sEMG Signal Processing Methods: A Review

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Abstract. Surface electromyography (sEMG) is one type of bioelectrical signal produced by the human body. sEMG contains meaningful information associated with muscle activity and has numerous applications in motor control and neuromuscular physiology. sEMG signals can be used to identify the movement intention and evaluate the function status of muscles. sEMG is also applied in virtual reality with the advances of technology development. In this review paper, sEMG feature extraction methods and classification methods are summarized, and the future development is prospected.

1. Introduction
The surface electromyography (sEMG) signal is a complex interference pattern of the electrical activity during the muscle contraction[2]. It is closely related to muscle activity and exercise status. Its amplitude is generally 0.01mV to 10mV and its main energy is concentrated between 0Hz and 500Hz frequency band[1]. Detection of sEMG signals is a non-invasive method, which is of great importance in clinical diagnosis, rehabilitation medicine and intelligent prosthetic control[3]. In recent years, EMG has been used in the gesture recognition of sign language, game control and wearable device.

Once the sEMG signals are acquired, the next step involves the signal processing. The sEMG signal can be easily contaminated by other types of signals; therefore it is important to reduce the noise mixed in the sEMG signal. In addition, how to extract useful feature information from the original one-dimensional time series sEMG signal is a critical component in sEMG data analysis. In this paper, sEMG denoising methods are summarized. Also, we review representative algorithms for feature extraction methods and classification of sEMG signals.

2. sEMG signal processing algorithms

2.1. sEMG denoising
sEMG denoising involves two categories: hardware denoising and software denoising. The hardware denoising method improves the signal-to-noise ratio by improving the performance of the acquisition instrument, such as using a spatial filter. The software denoising method is widely used in sEMG signals, including filters and wavelet transforms. In recent years, the wavelet analysis theory, as an extension to traditional Fourier transform, has been increasingly explored in signal denoising. The
wavelet coefficients have different characteristics at each scale of noise and signal. So the basic idea is to remove the wavelet components generated by noise at each scale. The retained wavelet coefficients are basically the components of the original signal. Then, the wavelet inverse transform is used to reconstruct the original signal. There are three methods used for filtering, including modular maximal reconstruction filtering, spatial correlation filtering, and threshold filtering.

In order to eliminate the noise mixed in sEMG signal, a Hermite interpolation-based reconstruction algorithm was proposed by Luo et al. The experiment results showed that the method provided good performance in removing noise, improving the signal-to-noise ratio and reserving the detailed information[4]. Wei et al. used the maximal overlapping discrete wavelet transform (MODWT) algorithm to filter the noise in sEMG signals[5].

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2.2. sEMG feature extraction and classification

Traditional methods for extracting sEMG features, including time domain analysis and frequency domain analysis, are widely used in sEMG data analysis. Daniel first used time domain analysis techniques for feature extraction, and AR models were used to identify different arm movements. The classification accuracy can reach 85%[11]. Hargrove et al. combined Hudgins’time domain statistics and autoregressive features as a joint feature, and the ANN was used for classification[12]. Han et al. extracted mean of the absolute values as the characteristics of hand movements, and hierarchical Bayesian mode was used for classification. The classification accuracy reached 92%[13].

Frequency domain analysis methods, such as Fourier transform spectrum analysis and sequence spectrum analysis, are also used in sEMG data analysis. Bilodean et al. calculated and analyzed the power spectrum of sEMG signals and found the relationship between the change caused by the increase in force and the thickness of the skin volume conductor[14]. Balbinot extracted RMS value, variance, kurtosis and median frequency as feature values to identify nine distinguish movements, and the multinomial logistic regression and an optimization heuristic based on gradient descent were used for classification. The average classification accuracy was 90.2%[15]. An FA-FNN algorithm was proposed to optimize and regulate the scene control parameters in real time based on the detected fatigue feature of EEG and sEMG. The mean power frequency was used for feature extraction. The method can recognize the motion intention and estimate the fatigue state, and realize the control and parameter adjustment of the virtual scene[16].

However, these methods cannot accurately reflect the nature of sEMG signals[17]. In recent years, the time-frequency analysis method which combines the two characteristics of time domain and frequency domain represented by wavelet transform has attracted the attention of many researchers. The sEMG signals can be analyzed by the time-frequency domain technology, such as short-time Fourier transform and wavelet analysis theory. Davies et al. applied short-time Fourier transform and Wigner transform to sEMG fatigue analysis[18]. For the first time, Englehart et al. used wavelet
analysis theory to extract time-frequency eigenvalues[19]. In the end, the representative feature selection methods and classifier methods are listed in Table 1.

**Table 1. The representative feature selection methods and classifier methods.**

| Years | Author | Features | Feature selection methods | Classifier | Movement | Accuracy |
|-------|--------|----------|---------------------------|------------|----------|----------|
| 2016  | Wei [20]| The maximum value of wavelet coefficients | DWT | PSO-SVM | (1) Wrist down (2) Wrist up (3) Hand grasps (4) Hand extension | 98.75% |
| 2015  | Mane [21]| Mean of maxima and amplitude of wavelet coefficients | DWT | ANN | (1) Closed palm (2) Open palm (3) Wrist extension | 93.25% |
| 2015  | Gokgoz [22]| (1) Mean of the absolute values (2) Average power (3) Standard deviation (4) Ratio of mean values. | DWT | Random forest decision tree | Apply DWT and MSPCA approach for diagnosis of neuromuscular disorder. | 96.67% |
| 2016  | Sun [23]| (1) The maximum value of wavelet coefficients (2) Multi-scale coefficients (3) The singular values of wavelet coefficients | (1) DWT (2) Multiple mother wavelets | BPNN | (1) Upper step and lower step (2) Uphill and downhill | 98.7% |
| 2016  | Yang [24]| (1) The wavelet entropy (2) The approximate entropy | DWT | TSVM | (1) Left and right turning of head (2) Both-shoulders elevation (3) Left-shoulder elevation and right-shoulder elevation | 88.75% |
| 2014  | Omari [25]| The energies of wavelet coefficients | DWT | GRNN | Eight hand motions | 95% |
| 2013  | Zhang [26]| The energy ratio of each wavelet coefficient | WPT | BPNN | (1) Elbow flexion (2) Extension elbow (3) Forearm internal rotation (4) Forearm external rotation | 95% |
| 2012  | Hariharan [27]| (1) RMS (2) AR model coefficients (3) Waveform length | DWT | PNN/GRNN | The different types of wrist motions | 99% |
| 2017  | She [28]| The complex Morlet wavelet | Tensor linear laplacian discriminant (TLLD) | LDA | (1) Wrist flexion (2) Wrist extension (3) Forearm pronation (4) Forearm supination (5) Hand close (6) Hand open | 98% |

In recent years, nonlinear dynamics methods have begun to be applied to sEMG signals processing. Zou et al. proposed a method combining fuzzy entropy and multi-scale analysis. The multi-scale fuzzy entropy was extracted as feature values and SVM was used for classification. The average recognition rate reached 97%[29]. Zhang et al. presented a new method named ball-averaged Lyapunov exponents...
method to calculate Lyapunov exponents of nonlinear time-series signals. Multi-class classifier was constructed based on twin support vector machines (TSVM) with binary-tree. Experimental showed that the method had stronger anti-jamming capability than Rosenstein method, and the classification accuracy was above 96.0%[30]. Liu et al. extracted RMS, time-varying AR model coefficients, and nonlinear wavelet spatial strength as the features, and BP neural network was used to identify four modes in the walking cycle[31].

Several classification algorithms have been proposed such as LDA, SVM, and ANN, among others. This section presents the properties of a set of classifiers, in order to make it easier to choose an appropriate classifier for a given type of MCI. All classifier methods are listed in Table 2.

| Years | Advantages | Disadvantages |
|-------|------------|---------------|
| LDA   | (1)Simple structure | (1)Takes large training time and large storage space |
|       | (2)Low computation | (2)It is difficult to solve multiple types of motion problems with SVM |
| SVM   | (1)Good classification results can be obtained using a suitable kernel function | (3)It is very difficult to train large sample situations |
|       | (2)Mostly preferred in high-dimensional feature space | |
|       | (3)Improved SVM versions; TSVM, PSO-SVM, LS-SVM | |
| ANN   | (1)Resistance to noise | (1)High computational complexity |
|       | (2)Able to perform well on complicated and multivariate nonlinear domain | (2)Long calculation time |
| BPNN  | (1)Simple structure | (1)Slow convergence speed |
|       | (2)Many adjustable parameters | (2)In the training phase, it is easy to forget the old samples while learning new samples |
|       | (3)Good operability and adaptability | (3)The learning efficiency and convergence speed of BP neural network are easily limited by the number of training times |
|       | (4)Strong nonlinear fitting ability | |
|       | (5)It can calculate the desired output for any input in the training set | |
| GRNN  | (1)Network training is one-way training without iteration | (1)The selection of training samples directly determines the weight of the network, so the prediction results are affected by the quality of the sample. |
|       | (2)The number of neurons in the hidden layer is determined by the training samples adaptively | (2)Its performance is affected by spread |
| PNN   | (1)Fast learning convergence speed and good fault tolerance | (1)The number of samples is huge |
|       | (2)The number of neurons in each layer is relatively fixed, and it is easy to implement in hardware | (2)Large memory requirements and long calculation time |
|       | | (3)Predictive accuracy is not high when dealing with small sample problems |

### 3. Technical Difficulties and Prospects

In terms of feature extraction and classification, although the wavelet theory has been well developed, there are still some problems in its application, such as the selection of wavelet basis, the selection of the threshold function, and the unripe development of the multi-dimensional wavelet theory. Since the noise sources of myoelectric signals are complex, how to address the denoising issue remains to be further explored. Most of the above discussed methods only consider two dimensions (channels and time) in the data processing process. Therefore, it is necessary to develop methods for analyzing multidimensional information and extend them for feature extraction. Recently, research on deep learning applied to sEMG classification has caused increasing academic concern. When large dataset and labels are not available, training of deep learning models will not be successful. So, it is necessary to extract more comprehensive features from raw data.
4. Conclusions
Currently, the time-frequency analysis methods are widely employed in sEMG data analysis. Compared with the traditional filtering methods, the wavelet theory for denoising is widely employed. It can retain some useful local features of the signal. Most researches focus on feature extraction and pattern recognition of EMG signals from upper limbs. Combining the soft and hard threshold functions to obtain a new type of function is a major trend in the selection of the threshold function so far. Combining wavelet transform with other methods can improve the recognition accuracy. In the future, it is possible to consider the fusion of time-frequency domain, and spatial features.

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