ and } \Delta_i \geq \text{th} \\ 0, & \text{otherwise} \end{cases}$ |
| LOG     | Log detector | $\text{LOG} = \frac{1}{\Delta_i} \log |x_{i+1}/x_i|$ |
| SSC     | Slope sign change | $\text{SSC} = \sum_{i=1}^{N} f(\Delta_i)$, $f(\Delta_i) = \begin{cases} 1, & \text{if } \Delta_i \geq \text{th} \\ 0, & \text{otherwise} \end{cases}$ |
| WL      | Waveform length | $\text{WL} = \sum_{i=1}^{N} \sqrt{|x_{i+1} - x_i|}$ |
| WAMP    | Willison amplitude | $\text{WAMP} = \sum_{i=1}^{N} f(\Delta_i)$, $f(\Delta_i) = \begin{cases} 1, & \text{if } \Delta_i \geq \text{th} \\ 0, & \text{otherwise} \end{cases}$ |
| MFL     | Maximum fractal length | $\text{MFL} = \log_{10} \sqrt{\sum_{i=1}^{N} (x_{i+1} - x_i)}$ |
| MAX     | Maximum | $\text{MAX} = \max(x_1, x_2, x_3, ..., x_N)$ |
| MIN     | Minimum | $\text{MIN} = \min(x_1, x_2, x_3, ..., x_N)$ |
| MM      | Max-min | $\text{MM} = \max(x_1, x_2, x_3, ..., x_N) - \min(x_1, x_2, x_3, ..., x_N)$ |
| Sk1     | Standard skewness | $\text{Sk1} = \frac{1}{(N-1)(N-2)} \sum_{i=1}^{N} (x_i - \mu)^3$ |
| Sk2     | Skewness based on quartiles | $\text{Sk2} = \frac{(Q_{0.75} - Q_{0.25}) - (Q_{0.85} - Q_{0.05})}{Q_{0.75} - Q_{0.25}}$ |


| Feature                | Formula                                      |
|------------------------|----------------------------------------------|
| Sk3                    | \[ Sk3 = \frac{\mu - q_{0.5}}{E[|x - \mu|]} \] |
| Sk4                    | \[ Sk4 = \frac{\mu - q_{0.5}}{\sigma} \]    |
| Kr1                    | \[ Kr1 = \frac{N(N + 1)}{(N - 1)(N - 2)(N - 3)} \sum_{i=1}^{N} (x_i - \mu)^3 - \frac{(N - 1)^3}{(N - 2)(N - 3)} \] |
| Kr2                    | \[ Kr2 = \frac{(q_{0.975} - q_{0.025}) + (q_{0.25} - q_{0.25})}{q_{0.75} - q_{0.25}} \] |
| Kr3                    | \[ Kr3 = \frac{E|x| > q_{1.5}}{E|x| > q_{1.5}} - \frac{E|x| < q_{1.5}}{E|x| < q_{1.5}} \] |
| Kr4                    | \[ Kr4 = \frac{q_{\text{ur}5} - q_{\text{ul}5}}{q_{\text{ul}5} - q_{\text{ur}5}} \] |
| TTP                    | \[ TTP = \sum_{i=1}^{N} p_i \] |
| MNF                    | \[ MNF = \frac{\sum_{i=1}^{N} f_i p_i}{\sum_{i=1}^{N} p_i} \] |
| MDF                    | \[ MDF = \sum_{i=1}^{N} p_i = \sum_{i=MDF}^{N} p_i = \frac{1}{2} \sum_{i=1}^{N} p_i \] |
| MNP                    | \[ MNP = \frac{1}{N} \sum_{i=1}^{N} p_i \] |
| PKF                    | \[ PKF = \max(p_1, p_2, p_3, ..., p_N) \] |
| MOACi                  | \[ \text{MOAC}_i = \frac{|c_i|}{n} \] |
| APOCi                  | \[ \text{APOC}_i = \frac{1}{N} \sum_{i=1}^{N} (c_i)^2 \] |
| STDOCi                 | \[ \text{STDOC}_i = \frac{1}{n} \sum_{i=1}^{N} (c_i - \mu)^2 \] |
| Ri                     | \[ R_i = \frac{\text{MOAC}_{i+1}}{\text{MOAC}_i} \] |

1. **Envelope sEMG signal is obtained after the raw signal amplification, rectification, integration and other processing. Compared with the raw sEMG signal, although the envelope sEMG signal loses many frequency components in the frequency domain, its amplitude and shape of the waveform in the time domain are more regular. Therefore, the wavelet decomposition and denoising method is used to eliminate the fluctuations and burrs caused by interference, so that the envelope sEMG signal tends to be smoother [25]. The meaning of wavelet transform is that after a certain basic wavelet function which is displayed by \( \tau \), at different scales \( a \), the inner product of the signal \( x(t) \) to be analyzed is achieved.**
FIGURE 7. Denoising preprocessing process of the envelope sEMG signal and the raw sEMG signal.

The specific principle formula is as follows:

\[ \text{WT}_x(a, \tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t) \psi^*(\frac{t - \tau}{a}) dt \]  

where \( a > 0 \) is called scale factor, and its function is to expand and contract the basic wavelet function \( \psi(t) \); \( \tau \) responds to displacement, and its value can be positive or negative. Here db4 is used as the wavelet basis function. The denoising preprocessing of the two kinds of signals is shown in Fig.7.

C. FEATURE EXTRACTION

sEMG signal is the continuous non-stationary random time series, it covers information in time domain, frequency domain, time-frequency domain, and parameter model, etc. Researchers also focus on several or all of the four aspects to extract features, so the signal features extracted by the sEMG control system are widely divided into four categories: time domain features, frequency domain features, time-frequency features, and parameter models at present. The time domain feature is based on the signal amplitude, and related calculations such as waveform length (WL) and slope sign change (SSC) are performed; the frequency domain features pay attention to the signal spectrum distribution characteristics; the time frequency domain feature also takes into account the signal’s time domain information and frequency domain information, typically represented by wavelet transform; and the parameter model regards the short-time sEMG signal as a random non-stationary time series, establishes the model and extracts the model parameters, such as AR model [6], [24], [26]–[28]. In order to ensure the uniqueness of each gesture after feature optimization, we extract as many features as possible to ensure sufficient feature types. The features extracted in this paper are as follows: time domain features(27), frequency domain features(5), time-frequency domain features(15), AR parametric model features(5). The raw sEMG signal is an unprocessed original biological signal collected directly from the skin surface of the muscle group, and contains abundant motion information. Therefore, a total of 52 signal features are extracted from the above four aspects. The specific types and calculation methods of these features are shown in Table 2 [27]. The envelope sEMG signal is one that has been processed by amplification and rectification, and contains few frequency components. Therefore, the time domain features such as amplitude and waveform are the main features, and finally 24 signal features are extracted.

D. FEATURE OPTIMIZATION

Since this paper uses two-channel sEMG signals, the total number of features is 76 Features * 2 Channels, which totals 152-dimensional signal features. For classifiers, there may be dimensional disasters. Feature optimization is a kind of mapping from a high-dimensional feature space to a low-dimensional feature space through a certain operation on the premise of ensuring the maximum classification accuracy, thereby improving the quality of features and avoiding dimensional disasters. In order to reflect the difference of nine subtle gestures and ensure the accuracy of the classification results, Pearson correlation coefficient is used for feature optimization which belongs to the univariate feature selection algorithm [29], and the calculation formula is as follows:

\[ r_i = \frac{\text{cov}(X_i, Y)}{\sigma_{X_i} \sigma_Y} \]  

where \( X_i \) is the ith characteristic variable; \( Y \) represents the target value, that is, the output value; \( \sigma_{X_i} \) and \( \sigma_Y \) are the standard deviations of \( X_i \) and \( Y \); \( r_i \) ranges from \([-1, 1]\).

Before optimizing, the characteristic values have to be normalized to eliminate the influence of different dimensions. Then Pearson correlation coefficient can be calculated for the normalized features, and the features are sorted according to the calculated correlation coefficient absolute value. The greater the absolute value is, the more relevant the feature is to the classification result, and the greater the role it plays in the...
classification of gestures. Based on the Pearson correlation coefficient values of the nine gestures, and at the same time, 18 signal features are finally selected based on references. Taking IC gestures as an example, the corresponding feature types and corresponding Pearson correlation coefficient values are shown in Fig. 8.

E. CLASSIFIERS
Based on the idea that different classification algorithms may be suitable for different types of gestures [6], it can be seen that SVM and KNN are generally more suitable for conventional gestures with larger amplitude and strength, such as palm extension [8]. Considering that the objects recognized in this study are subtle gestures, LDA and QDA which are the parameter estimation classifiers based on probability density are selected to explore the most suitable classifier for subtle gestures [6], [21], [30]–[32].

1) LDA
Both LDA and QDA are classifiers based on the Bayesian minimum error criterion, which belongs to parameter estimation. That is, the distribution model of the category needs to be assumed in advance, and then the training data is used to adjust each parameter in the probability density [24]. In the research of sEMG signal, LDA is often used as a pattern recognition classifier, and can also be used for feature conversion to achieve the purpose of feature dimensionality reduction [33]. LDA is similar to anova and regression analysis, and its idea can be summarized as follows: after projection, the intra-class variance is the smallest and the inter-class variance is the largest, which means the data is projected in a low dimension. After projection, it is expected that the projection point of each category of data is as close as possible, at the same time, the distance between the category centers of different categories of data is as large as possible. In short, projection is the main idea of this method. Finding feature vectors is the first step, and the original data set is projected from a high dimension to a low dimension, so that simple classification can be performed. At the same time, LDA tries to make the data of different classes separate, and keeps the data in the same group class as close as possible, so as to classify the samples. The discriminant function is as follows:

\[
h_n(f) = \ln \left[ P(C_n) \right] - \frac{1}{2} (f_n - \lambda_n)^T \Sigma_n^{-1} (f_n - \lambda_n) + \ln \left[ \prod C_n \right] + \frac{1}{2} \ln \left| \Sigma_n \right|
\]

where \( P(C_n) \) is the priori probability of the nth data type, \( f_n \) is the feature matrix, and \( f_n = [f_1, f_2, \ldots, f_k] \), \( \lambda_n \) is the mean vector; \( \Sigma_n \) is the covariance. Assuming that each classifier has the same covariance matrix, the discriminant function is the LDA linear discriminant function, and the interface of this function is composed of some linear hyperplanes, which is the LDA classifier.

2) QDA
QDA is also a classifier based on the Bayesian minimum error criterion [6], [34]. The structure of the QDA classifier is simple, and the model and parameters of the entire classifier are directly determined by the training process. Therefore, there is no need to conduct a large number of experiments to verify the classification effect during the experiment, saving a lot of time. The discriminant function is the same as the
TABLE 3. Classification accuracy of QDA (Unit: %).

| Subjects | IC  | MC  | LC  | IP  | MP  | FP  | BF  | BK  | PC  | Mean |
|----------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|
| 1        | 92.01 | 92.01 | 80.02 | 88.02 | 100.00 | 96.01 | 100.00 | 100.00 | 96.02 | 93.79 |
| 2        | 95.26 | 88.37 | 92.86 | 81.40 | 97.62 | 100.00 | 100.00 | 97.67 | 97.62 | 94.53 |
| 3        | 100.00 | 88.38 | 100.00 | 95.24 | 100.00 | 97.62 | 100.00 | 100.00 | 97.60 | 97.65 |
| 4        | 95.23 | 100.00 | 100.00 | 97.67 | 97.62 | 100.00 | 97.62 | 97.67 | 97.61 | 98.16 |
| 5        | 95.24 | 100.00 | 100.00 | 97.67 | 100.00 | 95.24 | 97.62 | 100.00 | 98.42 |
| 6        | 92.86 | 62.79 | 85.72 | 100.00 | 95.35 | 100.00 | 97.62 | 97.66 | 97.62 | 92.18 |
| 7        | 97.78 | 100.00 | 97.78 | 95.56 | 97.67 | 100.00 | 95.56 | 97.77 | 97.78 | 97.77 |
| 8        | 96.02 | 92.01 | 76.02 | 88.01 | 100.00 | 96.00 | 100.00 | 100.00 | 96.01 | 93.79 |
| Mean     | 95.55 | 90.45 | 91.55 | 92.95 | 98.53 | 98.70 | 98.26 | 98.55 | 97.53 | 95.79 |

LDA result, so the idea is similar. The difference is that when the covariance matrix of each classification data is different, the discriminant function is transformed into a quadratic discriminant function, and the interface of this function is composed of some quadratic hyperplanes, which is the QDA classifier.

3) KNN

KNN can directly estimate the probability density from the training samples, so it belongs to the parameterless estimation classifier based on probability density, it is characterized by high accuracy, insensitivity to outliers and no data input assumptions, and suitable for multi-classification problems [26], [34]. The basic idea of KNN is that the intra-class distance is small and the inter-class distance is large. In order to determine the category of unlabeled samples, all known category samples are used as reference, the distance between each unknown sample and all known category samples are calculated, and the k nearest known examples are selected. According to the voting rule of majority rule, the unknown samples to be classified are classified into the category with the largest number of k nearest neighboring samples. The algorithm process is as follows:

1) Specify the sample set of known category labels \(X = \{X_1, X_2, \ldots, X_m\}\), and the sample set of unknown labels to be classified \(Y = \{Y_1, Y_2, \ldots, Y_n\}\). Calculate the distance between each data \(X_i\) in the sample set \(X\) and all \(Y_j\) in the sample set \(Y\) which is to be classified. In our work, we choose the Euclidean distance:

\[D_{ij} = \|X_i - Y_j\|\]  \hspace{1cm} (5)

2) According to \(D_{ij}\), select the top \(k\) sorted samples that are closest to the sample \(Y_j\) to be classified from the sample set \(X\).

3) In accordance with the principle of majority rule, the unknown samples are classified into the category with the largest number of known instances in the \(k\) known instances.

In our study, \(k\) value is set to 5, at which point the classification performance is better.

4) SVM

The classification rules of SVM are represented by some form of discriminant function. The parameters in the function can be calculated by training samples, and then the discriminant function is used to directly classify the testing data. The characteristic behavior of SVM is to construct high-dimensional hyperplanes of small samples and nonlinear models, and classify samples by calculating the maximum distance of training data points on the hyperplane. SVM shows many unique advantages in solving small sample, nonlinear and high-dimensional pattern recognition, and can be widely applied to other machine learning problems such as function fitting [29], [34]. The model is as follows:

\[
\min \frac{\|w\|^2}{2} + C \sum_{i=1}^{N} \xi_i \\
\text{s.t. } y_i (w^T x_i + b) \geq 1 - \xi_i, \quad i = 1 \ldots N \]  \hspace{1cm} (6)

where \(N\) is the number of sample data points; \(w\) is the vector representing the parameters of the adaptive model; \(\xi_i\) is the relaxation variable; \(C\) is the weight of the outliers (that is, the penalty factor), the larger \(C\) is, the greater the influence of outliers on the target is; \(x_i\) is the vector representing the data points; \(y_i\) is the label associated with the data point \(x_i\), the value is \(-1\) or \(1\); \(b\) is the intercept of the hyperplane. By calculating the above formula, two types of hyperplane classification can be obtained:

\[w^* x + b^* = 0\]  \hspace{1cm} (7)

IV. RESULTS AND DISCUSSION

A. DE_NOISING PREPROCESSING ANALYSIS

This paper analyzes two denoising methods of Butterworth band-pass filter and wavelet denoising, and realizes the noise
reduction processing of the raw sEMG signal and the envelope sEMG signal. The comparisons before and after denoising are shown in Fig. 7. It can be seen from Fig.c1 and Fig.d1 that there is a significant baseline drift at the tail of the waveform before filtering, and the waveform has a lot of glitches during the relaxation phase. After filtering, it can be seen from Fig.c2 and Fig.d2 that the waveform at the relaxation stage is basically at the baseline and the glitch is improved; Fig. a1 and Fig.b1 can observe the waveform jitter introduced by various interferences, while Fig.a2 and Fig.b2 show that the envelope sEMG signal is smoother after filtering, and the original trend of signal envelope is retained.

B. FEATURE EXTRACTION AND OPTIMIZATION ANALYSIS
From the perspective of time domain, frequency domain, time-frequency domain, and parameter model, a total of 76 signal features are extracted. 52 features are extracted for the raw signal, and 24 features are extracted for the envelope signal, feature extraction is more comprehensive. Because the two-channel signals are collected in the experiment, considering the processing time of the subsequent classifier for pattern recognition, the Pearson correlation coefficient is selected to reduce the dimension of the extracted features. Finally, 18 corresponding features are extracted for each gesture. Since the waveform trend and amplitude of each gesture are different, the extracted features must be different. The advantage of feature optimization is that it not only avoids the “dimensional disaster”, but also reduces the time for classifying subsequent actions; at the same time, it ensures the uniqueness of each gesture, and further ensures the accuracy of pattern recognition.

C. ANALYSIS OF CLASSIFICATION RESULTS
The results of the four classifiers are shown in Table 3 to Table 6.

For the average recognition rate of the nine kinds of gestures and the eight testing subjects, it can be seen from the comparison of Fig.9 and Fig.10 that the overall trend of the recognition rate distribution of each gesture and each subject under the four classifiers is the same, which indicates...


TABLE 6. Classification accuracy of KNN (Unit: %).

| Subjects | IC  | MC  | LC  | IP  | MP  | FP  | BF  | BK  | PC  | Mean |
|----------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|
| 1        | 90.02 | 89.98 | 90.01 | 76.66 | 96.67 | 96.69 | 93.33 | 100.00 | 100.00 | 92.60 |
| 2        | 92.86 | 83.72 | 80.95 | 55.81 | 97.61 | 95.34 | 95.24 | 95.35 | 97.62 | 88.28 |
| 3        | 97.62 | 95.35 | 100.00 | 97.67 | 97.62 | 95.35 | 83.33 | 81.40 | 97.61 | 94.00 |
| 4        | 73.81 | 95.34 | 80.95 | 83.72 | 97.60 | 90.70 | 95.24 | 93.00 | 97.63 | 89.78 |
| 5        | 80.95 | 97.67 | 100.00 | 95.35 | 97.63 | 97.67 | 97.62 | 97.64 | 100.00 | 96.06 |
| 6        | 85.71 | 53.49 | 76.19 | 93.02 | 95.24 | 86.05 | 97.60 | 93.04 | 97.61 | 86.44 |
| 7        | 100.00 | 90.70 | 97.62 | 100.00 | 95.23 | 95.35 | 85.71 | 86.05 | 100.00 | 94.52 |
| 8        | 100.00 | 84.01 | 80.00 | 48.11 | 100.00 | 92.00 | 76.01 | 84.00 | 100.00 | 84.90 |

As for the average recognition rate of the nine gestures, it can be seen from Fig. 9 that the recognition rate of all gestures corresponding to QDA is above 90%, higher than the average recognition rate, and the trend distribution of QDA is relatively flat, indicating that the classification result of QDA is better than that of the other three classifiers, and the classification algorithm is relatively stable. As for the recognition rate of each of eight testing subjects, recognition rate of QDA and LDA is higher than the average. Among them, the average recognition rate of QDA for each subject’s nine gestures reached more than 92%, which is higher than SVM and KNN. Comparing the overall classification recognition rates of the nine gestures of the eight subjects, from Table 3 to Table 6, it can be seen that the average recognition rates of SVM and KNN are only 93.78% and 90.82%, while the average recognition rates of QDA and LDA are 95.79%, 95.01%, all reached more than 95%. It can be seen that the parameter estimation classifiers QDA and LDA based on probability density are more suitable for recognition classification including subtle gestures.

For individual differences, comparing the average recognition rate of male subjects (No. 1, No. 2, No. 3, No. 4) and female subjects (No. 5, No. 6, No. 7, No. 8), as shown in Fig. 11, the average recognition rate of male subjects is generally higher than that of the female. This indicates that the differences in the physiological structure and the strength of body muscles between the male and female make the signal strength of the same gesture may different, which in turn lead to a certain gap in overall recognition results between the male and female. The recognition rate of all gestures of subject 6 and subject 8 are generally low, indicating that the amplitude of the signal generated by subject 6 and subject 8 are lower than the average level, which shows that individual differences can not be ignored. Of course, this illustrates the authenticity of the data in this study on the other hand. The program of the classifiers algorithm is implemented on a 64-bit Windows operating system, with a 3.30 GHz Intel Core i5-6600 CPU and 8.00 GB of RAM. 

FIGURE 9. Classification accuracy of four classifiers corresponding to nine subtle gestures.

FIGURE 10. Classification accuracy of four classifiers corresponding to eight testing subjects.
time for QDA and LDA is shown in Table 7 and Table 8. As for all subjects, the total training time is 0.43151s and the total testing time is 0.02697s for QDA, also the total training time is 0.44319s and the total testing time is 0.00580s for LDA. It indicates that QDA and LDA can be well trained and analyzed in a short period, which provides the possibility of real-time human-computer interaction.

V. SUMMARY

In this paper, a subtle gestures recognition system based on two-channel sEMG signal and parameter estimation classifiers based on probability density is proposed to study the subtle gestures with the small amplitude such as clicking or pinching or holding objects with multiple fingers. First, by using the two-channel sensors and combining with the raw sEMG signal and the envelope sEMG signal, we explored the suitable placement positions of sensors for subtle gestures in the muscle groups, that is, extensor carpi radialis longus muscle and flexor radial extensor carpi ulnaris muscle of the posterior forearm muscle group. Then, it is proposed to use the Pearson correlation coefficient to implement feature optimizing on the extracted features. The advantage is that while ensuring the uniqueness of each gesture, it not only avoids the “dimension of dimensionality”, but also reduces the impact of individual differences of different subjects, and effectively ensures the accuracy of classification and recognition. Finally, in the sections of gestures classification and recognition, the potential advantages and feasibility of parameter estimation classifiers QDA and LDA based on probability density for subtle gestures are proved. Aiming at the characteristics of subtle gestures with small amplitude and weak signal, this paper adopts feature optimization algorithm, combining the two-channel raw sEMG signal and the envelope sEMG signal, and achieves subtle gestures recognition with relatively small number of channels, which is different from the conventional approach by increasing the number of channels to expand the data volume and improve the recognition rate. The proposed method ensure the recognition rate of subtle gestures while reducing the amount of data.

Referring to previous research, SVM and KNN are more suitable for the recognition of conventional gestures. This paper confirms that QDA and LDA are more suitable for the classification and recognition of subtle gestures. On this basis, if the gestures to be recognized include different types such as regular gestures and subtle gestures, it can be considered to use different types of classifiers suitable for various types of gestures to classify and recognize at the same time, that is, multiple gestures-multiple classifier ideas, rather than using the single classifier to recognize all gestures. Although this study only explores the classifiers suitable for subtle gestures, This idea may develop a new recognition idea of simultaneous multi-type gesture recognition. Based on this idea, we will carry out the research on simultaneous pattern recognition of different classifiers for multiple types gestures in the future studies.

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YANSHENG WU received the master’s degree in circuits and systems from Northeast Normal University, Changchun, China, in 2019. His current research interests include biomedical signal processing, pattern recognition, and intelligent control systems.

SHIFENG YAN received the B.E. degree in electronic information science and technology, in 2019. He is currently pursuing the master’s degree in electronics and communication engineering with Northeast Normal University, Changchun, China. His current research interests include pattern recognition and artificial intelligence.

JIPENG HUANG received the B.S. degree in electronic information and technology from Northeast Normal University, China, in 2007, and the Ph.D. degree from the Changchun Institute of Optics, Fine Mechanics and Physics, Changchun, China, in 2012. He is currently an Associate Professor and a Supervisor of master’s students with Northeast Normal University. His research interests include biomedical testing, image processing, and the design of photonic instruments and equipment.