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Evaluation of higher order statistics parameters for multi channel sEMG using different force levels

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Abstract—**The electromyograpy (EMG) signal provides information about the performance of muscles and nerves. The shape of the muscle signal and motor unit action potential (MUAP) varies due to the movement of the position of the electrode or due to changes in contraction level. This research deals with evaluating the non-Gaussianity in Surface Electromyogram signal (sEMG) using higher order statistics (HOS) parameters. To achieve this, experiments were conducted for four different finger and wrist actions at different levels of Maximum Voluntary Contractions (MVCs). Our experimental analysis shows that at constant force and for non-fatiguing contractions, probability density functions (PDF) of sEMG signals were non-Gaussian. For lesser MVCs (below 30% of MVC) PDF measures tends to be Gaussian process. The above measures were verified by computing the Kurtosis values for different MVCs.**

I. Introduction

Electromyography (EMG) signals detected directly using needle electrodes or surface EMG show a train of motor unit action potentials (MUAP) plus noise. An MUAP is sum of a large group of muscle fiber action potentials (MFAP), where each MFAP consists of superimposed information of the muscle and neuron firing signals [1]. The origin of each of the MUAP is inherently random and the electrical characteristics of the surrounding tissues are non-linear. The MUAP firing pulses are generally considered a random function of time which is non-Gaussian in nature [2]. Due to the nature of this signal the amplitude of the EMG signal is pseudo-random and the shape of the probability distribution function (PDF) resembles a Gaussian function. Surface EMG is a non-invasive recording, requires relatively simple equipment, and this opens it for numerous applications. The close relationship of surface EMG with the force of contraction of the muscle is useful for number of applications such as sports training and for machine control [3-5].

While there are numerous applications for surface EMG, these are limited due to reliability issues. There are many factors which can affect the appearance of the MUAP such as:

- Type of electrodes (invasive or non-invasive)
- The muscle anatomy (number of active motor units, size of the motor units, the spatial distribution of motor units)
- Muscle physiology (trained or untrained, disorder, fatigue).
- Nerve factors (disorder, neuromuscular junction).
- Contraction types (level of contraction, speed of contraction, isometric/non-isometric).
- Artefacts (crosstalk between muscles, ECG interference).
- Recording apparatus factors (recording-method, noise, electrode's properties and recording sites)

The amplitude of the MUAP in the EMG signal is related to a certain extent to the force of muscle and level of contraction. Peripheral factors such as spacing, type and size of electrodes may also have an influence on the signal, and to obtain reliable information, considering such factors is critical. Some of these factors may be handled through careful skin preparation, and by selecting proper anatomical landmarks for the placement of electrodes. These factors can easily influence the sEMG signal strength when there is different force levels (different levels of muscle activity), such as dynamic hand or finger movements [6, 7]. In these situations, cross-talk among the different muscle groups is one of the major obstacles for the sEMG. To minimise the cross-talk, it is important to identify the muscle activity of each of the muscles responsible for the action. Similarity in the spectrum and other properties of the activity from the different muscles makes the separation of these difficult. There is a need to separate the muscle activity originating from different muscles. With little or no prior information of the muscle activity from the different muscles, this is a blind source separation (BSS) task. Independent component analysis (ICA) is an iterative BSS technique which is a non-Gaussian scheme and has been found to be very successful in audio and biosignal applications [8-10].

Signals such as Surface EMG have probability densities that are close to Gaussian while artefacts such as ECG and motion artefacts have non Gaussian distributions. From the above, it can be suggested that ICA may suitably isolate some of the above signals, while its efficacy for separating the others maybe questionable. It is difficult to identify the quality of separation of EMG from one muscle and the neighbouring muscles, or that of EEG from one channel to the neighbouring recording sites, making it difficult to confirm or negate the above. Hence this paper reports the

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preliminary analysis required for measuring the Gaussianity of the functions prior to using ICA. Our objective is to illustrate the degree of non-Gaussianity of sEMG, and to establish the validity of employing the higher order statistics (HOS) parameters in sEMG signal processing, as these statistics are applicable only to non-Gaussian (or possibly nonlinear) processes.

II. HOS THEORY FOR sEMG ANALYSIS

Conventional signal processing techniques are generally based on the analysis of the first and second order moments and cumulants (i.e. mean, correlation and variance) and their spectral representation (e.g. power spectrum). These techniques provide all the information available from the signal only if the underlying process is Gaussian and is operated on by a linear system. For non-Gaussian processes and nonlinear systems, more information can be obtained from the higher order moments and cumulants (3rd order to *N*th order) and their spectral representation (higher order spectra). The second order spectrum suppresses phase relationships, whereas information about the phase of the underlying system is available from higher order spectra [11]. Higher order statistics are useful in BSS methods and system recovery. Since they do not suppress phase information, they are able to recover information about non-Gaussian signals.

A. Non-Gaussianity and Independence

There are several measures of non-Gaussianity that can be used. The classical one is Kurtosis value or fourth order cummulant. This value is zero, negative and positive for Gaussian, sub-Gaussian and super-Gaussian data respectively. Gaussianity also implies the degree of randomness of a signal and is related to information content of a signal. According to central limit theorem the distribution of a sum of independent signals with arbitrary distributions tends toward a Gaussian distribution under certain conditions. The sum of two independent signals usually has a distribution that is closer to Gaussian than distribution of the two original signals. Thus a Gaussian signal can be considered as a linear combination of many independent signals. This also explains that separation of independent signals from their mixtures can be achieved by finding a transformation that yields non-Gaussian distributions [12, 13]. Non-Gaussianity is an important and essential principle in ICA estimation. To use non-Gaussianity in ICA estimation, there needs to be quantitative measure of non-Gaussianity of a signal. Before using any measures of non-Gaussianity, the signals should be normalised [14, 15]. Some of the commonly used measures are Kurtosis and entropy measures. Kurtosis is the classical method of measuring Non-Gaussianity. When data is preprocessed to have unit variance, Kurtosis is equal to the fourth moment of the data. The Kurtosis of signal (*s*), denoted by kurt (*s*), is defined by

$$kurt\,(s) = E\left\{s^4\right\} - 3\left(E\left\{s^4\right\}\right)^2 \tag{1}$$

Kurtosis can be either positive or negative. Random variables that have a negative Kurtosis are called sub-Gaussian, and those with positive Kurtosis are called super-Gaussian. Super-Gaussian random variables have typically a "spiky" PDF with heavy tails, i.e. the PDF is relatively large at zero and at large values of the variable, while being small for intermediate values. Sub- Gaussian random variables, on the other hand, have typically a "flat" PDF, which is rather constant near zero, and very small for larger values of the variable [8-10]. Normally non-Gaussianity is computed by the absolute value of Kurtosis. In this research Kurtosis parameters are used for evaluation of Gaussianity in sEMG signals.

B. Gaussianity and ICA

Gaussianity is a cost-function when ICA estimates the mixing matrix and signals from Gaussian sources cannot be separated from their mixtures using ICA [8-10]. Mathematical manipulation demonstrates that all matrices will transform this kind of mixtures of Gaussian signals to another set of Gaussian signals. However, a small deviation of the density function from Gaussian may make it suitable as it will provide points on the ICA optimization landscape, making Gaussianity based cost function suitable for iteration. If one of the sources has density far from Gaussian, ICA will easily detect this source because it will have a higher measure of non-Gaussianity and the maximum point on the optimization landscape will be higher. If more than one of the independent sources has non Gaussian distribution, those with higher magnitude will have the highest maximum point in the optimization landscape. Given a few signals with distinctive density and

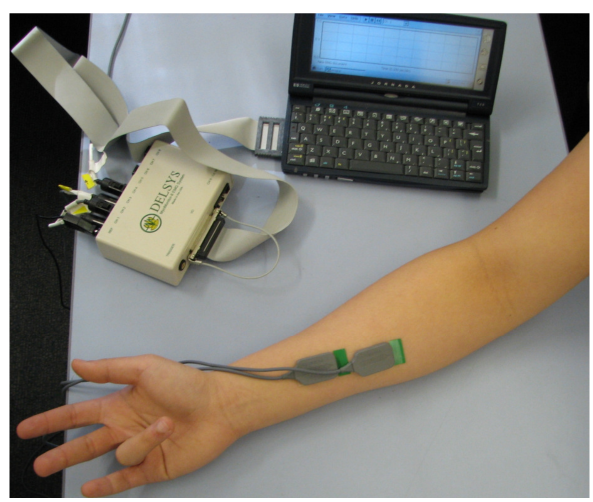

Fig. 1. The experimental setup for finger flexion experiment.

significant magnitude difference, the densities of their linear combinations will tend to follow the ones with higher amplitude. Since ICA uses density estimation of a signal, the components with dominant density will be found easier.

III. Methodology

A. sEMG experiments for different force levels

The experiments were approved by the human ethics committee in accordance with Australian NHMRC guidelines. Ten healthy participants with no history of major neurological disorder participated in the study. Experiments were conducted where sEMG from the Flexor digitorum superficialis (FDS) muscle was recorded when the participants maintained specific finger flexion. FDS lies in the anterior compartment of the forearm, which has a primary function of flexing the digits in finger movements [16]. The two electrodes were placed on FDS muscle as shown in Figure 1. The force of contraction was measured using FlexForce sensor. The FlexiForce A201 (Tekscan, Boston, MA, USA) force sensor is an ultra-thin, flexible force sensor that can be fixed to measure the force of contraction from each of the fingers.

At the start of the experiment, the participants were made to generate maximum voluntary contraction (MVC) for 10 seconds and this was repeated 5 times. Based on the study of Basmajian and De Luca [17], the average of these five recordings was considered to be the MVC. Four different finger and wrist actions were used as protocol to record sEMG from the participants: *Wrist flexion*, *Middle finger flexion*, *Ring finger flexion* and *Little finger flexion*.

The participants were asked to maintain each flexion for 7-8 secs for three different levels of forces i.e., 20%, 50% and 80% of MVC. The duration of each run of the experiment was 120 secs. The sampling rate for recording sEMG was 1024 samples/sec. The change in resistance of the FlexiForce is the measure of force of the sensor. To

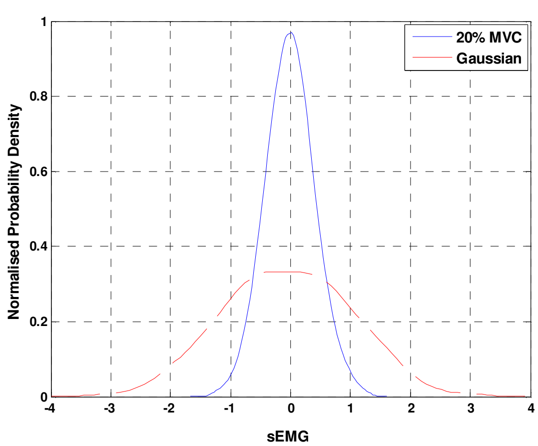

Fig. 2. sEMG with 20% force levels (MVC).

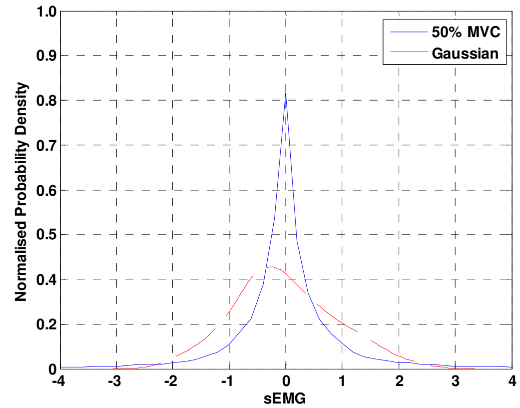

Fig. 3. sEMG with 50% force levels (MVC)

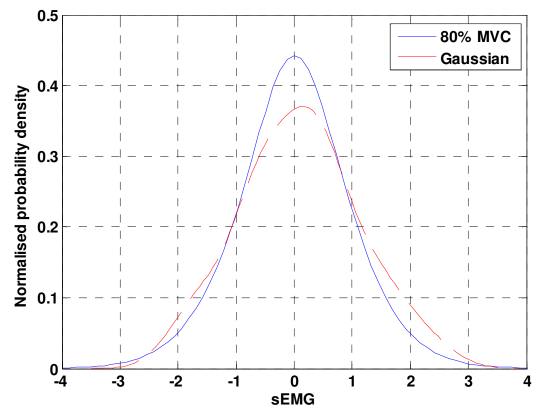

Fig. 4. sEMG with 80% force levels (MVC)

record the force exerted on the sensor, voltage across a fixed resistance in series with FlexiForce force sensor was recorded at 1024 samples/sec along with sEMG signal. Visual feedback of the force sensor output was given to the user to maintain steady muscle contraction.

B. Data Analysis

The experimental data for different MVCs (20%, 50%, and 80%) was analysed using two prominent higher order measures. They are

- Non-Gaussianity measure (PDFs) and
- Kurtosis measures.

The Non-Gaussianity measures were plotted using the Gaussianity as reference. The Kurtosis values were calcuted using the Equation (1). Finally the computed Kurtosis values were plotted with respect to different force levels.

IV. Results

The results for Gaussinity and non-Gaussianity measures are plotted for different MVCs. The results for 20%, 50% and 80% MVCs are shown in Figure 2, 3 and 4 respectively. The average Kurtosis values for the different MVC parameters are tabulated in Table 1. The Kurtosis vs. different force level plot is shown in fig. 5.

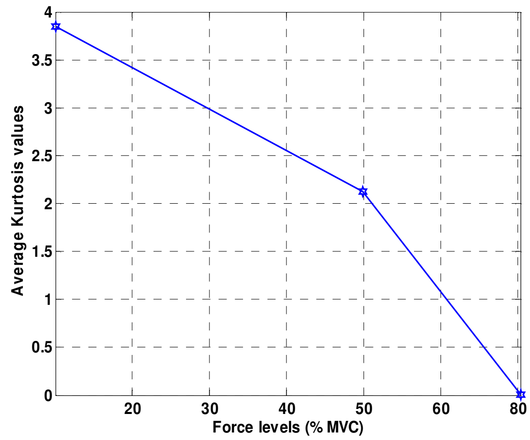

Fig. 5. Average Kurtosis vs. force levels (% of MVC)

TABLE I
AVERAGE KURTOSIS VALUES FOR DIFFERENT MVCs

MVCs (%)	Kurtosis
20	3.4053
50	2.1233
80	0.003

V. DISCUSSIONS AND CONCLUSION

The results demonstrated the importance of HOS parameter calculations in sEMG signal processing. One of the main reasons is that, second order spectrum suppresses phase relationships, whereas information about the phase of the underlying system is available from higher order spectra. Furthermore, due to cross-talk and other related factors the MUAP under different force levels tends to be Gaussian in nature. Hence the results from these studies could be used as pre-processing technique before computation of ICA.

In the recent past it has been assumed that the sEMG signal recorded under constant-force and non-fatiguing conditions can be modeled as a zero mean Gaussian process. This research study shows that the PDF of the signal may become more or less Laplacian (super-Gaussian) depending on the level of MVC. Based on the research it can be inferred that during low MVCs fewer motor units are active, as the MVCs increases more motor units are fired and thus making the signal less super-Gaussian. This is also tested using Kurtosis where the Kurtosis values decreased as the MVCs increased.

Using Gaussianity as a criterion for measuring the quality of the source separation, we have shown that usually the density shape is closer to Laplacian (super Gaussian) in light forces and tends towards Gaussian with increasing the level of MVC. We think that with increasing the force level during the contraction, more motor unit action potentials will be fired. As the sEMG signal is the superposition of these potential, it tends to a Gaussian process in high force levels.

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