EMG SIGNAL DE-NOISING USING INDEPENDENT COMPONENT ANALYSIS ALGORITHM AND FILTERS

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Abstract
Electromyography (EMG) signals provide a very useful means of control of robotic prosthetics. In recent years research in biomedical engineering and other similar areas, along with advancements in electro mechanics, have led to the creation of advanced and accurate robotics prosthetics. When measuring motor unit action potentials, it can be hard to assure that the acquired signal is that of the muscle under examination. Similar to other electrophysiological signals, EMG signals are small and need to be amplified by an amplifier designed to measure physiological signals. the simulation is done using MATLAB. The simulation result demonstrate that EMG signals are effectively extracted from their respective recordings and isolating it from artifacts associated with it at the time of recording. In this work Chebyshev band pass filters are used as preprocessing filter and adaptive filter as post processing filter which removed the noise. Thus using of FASTICA algorithm, Chebyshev band pass filter and adaptive filter efficiently isolate EMG signal from unwanted noise.

Index Terms: **EMG, Independent Component Analysis (ICA), FASTICA.**

I. INTRODUCTION

EMG stands for electromyography. It is the study of muscle electrical signals. EMG is sometimes referred to as myoelectric activity. EMG is measured using similar techniques to that used for measuring EEG or other electrophysiological signals. Electrodes are placed on the skin overlying the muscle. Alternatively, wire or needle electrodes are used and these can be placed directly in the muscle.

When EMG is acquired from electrodes mounted directly on the skin, the signal is a composite of all the muscle fiber action potentials occurring in the muscle(s) underlying the skin. These action potentials occur at somewhat random intervals so at any one moment, the EMG signal may be either positive or negative voltage. Individual muscle fiber action potentials are sometimes acquired using wire or needle electrodes placed directly in the muscle.

There are many, many applications for the use of EMG. EMG is used clinically for the diagnosis of neurological and neuromuscular problems. The signal is susceptible to numerous technical problems. These include signal interference like hum, signal acquisition problems like clipping or baseline drift, skin artifacts, signal processing errors, and many other kinds of interpretation problems. First, the signal is picked up at the electrode and amplified. Typically, a differential amplifier is used as a first stage amplifier. Additional amplification stages may follow. Before being displayed or stored, the signal can be processed to eliminate low-frequency or high-frequency noise, or other possible artifacts. Frequently, the user is interested in the amplitude of the signal. Consequently, the signal is frequently rectified and averaged in some format to indicate EMG amplitude. However, there are many types of EMG analysis schemes.

The EMG signal is typically described using a variable related to the size or amplitude of the signal. Rectified, averaged EMG, integrated EMG, and linear envelope displays are all ways to display the amplitude of the EMG signal. Frequency analysis comprises the second category of analysis for the EMG signal, and there are many ways to conduct frequency analysis, including analysis of zero crossings, spectral analysis, numerous time-frequency algorithms, and many other techniques[3].

II. INDEPENDENT COMPONENT ANALYSIS

In biomedical data processing, the aim is to extract clinically, biochemically or pharmaceutically relevant information (e.g. metabolite concentrations in the brain) in terms of parameters out of low quality measurements in order to enable an improved medical diagnosis .Typically, biomedical data are affected by large measurement errors, largely due to the noninvasive nature of the measurement process or the severe constraints to keep the input signal as low as possible for safety and bio-ethical reasons. Accurate and automated quantification of this information requires an ingenious combination of the following four issues:

1.An adequate pretreatment of the data,

2.The design of an appropriate model and model validation,

3.A fast and numerically robust model parameter quantification method and

An extensive evaluation and performance study, using in-vivo and patient data, up to the embedding of the advanced tools into user friendly user interfaces to be used by clinicians. A great challenge in biomedical engineering is to non-invasively asses the physiological changes occurring in different internal organs of the human body.

To rigorously define ICA, we can use a statistical “latent variables” model. We observe n random variables x1; :::; xn, which are modeled as linear combinations of n random variables s1; :::; sn: xi = ai1s1 + ais2 + ::: + ainsn; for all i = 1; :::; n (7.4) where the aij ; i; j = 1; :::; n are some real coefficients. By definition, the si are statistically mutually independent. This is the basic ICA model. The ICA model is a generative model, which means that it describes how the observed data are generated by a process of mixing the components sj . The independent components sj (often abbreviated as ICs) are latent variables, meaning that they cannot be directly observed. Also the mixing coefficients aij are assumed to be unknown. All we observe are the random variables xi , and we must estimate both the mixing coefficients aij and the ICs s_i using the xi . This must be done under as general assumptions as possible[1].

To define the concept of independence, consider two scalar-valued random variables *y*1 and *y*2. Basically, the variables *y*1 and *y*2 are said to be independent if information on the value of *y*1 does not give any information on the value of *y*2, and vice versa. Above, we noted that this is the case with the variables *s*1, *s*2 but not with the mixture variables *x*1,*x*2.

Technically, independence can be defined by the probability densities. Let us denote by *p*(*y*1,*y*2) the joint probability density function (pdf) of *y*1 and *y*2. Let us further denote by *p*1(*y*1) the marginal pdf of *y*1, i.e. the pdf of *y*1 when it is considered alone:

$$p1(y1)=p(y1,y2)dy2$$

And similarly for *y*2. Then we define that *y*1 and *y*2 are independent if and only if the joint pdf is *factorizable* in the following way:

$$p(y1,y2) = p1(y1)p2(y2$$

This definition extends naturally for any number *n* of random variables, in which case the joint density must be a product of *n* terms.The definition can be used to derive a most important property of independent random variables. Given two functions, *h*1 and *h*2, we always have

$$E\{h1(y1)h2(y2)\}= E\{h1(y1)\}E\{h2(y2)\}$$

As the name implies, the basic goal is to find a transformation in which the components Si are statistically as independent from each other as possible. ICA can be applied, for example, for blind source separation, in which the observed values of x correspond to a realization of an m-dimensional discrete-time signal x(t), t = 1, 2,3,…. Then the components Si(t) are called source signals, which are usually original, uncorrupted signals or noise sources. Often such sources are statistically independent from each other, and thus the signals can be recovered from linear mixtures Xi by finding a transformation in which the transformed signals are as independent as possible, as in ICA. Another promising application is feature extraction, in which Si is the coefficient of the i^{th} feature in the observed data vector X. The use of ICA for feature extraction is motivated by results in neurosciences that suggest that the similar principle of redundancy reduction explains some aspects of the early processing of sensory data by the brain. ICA has also applications in exploratory data analysis in the same way as the closely related method of projection pursuit[4].

ICA is very closely related to the method called blind source separation (BSS) or blind signal separation. A "source" means here an original signal, i.e., independent component, like the speaker in the cocktail-party problem. "Blind" means that we know very little, if anything, of the mixing matrix, and make very weak assumptions on the source signals. ICA is one method, perhaps the most widely used, for performing blind source separation[1].

III.BLIND SOURCE SEPARATION

Blind source separation (BSS) is the method that decomposes the signal mixtures into the original sources. The technique of **Independent component analysis (ICA)** can be used to estimate the mixing block and the original sources based on the information of their independence's by ICA is important research field because of a lot of applications in biomedical signal processing, geophysical data processing, data mining, speech recognition and enhancement, wireless communication and so on.

Because ICA with same number of sources and mixtures has the square mixing matrix, the sources can be reconstructed almost perfectly by learning the inverse of mixing matrix with the independency of sources.

Blind source separation consists of recovering a set of signals of which only mixtures are observed. Neither the structure of the mixtures nor the source signals are known to the receivers. The aim is to identify and decouple the mixtures[2].

IV.BLOCK DIAGRAM AND DESIGN

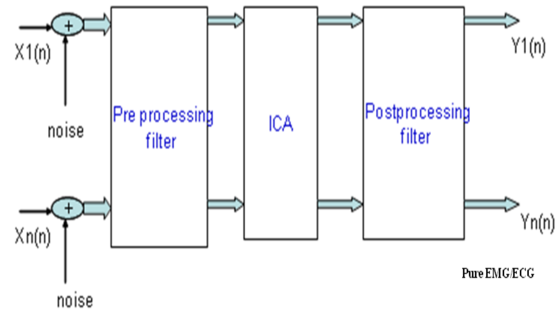

Fig 1: Basic block diagram of

In the above figure we have shown the extraction of EMG signals using different filters and tools. Naturally obtained EMG signals are not the pure signals, rather it consist of unwanted additional unknown noise signals. Here we add known value of Gaussian noise in to the EMG signals in order to measure the performance of the system, these mixture is passed through a pre-processing filter, let it be a conventional FIR or IIR filter. After filtering, this mixture is passed through ICA (Independent Component Analysis), it is a technique that recovers a set of independent signals from a set of mixed signals. At the output of ICA as shown above we get four/eight independent signals on four/eight channels. These signals are again passed through a post-processing filter i.e Adaptive filter as it can give original expected signal at the output with negligible noise[6].

Number of digital filters are been specified for biomedical signal processing to reduce the noise content. In this project we use Chebyshev filter and adaptive filter and also we are checking out the performance results of these filters by calculating SNR and PSD. The adaptive filter is best suited for biomedical signal processing, which uses LMS algorithm. In this project two different filters are used because some of the EMG signal may be overlapped with noise spectrum. In order to extract this hidden signal in noise we go for Adaptive filter. Here Adaptive filter uses LMS algorithm[5].

Pseudo code

Take four mixed signals
Plot the mixed signal //EMG signals mixed with noise
Call band pass chebyshev filter for pre processing
Plot preprocessed signals

Call FASTICA
Plot separated signals
Call adaptive filter for post processing
Plot filtered signals

IV. SIMULATION RESULT

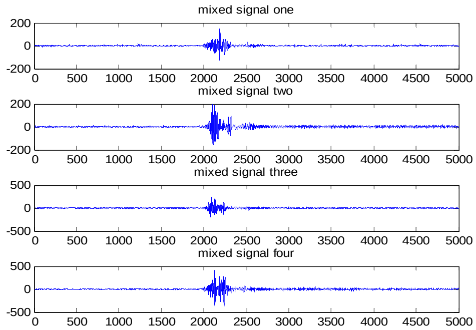

Figure 2: Mixed EMG signal

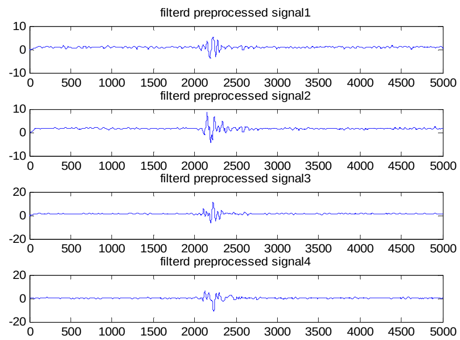

Fig 3: Preprocessed signal using chebyshev band pass filter

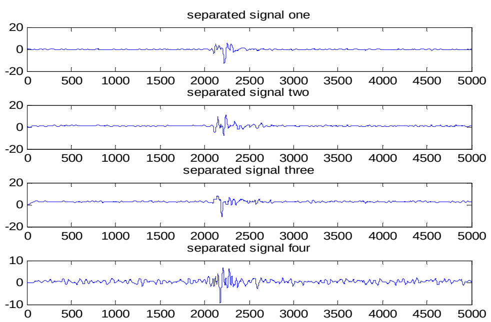

Fig 4: separated signals after ICA

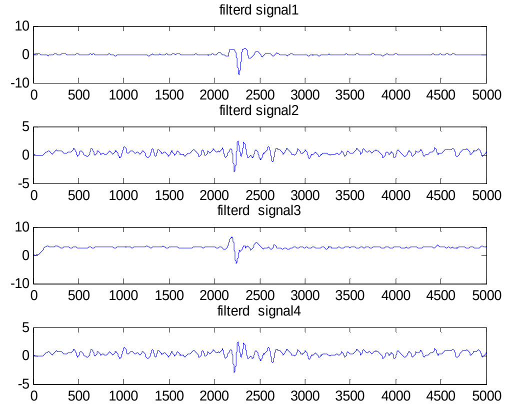

Figure 5: Post Processed Signals Using Adaptive Filter

VI. CONCLUSION

Biomedical signals are collective electrical signal acquired from any organ that represents a physical variable of interest. These signals are complexed in nature as it contains various artifacts with it, the main criterion is to extract and analyze these signals independently. The algorithm used here i.e. Independent Component Analysis (ICA) is a member of a class of BSS (Blind Source Separation). Detection of EMG signals with powerful and advance methodologies is becoming a very important requirement in biomedical engineering. The main reason for the interest in EMG or s is in clinical diagnosis and biomedical applications.

The result demonstrate that signal of EMG signals are effectively extracted from their respective recordings and isolating it from artifacts associated with it at the time of recording. In our project, we used Chebyshev band pass filter as preprocessing filter and adaptive filter as post processing filter which removed the noise. Thus we conclude that using of FASTICA algorithm, Chebyshev band pass filter and adaptive filter efficiently isolate EMG signal from unwanted noise, proving it by power spectral density plot. In this work 4 EMG recorded signal are used. So, this can be enhanced by processing real time biomedical signal such as EEG, ECG, EMG and MEG. In case processing ECG signal, QRS complex can detected by applying QRS detection algorithm. Increasing the order of the signal i.e. by considering more number of inputs. This need higher order matrices. The processing of biomedical signals can be implemented in to hardware.

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