NEGENTROPY ANALYSIS OF SURFACE ELECTROMYOGRAM SIGNAL

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ABSTRACT

This study deals with measuring the non-Gaussianity in Surface Electromyogram signal (sEMG). The signal was obtained from biceps brachii muscle during elbow flexion at four different levels of Maximum Voluntary Contraction (MVC). Typically the sEMG generated from constant-force, constant angle, non-fatiguing contractions is modelled as a stochastic process, and its probability density function (pdf) is assumed to be Gaussian. Results of utilizing negentropy for characterizing the non-Gaussianity of sEMG signal indicate that its pdf is clearly non-Gaussian during light contractions (below 30% of MVC) and it tends to a Gaussian process at higher force levels. The results validate the application of Higher Order Statistics (HOS) based methods in sEMG signal processing at low levels of MVC.

1. INTRODUCTION

Electrical activities recorded from muscles during contractions are known as Electromyogram signals (EMGs). An EMG emanates from activation of a group of muscle fibers by impulses sent down to motor neurons from the spinal cord. Surface EMG is obtained non-invasively on the skin via appropriate electrodes. It has long been held that the sEMG recorded during constant-force, constant-angle, non-fatiguing contractions can be modelled as a zero mean, correlation ergodic, stochastic complex process with Gaussian distribution [1]. In [2] it is stated that the Gaussian density precisely describes the experimental density for various contraction strength, and for one biceps sEMG pdf estimation, using Chi-square test, the probability of deviation from Gaussian distribution was less than 10^{-3}.

Although in the literature, the pdf of the sEMG is frequently assumed to be Gaussian, a few studies have reported that the above pdf is more Laplacian than Gaussian; and that it is decidedly dependent on the level of MVC. In [3] it is reported that during isometric contractions, the pdf of sEMG is more sharply peaked near zero than the Gaussian distribution. In [4], the pdf of sEMG signal recorded from biceps in constant forces (20%, 40%, 60%, and 80% of MVC) was studied, and by using Shapiro-Wilk test, it was found that sEMG has a non-Gaussian amplitude distribution, which approached a Gaussian distribution for higher force levels.

In a few studies, non-Gaussianity in sEMG [5], [6] was implicitly assumed. In [5], higher order cumulants were used to decompose the sEMG into Motor Unit Action Potentials (MUAPs), but without explicitly mentioning that the sEMG's pdf may be non-Gaussian. The results are interesting, but their approach is valid when the number of active MUAPs is small. In [6], a non-Gaussian scheme, namely the Independent Component Analysis (ICA) method was employed for pre-processing sEMG. Garcia et al. in [6] obtained acceptable results for sEMGs recorded in muscular contractive forces below 30% of MVC. We will show that the pdf of the sEMG is clearly non-Gaussian when the number of fired MUAPs is few or when the applied force does not exceed 30% of MVC.

Our objective is to illustrate the degree of non-Gaussianity of sEMG, and to establish the validity of employing the HOS in sEMG signal processing, as these statistics are applicable only to non-Gaussian (or possibly nonlinear) processes [7]. For this purpose we exploited negentropy, the information theory's classic measure of non-Gaussianity, whose value is zero for Gaussian distributions and is positive for all other densities. Since obtaining exact values of negentropy is very computation intensive, we use approximations by employing non-polynomial functions.

We will show that the pdf of sEMG lies between Gaussian and Laplacian densities. Generally, the pdf is closer to Laplacian (super Gaussian) in light forces, and tends towards Gaussian with increasing the level of MVC.

This paper is organized as follows. In Section 2 we describe our experimental procedures for recording sEMG and the kernel smoothing method for estimating the pdf of the sEMG. Subsequently, we present the negentropy, its approximation, and its application to the analysis of the pdf of the sEMG. Sections 3 and 4 contain the results and our conclusions, respectively.

2. METHOD

In this Section, we describe our experimental procedure for recording sEMG. Furthermore, we explain the normalization method as well as the use of kernel smoothing technique in sEMG probability density estimation. The definition of negentropy and its approximation are also explained.

2.1. sEMG Detection System

The sEMG was recorded from biceps brachii muscle of a healthy 24 years male by a pair of Ag/AgCl electrodes**.** The electrode contacts were separated from one another by 20 mm (centre to centre). The sEMG signal was amplified and band-pass filtered between 20-400Hz. The sampling rate was set at 800 samples per second using a 12 bit A/D converter. The main parameters of the system are as follows:

Input impedance:	10 $M\Omega$;
Common mode rejection ratio:	> 90dB;
Amplification scale:	10~20,000.

A 50 Hz notch filter was then applied to the detected signal. The subject was asked to perform the isometric elbow flexion with four levels of 10%, 25%, 50% and 75% of MVC. Continuous recordings were made from bicep for 5 seconds periods. Each epoch was subdivided into 200 ms segments, yielding 25 stationary time series per contraction. The subject did the experiment three times for each level of MVC. A typical sEMG signal recorded from biceps at 50% of MVC is shown in Fig. 1.

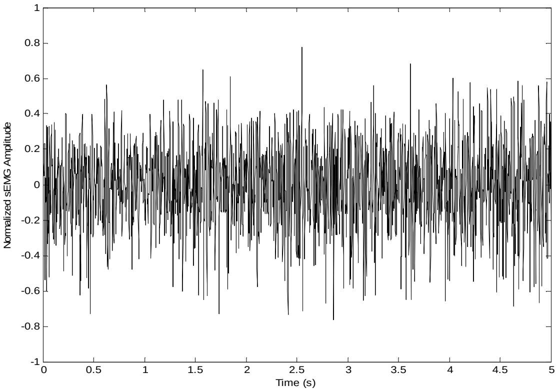

Figure 1. Sample sEMG signal detected from biceps during flexion with 50% of MVC.

2.2. Normalization

To provide uniformity, we normalize the raw sEMG signal in the following manner. For N available sEMG samples y_i we have

$$\bar{y} = \frac{1}{N}\sum_{i=1}^{N} y_i\ , \quad \sigma^2 = \frac{1}{N-1}\sum_{i=1}^{N}(y_i - \bar{y})^2 \qquad (1)$$

$$X_i = \frac{y_i - \bar{y}}{\sigma} \qquad (2)$$

where $\bar{y}$ is the mean, σ^2 is the variance, and X_i is the normalized value of y_i with zero mean and unit variance.

2.3. sEMG pdf Estimation

An estimate of the probability density function of the stochastic complex sEMG signal X can be built from a set of data $X_i\ , i = 1, \cdots, n$, by means of a smoothing function or the kernel function $K(x, X_i)$ [8]. In the method proposed by Parzen [9], an estimate of the unknown density is given by

$$\hat{p}_n(x) = \frac{1}{n}\sum_{i=1}^{n} K(x, X_i)\,. \qquad (3)$$

Choosing the kernel is critical. The kernel must be a proper pdf and usually chosen to be unimodal and symmetric about zero. A possible choice for the function $K(x, X_i)$ among those satisfying the conditions for (asymptotic) unbiasedness and consistency of the estimator [9] is the Gaussian kernel of the fixed width σ_0

$$K(x, X_i) = \frac{1}{2\pi{\sigma_0}^2}\, e^{-\left|x - X_i\right|^2 / 2{\sigma_0}^2}\,. \qquad (4)$$

Figure 2 shows the estimated probability densities of sEMG time segments for the four MVC levels, where solid and dotted lines indicate the Laplacian and Gaussian densities, respectively. It is evident that the pdf of sEMG segments are closer to the Laplacian than the Gaussian densities for small muscular contractive forces and tend towards Gaussian as the force level increases.

2.4. Negentropy

It is well established that the Negentropy is a proper measure of non-Gaussianity [10]. Negentropy is based on the information-theoretic quantity of (differential) entropy. Entropy is the basic concept of information theory. The entropy of a random variable can be interpreted as the amount of information obtainable from the observation of the variable. The more random, i.e., unpredictable and unstructured the variable is, the larger its entropy becomes [10]. Entropy H is defined for a discrete random variable X as

$$H(X) = -\sum_i P(X = a_i)\log P(X = a) \qquad (5)$$

where a_i is the possible values of X . For continuous-valued random variables and vectors, the entropy can be generalized, in which case it is often called differential entropy. The differential entropy H of a random vector x with density $p(x)$ is defined as

$$H(x) = -\int p(x)\log p(x)dx\ . \qquad (6)$$

Entropy is a measure of non-Gaussianity since a Gaussian variable has the largest entropy among all

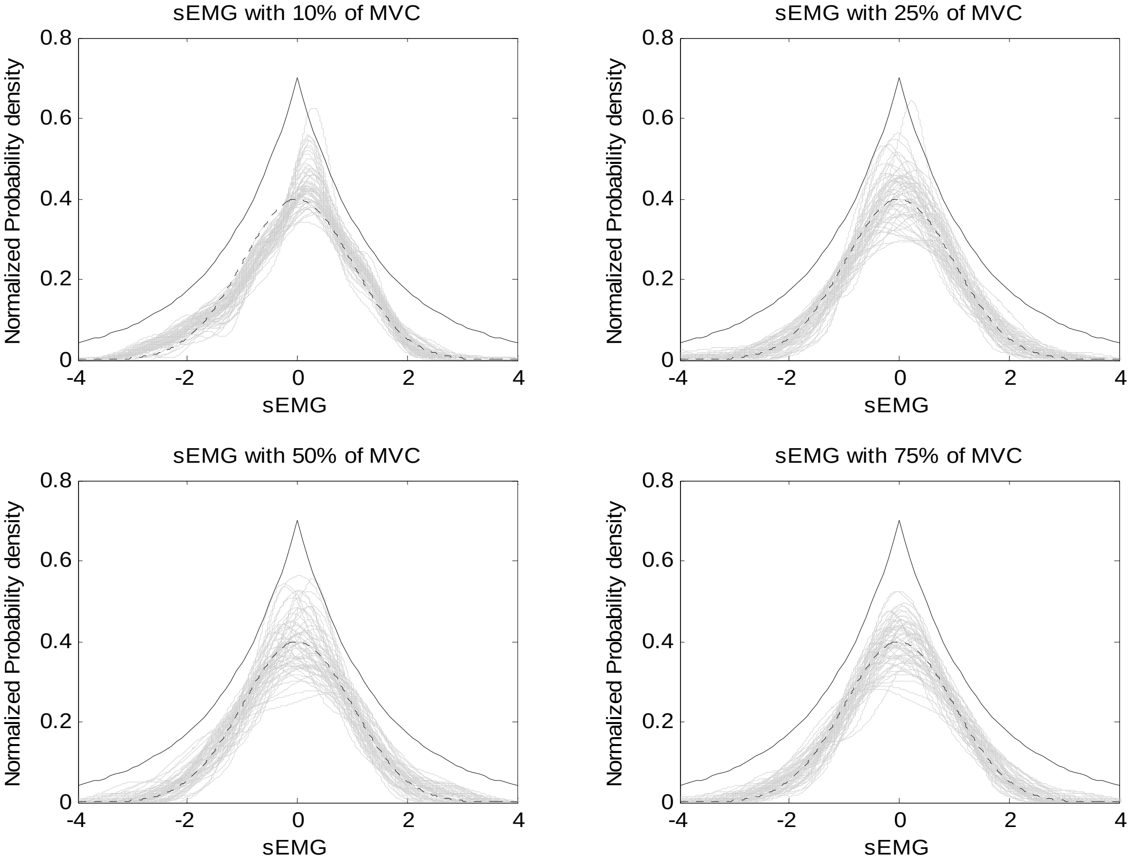

Figure 2. Shaded regions indicate the pdf of all the sEMG time segments for each of the four contraction levels. Solid and dotted lines indicate the Laplacian and Gaussian densities, respectively.

random variables of equal variances [10]. A slightly modified definition of differential entropy, or negentropy J, has been proposed in [11]. Negentropy is zero for a Gaussian variable and always non-negative for other distributions. The negentropy is defined as

$$J(x)=H(x_{Gauss})-H(x) \tag{7}$$

where x_{Gauss} is a Gaussian random variable with the same covariance matrix as x. Negentropy is in some sense the optimal estimator of non-Gaussianity. However, since in (6) the pdf of the sEMG signal is unknown, obtaining exact values of negentropy is very computation intensive.

2.5. Approximation to Negentropy

The classical method of approximating negentropy is using higher-order moments. For a zero mean and unit variance random variable x, we have

$$J(x)\approx\frac{1}{12}E\left[x^3\right]^2+\frac{1}{48}kurt(x)^2 . \tag{8}$$

where $E[.]$ is the expectation operator and $kurt(x)$ is the kurtosis of x. Unfortunately, this approximation suffers from the non-robustness encountered with kurtosis when dealing with outliers. Another approximation approach is based on the maximum-entropy principle;

$$J(x)=\sum_{i=1}^{p}k_i\left[E\left[G_i(x)\right]-E\left[G_i(\nu)\right]\right]^2 \tag{9}$$

where each k_i is a positive constant, and ν is a Gaussian variable of zero mean and unit variance. The variable x is assumed to be of zero mean and unit variance, and each function G_i is a non-quadratic function [11]. If we choose only one non-quadratic function G, the approximation to negentropy becomes;

$$J(x)\propto\left[E\left[G(x)\right]-E\left[G(\nu)\right]\right]^2 \tag{10}$$

where the non-parametric function G is

$$G(x)=\frac{1}{a}\log\cosh(ax)\quad 1\le a\le 2 \tag{11}$$

and a is taken equal to 1 as usual [10]. This approximation is computationally simple, fast, and has interesting statistical properties, such as robustness to outliers [11]. The results of negentropy estimation to ascertain the transition of the sEMG signal's pdf from non-Gaussianity to Gaussianity with respect to force level (% of MVC) is shown in Figure 3.

3. RESULTS

For each of the sEMG time segments, we have estimated and normalized the negentropy, the average of which is shown in Fig. 3. This Fig. is for the estimated pdfs shown in Figure 2, where the sEMG is highly non-Gaussian and tends towards Gaussian as the force level increases.

This transition from near Laplacian to the Gaussian pdf validates the application of non-Gaussian signal processing methods in sEMG analysis for low levels of MVC, such as in [5], [6] that obtained acceptable results only for low levels of MVC, but without providing any explanation as to why their assumptions are correct.

In [12], we have proposed a novel approach for sEMG signal processing and pattern classification at low levels of MVC using HOS. Again, our results in this paper validate our approach in [12].

4. CONCLUSION

It has been long held that the sEMG signal recorded during constant-force, constant-angle and non-fatiguing contractions can be modelled as a zero mean Gaussian process. Recent studies have shown that depending on the level of MVC, the probability density function of the sEMG may become more Laplacian than Gaussian. Using negentropy as a criterion for measuring non-Gaussianity, we have shown that generally the density shape is closer to Laplacian (super Gaussian) in light forces and tends towards Gaussian with increasing the level of MVC. We elaborated on the transition from the Laplacian pdf to the Gaussian pdf and established the application and the exploitation of HOS based approaches in sEMG signal processing and pattern classification at low levels of MVC

We believe 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 as the Central Limit Theorem [13] indicates.

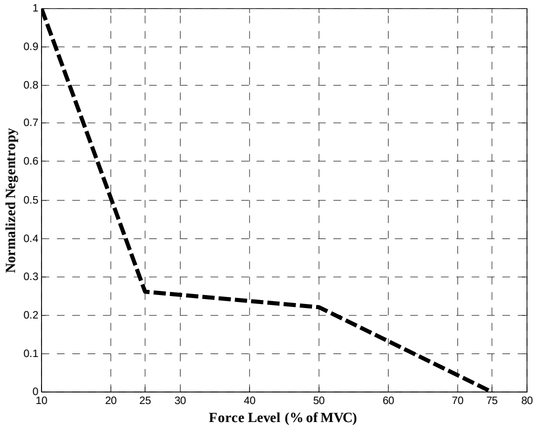

Figure 3. Normalized Negentropy vs. Force Level (% of MVC).

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