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A novel pre-processing procedure for enhanced feature extraction and characterization of electromyogram signals

Omkar S. Powar*, Krishnan Chemmangat, Sheron Figarado

Department of Electrical and Electronics Engineering, National Institute of Technology Karnataka, Surathkal, Mangalore 575025, India

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ABSTRACT

In the analysis of electromyogram signals, the challenge lies in the suppression of noise associated with the measurement and signal conditioning. The main aim of this paper is to present a novel pre-processing step, namely Minimum Entropy Deconvolution Adjusted (MEDA), to enhance the signal for feature extraction resulting in better characterization of different upper limb motions. MEDA method is based on finding the set of filter coefficients that recover the output signal with maximum value of kurtosis while minimizing the low kurtosis noise components. The proposed method has been validated on surface electromyogram dataset collected from seven subjects performing eight classes of hand movements (wrist flexion, wrist radial deviation, hand close, tripod, wrist extension, wrist ulnar deviation, cylindrical and key grip) with only two pairs of electrodes recorded from flexor carpi radialis and extensor carpi radialis on the forearm. The performance of the MEDA has been compared across four classifiers namely J-48, k-nearest neighbours (KNN), Naives Bayes and Linear Discriminant Analysis (LDA) attaining the classification accuracy of 85.3 ± 4%, 85.67 ± 5%, 76 ± 6% and 91.2 ± 2% respectively. Practical results demonstrate the feasibility of the approach with mean percentage increase in classification accuracy of 20.5%, without significant increase in computational time across seven subjects demonstrating the significance of MEDA in classification.

1. Introduction

Electromyography is the process of recording and analysing the electrical activity produced from the muscles contraction, and the signal is known as Electromyogram (EMG) [1]. They are useful electrophysiological signals which are non-stationary, non-linear, and high complex signals with large variations that carries the distinct signature of voluntary intent of central nervous system [2]. EMG signals are measured by electrodes that are placed on the target muscles using needle electrode (invasive method) or surface electrode (non invasive method), since the use of needle electrode involves medical skill and can cause pain and discomfort to the subject [3], surface electrodes have been used in this work. Surface EMG (sEMG) finds its application in the field of electric wheel chair control, determination of muscle fatigue and muscle contraction, cursor control, biomechanics, ergonomics, diagnosis of neuromuscular disorder and prosthetics control [4,5]. In this paper, the application of sEMG for the identification of hand motion commands for the control of upper limb prostheses is paid attention.

The prosthetic hand is controlled by sEMG signals from subjects forearm or other locations. Biosignal processing of sEMG signals involves three main steps. First step involves sEMG data acquisition, signal conditioning and pre-processing which includes mean removal, bandpass filtering and powerline attenuation. The second step of processing, consists of three parts: (1) feature extraction, (2) dimensionality reduction and (3) classification. Feature extraction highlights the relevant structures which are hidden in the data stream, and removes the interferences as well as irrelevant sEMG signals [6]. The features extracted may be in time domain, frequency domain or time-frequency domain. The obtained features should have maximum class separability, robustness and low computational complexity [7]. Dimensionality reduction aims to select a subset of features with the aim to reduce feature set dimensionality, which is achieved by removing irrelevant and redundant features. This reduces the computational complexity and results in better generalization for classifier [8]. The classifier generates the control command by mapping the extracted features to the target class. Finally the control algorithm takes the command from the classifier to control the actuators. In this paper the focus is on the first section, particularly pre-processing of sEMG signals.

* Corresponding author.
E-mail addresses: omkarpowar1991@gmail.com (O.S. Powar), cmckrishnan@nitk.edu.in (K. Chemmangat), sheron@nitk.edu.in (S. Figarado).

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The main challenges in pre-processing sEMG signal is the limited tools that can be used to minimize the noise such as power line interface, electrode noise, broad band noise from instrument, motion artifacts, white Gaussian noise [9] and to enhance the feature. Here we also use the white Gaussian noise assumption. This paper proposes a pre-processing procedure for the sEMG signal namely the Minimum Entropy Deconvolution Adjusted (MEDA) before feature extraction. MEDA differentiates the original EMG signals from noise using higher order statistics such as kurtosis, which is the fourth moment of distribution. This motivated the use of MEDA for sEMG signals in this research work to enhance features and identify patterns for efficient classification. To the authors knowledge, the current study is the first to use MEDA in sEMG signal analysis.

The paper mainly focuses on the following aspects: (1) To study the classification accuracy of sEMG feature extraction without and with the pre-processing step using MEDA, (2) After pre-processing step with MEDA, removing redundant features in the classifier and finding the most stable feature combination with different classifiers.

The paper is organized as follows: Section 2 discusses the material and data collection strategy. Section 3 provides the background of MED (Minimum Entropy Deconvolution). Section 4 discusses the methodology of MED and MEDA pre-processing tools, the feature extraction process and classification in detail. Experimental results are presented in Section 5 with detailed discussions and finally, Section 6 concludes the paper with some possible future directions.

2. Material and data collection

Seven subjects, three males and four females, aged between 25 and 35 years participated in the study. The subjects were normally limbed with no neurological or muscular disorder. Before participating, all the subjects gave their written consent to participate in this study and were briefed about the experiment. The required ethical approval was obtained from National Institute of Technology Karnataka, Surathkal. To display and store signals, a Virtual Instrument was developed in LABVIEW (NI). To avoid the effect of different limb position on the generated sEMG signals, subjects were seated on an armchair, with their arm supported and fixed at one position (the shoulder adducted and neutrally rotated, elbow flexed at 90°, forearm and wrist in neutral position).

The sEMG data was recorded from flexor carpi radialis (channel 1) and extensor carpi radialis (channel 2) of a subject by using two pairs of surface electrodes (3M red dot Ag/AgCl) on the right forearm [15]. This muscle group represents the most important location on human forearm and these muscles largely contribute to wrist movements [16]. Reducing the number of electrodes, simplifies the requirements for controlling prostheses without compromising on the classification accuracy. To avoid crosstalk between two muscles, the inter-electrode distance of 20 mm was maintained for a 5 mm diameter electrode. The sEMG signal collected from the electrodes was amplified with a gain of 1000. A 16 bit analogue to digital converter (National Instruments, PXIe-4300) was used to sample the signal at 2000 Hz. A band pass filter with a frequency band of 20–500 Hz was used to extract the sEMG signal with an additional notch filter at 50 Hz to remove the power line interference.

For the experiment, subjects were asked to perform eight different hand movements: wrist flexion (FX), wrist radial deviation (WRD), hand close (HC), tripod (TD), wrist extension (EX), wrist ulnar deviation (WUD), cylindrical (CL) and key grip (KG) as shown in Fig. 1. The subject performed each movement for a duration of 3 s and a rest period of 5–8 s between each movement. Each movement was repeated 5 times. The movements were performed sequentially.

3. Background

MED was originally proposed by Ralph Wiggins in 1978 to aid extraction of reflectivity information in subterranean layers in seismic data [11]. MED was originally applied in the field of multisensor data fusion, pitch period estimation, restoration of star field images, seismic signal processing, ultrasonic inspection of composite materials and pipes and machine fault diagnosis [12,13]. It was used by Endo and Randall in machine condition monitoring field to detect gear tooth fault [14]. MED operator suppresses frequencies over which the signal to noise ratio is low and emphasizes dominant signals. MED iteratively selects an FIR filter to minimize the entropy of filtered signal thereby enhancing the kurtosis information in the signal. A higher value of entropy associated with the signal indicates a lower SNR [12].

4. Methodology

4.1. Minimum Entropy Deconvolution (MED)

Here, a kurtosis norm is defined and then a FIR filter is designed such that the filtered output sEMG signal reaches a maximum according to the norm. The signal is assumed to be corrupted with noise and is expressed as:

$$\vec{x} = \vec{d} + \vec{e} \tag{1}$$

In Eq. (1), $\vec{x} \in R^N$ is the final measured sEMG signal with noise, and $\vec{d} \in R^N$ is Original sEMG, and $\vec{e} \in R^N$ is White Gaussian noise.

Generally, for sEMG signal, Kurtosis is large for $\vec{d}$ when compared to noise $\vec{e}$. Selection of FIR filter with coefficients $\vec{f}$ to maximize kurtosis leads to a filter design that extracts high kurtosis EMG, which minimizes the noise component.

An approximation $\vec{y} \in R^N$ of the signal $\vec{d}$ is reconstructed by convolving the FIR filter $\vec{f} \in R^L$ with the measured sEMG signal $\vec{x}$.

$$\vec{y} = \vec{f} * \vec{x} \tag{2}$$

where '*' denotes convolution.

$$y_k = \sum_{l=1}^{L} f_l x_{k-l+1}, \quad k = 1, 2, \ldots, N$$

where 'L' and 'N' denote the filter length and input sample length respectively.

In matrix form:

$$\vec{y} = \bar{X}_0^T \vec{f}, \tag{3}$$

$$\bar{X}_0 = \begin{bmatrix} x_1 & x_2 & x_3 & \ldots & \ldots & x_N \\ 0 & x_1 & x_2 & \ldots & \ldots & x_{N-1} \\ 0 & 0 & x_1 & \ldots & \ldots & x_{N-2} \\ \vdots & \vdots & \vdots & \ddots & \ldots & \vdots \\ 0 & 0 & 0 & \ldots & \ldots & x_{N-L+1} \end{bmatrix}_{LbyN}$$

The filtered signal $\vec{y}$ should approach the original sEMG $\vec{d}$ and this is found by selecting filter $\vec{f}$ to minimize the noise effect $\vec{f} * \vec{e} \longrightarrow 0$ and extracting original sEMG signal $\vec{f} * \vec{x} \simeq \vec{d}$. For MED to work satisfactorily, the signal $\vec{d}$ is expected to have very high kurtosis while $\vec{e}$ is of very low kurtosis.

To achieve this, an optimization problem is formulated with objective function under assumed zero mean output $\vec{y}$,

$$\max_{\vec{f}} kurtosis = \max_{\vec{f}} \frac{\sum_{n=1}^{N} y_n^4}{\left(\sum_{n=1}^{N} y_n^2\right)^2} \tag{4}$$