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SEMG Signal Processing using DWT for Neuromuscular Disorders Detection

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ABSTRACT: The Electromyogram (EMG) signals arising from muscle activities have become a useful tool for clinical diagnosis, rehabilitation medicine and sport medicine. These signals are essentially non-stationary may contain indicators of current category, or even warnings about impending events. Wavelet analysis is often very effective because it provides a simple approach for dealing with local aspects of a signal. It is shown that wavelet representation can be practical in detecting particular spikes in EMG signals and may be constructive for the detection of active segments. This manuscript presents a signal analysis based on the wavelet transform which describes an approach for classifying Electromyography (EMG) signals via Matlab between three types of muscle diseases. Three diverse cases of EMG signals have been considered, filtered and compared with the Butterworth filter results. The present work describes the application of Wavelet Transform to provide a more accurate picture of the localized time-scale features indicative of disease abnormalities. The first step includes Processing and Filtering of EMG signal. The second step includes the comparison of the signal under DWT filter and Butterworth filter.

Keywords—Biomedical, Electromyography, Signal processing, Discrete wavelet Transform, Neuropathy, Myopathy

1. Introduction

The surface electromyography (sEMG) signal is a complex interference pattern of the electricalactivity 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 sEMGsignal can be easily contaminated by other types of signals; therefore it is important to reduce thenoise 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

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 explore 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].

A major limitation of the sEMG signals is about the power frequency noise, which is hard to avoid. So we need to find some ways to filter out the power frequency noise while using wavelet denoising. Su et al. combined wavelet transform and independent component analysis for sEMG denoising [6]. The experiment results showed that it provided better performance than that of wavelet denoising. It can filter out the power frequency noise while filtering out the high-frequency noise. Zuo et al. proposed an improved FastICA algorithm based on the falling Newton method. The sEMG signal obtained after separation is similar to the original sEMG[7]. Mao et al. proposed an energy threshold filtering algorithm based on the wavelet transform, which can suppress 50Hz power frequency interference effectively and preserve the information of other frequency bands completely[8].

In recent years, the elimination of ECG signal interference caused by sEMG signals has been widely studied. Niegowski et al. used wavelet-based unsupervised learning methods to filter ECG signals[9]. Abbaspour et al. combined the adaptive neuro-fuzzy inference system with wavelet transform to eliminate the ECG signal interference. It is found that the performance of the proposed ANFIS–wavelet method is superior to other common methods such as the high-pass filter[10].

sEMG feature eextraction 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 theincrease 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].Forthe first time, Engle hartetal. used wavelet Analysis theory to extract time-frequency eigen values[19].In the end, the representative feature selection methods and classifier methods are listed in Table 1.

Table1.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) Wristdown (2) Wrist up (3) Handgrasps (4) Handextension	98.75%
2015	Mane [21]	Mean of maxima and amplitude of wavelet coefficients	DWT	ANN	(1) Closedpalm (2) Open palm (3) Wristextension	93.25%
2015	Gokgoz [22]	(1) Mean of the absolute values (2)Average power (3)Standarddeviation (4)Ratioofmean values.	DWT	Random forest decision tree	Apply DWT and MSPCAapproachfor diagnosis of neuromuscular disorder.	96.67%
2016	Sun [23]	(1)Themaximumvalue ofwaveletcoefficients (2)Multi-scale coefficients (3)Thesingularvalues ofwaveletcoefficients	(1)DWT (2)Multiplemother wavelets	BPNN	(1)Upperstepand lower step (2)Uphillanddownhill	98.7%
2016	Yang [24]	(1)Thewavelet entropy (2)Theapproximate entropy	DWT	TSVM	(1)Left and right turning of head (2)Both-shoulders elevation (3)Left-shoulder elevationandright-shoulder elevation	88.75%
2014	Omari [25]	Theenergiesofwavelet coefficients	DWT	GRNN	Eighthandmotions	95%
2013	Zhang [26]	Theenergyratioof eachwavelet coefficient	WPT	BPNN	(1)Elbowflexion (2) Extensionelbow (3) Forearminternal rotation (4) Forearmexternal rotation	95%
2012	Hariharan[27]	(1)RMS (2)AR model coefficients (3)Waveformlength	DWT	PNN/GRNN	Thedifferenttypesof wristmotions	99%
2017	She [28]	ThecomplexMorlet wavelet	Tensor linear laplacian discriminant (TLLD)	LDA	(1)Wrist flexion (2) Wrist extension (3) Forearmpronation (4) Forearmsupination (5) Handclose (6) Hand open	98%

In recent years, nonlinear dynamics method shave 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 ratereached97%[29].Zhangetal.presentedanewmethodnamedball-averagedLyapunovexponents

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 myo electric 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 thres hold 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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