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Muscle Activity Onset Detection Using Energy Detectors

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Abstract— **Muscle activity detection is important for clinical investigations leading to the identification of neuromuscular disorders. Myoelectric signal recorded via electrodes placed at skin surface can reveal important muscle excitation information about underlying limb movement. However, a primary difficulty in the detection of muscle activity period from myoelectric signals lies in the inherent variability of these signals and the noise added during the collection process. In the literature, the double threshold detector has been commonly used for detection of the muscle activity periods from myoelectric signals. In this study, we propose a new scheme based on the log-likelihood ratio test to detect muscle activity periods accurately. This scheme uses energy information contained in the myoelectric signal, which increases with the start of the activity. We demonstrate the viability of energy detection scheme via successful detection performed on synthetic as well as clinical myoelectric signals.**

I. INTRODUCTION

Detection of muscle activity from myoelectric signals is important for clinical studies that attempt to diagnose neuromuscular deficiencies such as caused by stroke and Parkinson's disease. These applications require an accurate detection of the onset, offset, and duration of the EMG (Electromyographic) burst while the patient performs a pre-determined task. Activity periods of the muscles are usually determined by experts based on the observation of processed (rectified and low pass filtered) EMG signals. However, due to the variability of results from human experts for this task, computer algorithms have also been proposed in the literature. For example, Di Fabio used a 50 sample window of the rectified and low-pass filtered EMG signal to make a baseline reference; the muscle was considered ON if 25 consecutive samples exceeded three standard deviations (σ) of the mean baseline activity [1]. Lidierth proposed a similar detection method with extended post-processing to improve detection results [2]. Hodges and Bui also extended the same algorithm [1] and compared different window sizes, low pass filter frequencies and standard deviations (σ) above base line to decide upon the value of the threshold [3]. Abbnik et al. extended the work of [3] with a change of cut-off frequency and window length [4].

All such algorithms [1], [2], [3], [4] can be classified as more of a heuristic nature, as detection is based upon defining a baseline followed by muscle activity detection using various thresholds. Bonato et al. proposed a statistical method based on selection of two thresholds, called the double threshold method which has become popular [5]. In Bonato's method, EMG signals were whitened (de-correlated) before application of the detection algorithm, yet methods of de-correlating EMG signal were not discussed. Researcher have proposed improvements to the double threshold method. For example, Generalized Likelihood Ratio (GLR) test was proposed by Micera et al. [6]. Staude extended the statistical methods to include other optimal change detection algorithms based on CUSUM-type (cumulative sum) and AGLR (approximated generalized likelihood ratio)[7]. Algorithms proposed by Ref. [6], [7] are complicated in their implementation, yet method of Ref. [7] successfully provides on-line detection capability. Recognizing the non-stationary nature of EMG signal, wavelet transforms have also been used by some authors for detecting muscle activity [8], [9], but these methods also suffer from implementation complexity. Solnik et al. [10] used Teager-Kaiser Operator as additional signal conditioning to improve the detection accuracy using the algorithms proposed by [5], [7].

In the following, we propose an efficient detection scheme based on Neyman-Pearson formulation of the energy detectors for stochastic signal buried in noise. This formulation uses the log-likelihood ratio test to develop a test statistic. The test statistic is then compared to a threshold for deciding on/off timings of the muscle activity and then marking activity periods. Results from synthetic as well as clinical EMG signal are presented to validate the proposed scheme.

II. ENERGY DETECTOR

Neyman-Pearson type energy detectors exploit energy information in the signal to detect the presence of the desired signal. Test statistic, which represents energy of the signal, is developed through hypothesis testing using the log-likelihood ratio test [11].

A. Mathematical formulation

Considering N samples of the noisy signal $x[n] : n = 0, 1, 2, \ldots, N-1$ as a zero-mean Gaussian process $s[n] \in \mathcal{N}(0, \sigma_s^2)$ corrupted by an independent zero-mean Gaussian additive noise, $w[n] \in \mathcal{N}(0, \sigma_n^2)$, the detection scheme is to distinguish between the hypothesis:

$$\begin{aligned} H_0 &: x[n] = w[n], \\ H_1 &: x[n] = s[n] + w[n]. \end{aligned} \tag{1}$$

Neyman-Pearson detector decides H_1 if the likelihood ratio exceeds a threshold γ,

$$L(\mathbf{x}) = \frac{p(\mathbf{x} : H_1)}{p(\mathbf{x} : H_0)} > \gamma, \tag{2}$$

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where $p(\mathbf{x}:H_0)$ and $p(\mathbf{x}:H_1)$ are the probability density functions (PDFs) of the recorded EMG signal under hypothesis H_0 and H_1. These PDFs are given as,

$$\begin{aligned} H_0 &: x[n] \in \mathcal{N}(0, \sigma_n^2), \\ H_1 &: x[n] \in \mathcal{N}(0, \sigma_n^2 + \sigma_s^2). \end{aligned} \tag{3}$$

By substitution of PDFs from (3) in (2), we get

$$L(\mathbf{x}) = \frac{\frac{1}{[2\pi(\sigma_s^2+\sigma_n^2)]^{\frac{N}{2}}} \exp\left[-\frac{1}{2(\sigma_s^2+\sigma_n^2)} \sum_{n=0}^{N-1} x^2[n]\right]}{\frac{1}{[2\pi\sigma_n^2]^{\frac{N}{2}}} \exp\left[-\frac{1}{2\sigma_n^2} \sum_{n=0}^{N-1} x^2[n]\right]}, \tag{4}$$

$$L(\mathbf{x}) = \left[\frac{\sigma_n^2}{(\sigma_s^2+\sigma_n^2)}\right]^{\frac{N}{2}} \exp\left\{\frac{1}{2}\left[\frac{\sigma_s^2}{\sigma_n^2(\sigma_s^2+\sigma_n^2)}\right] \sum_{n=0}^{N-1} x^2[n]\right\}. \tag{5}$$

Solving for the log-likelihood ratio, i.e., $l(\mathbf{x}) = \ln(L(\mathbf{x}))$, we get,

$$l(\mathbf{x}) = \frac{N}{2} \ln\left[\frac{\sigma_n^2}{\sigma_s^2+\sigma_n^2}\right] + \frac{1}{2}\left[\frac{\sigma_s^2}{\sigma_n^2(\sigma_s^2+\sigma_n^2)}\right] \sum_{n=0}^{N-1} x^2[n]. \tag{6}$$

We can solve (6) for some function of observed data $x[n]$, i.e, $\sum_{n=0}^{N-1} x^2[n]$ as:

$$\sum_{n=0}^{N-1} x^2[n] = f(\sigma_n^2, \sigma_s^2, N). \tag{7}$$

The term appearing on the right hand side of (7) can be termed as test statistic $T(\mathbf{x})$ for observed data $x[n]$. We define our test statistic as:

$$T(\mathbf{x}) = \sum_{n=0}^{N-1} x^2[n]. \tag{8}$$

The Neyman-Pearson detector decides H_1 if $T(\mathbf{x}) > \acute{\gamma}$, where $\acute{\gamma}$ is a threshold, which is computed using probability of false alarm P_{fa}. We note that the test statistic computes energy in the recorded signal and compares it to the threshold $\acute{\gamma}$ to decide about muscle activity onset, and is therefore named the **energy detector**.

To formulate the test statistic, $T(\mathbf{x})$ which follows χ^2 distribution of N degree of freedom (DOF), we have σ_n^2 and $(\sigma_n^2 + \sigma_s^2)$ as the variance of the observed signal under H_0 and H_1 hypothesis.

$$\begin{aligned} H_0 &: \frac{T(\mathbf{x})}{\sigma_n^2} \in \chi_N^2, \\ H_1 &: \frac{T(\mathbf{x})}{\sigma_n^2+\sigma_s^2} \in \chi_N^2. \end{aligned} \tag{9}$$

Defining the right tail probability of a χ_N^2 random variable as [11],

$$Q_{\chi_N^2}(x) = \int_x^{\infty} p(t)dt. \tag{10}$$

Equation (10) allows us to write P_{fa} as:

$$\begin{aligned} P_{fa} &= Pr[T(\mathbf{x}) > \acute{\gamma}|H_0] = Pr\left[\frac{T(\mathbf{x})}{\sigma_n^2} > \frac{\acute{\gamma}}{\sigma_n^2}|H_0\right] \\ &= Q_{\chi_N^2}\left(\frac{\acute{\gamma}}{\sigma_n^2}\right). \end{aligned} \tag{11}$$

Upon availability of estimate of σ_n^2, we can use (11) to calculate the value of $\acute{\gamma}$ as given below:

$$\acute{\gamma} = \sigma_n^2 Q_{\chi_N^2}^{-1}(P_{fa}). \tag{12}$$

Once P_{fa} is fixed, (12) is used to calculate the value of the threshold $\acute{\gamma}$. Also, for probability of detection (P_d), we have,

$$\begin{aligned} P_d &= Pr[T(\mathbf{x}) > \acute{\gamma}|H_1] \\ &= Pr\left[\frac{T(\mathbf{x})}{\sigma_n^2+\sigma_s^2} > \frac{\acute{\gamma}}{\sigma_n^2+\sigma_s^2}|H_1\right] \\ P_d &= Q_{\chi_N^2}\left(\frac{\acute{\gamma}}{\sigma_n^2+\sigma_s^2}\right). \end{aligned} \tag{13}$$

Defining signal to noise ratio (SNR) as,

$$\text{SNR} = 10\log_{10}\left(\frac{\sigma_s^2}{\sigma_n^2}\right). \tag{14}$$

Now, we can write P_d in terms of P_{fa} using (12), (13) and (14):

$$\begin{aligned} P_d &= Q_{\chi_N^2}\left(\frac{\acute{\gamma}}{(\sigma_n^2+\sigma_s^2)}\right) = Q_{\chi_N^2}\left(\frac{\sigma_n^2 Q_{\chi_N^2}^{-1}(P_{fa})}{(\sigma_n^2+\sigma_s^2)}\right) \\ &= Q_{\chi_N^2}\left(\frac{Q_{\chi_N^2}^{-1}(P_{fa})}{1+10^{\frac{\text{SNR}}{10}}}\right). \end{aligned} \tag{15}$$

Equation (15) provides relation between P_{fa} and P_d in terms of SNR of the signal. We will use this relation to present the performance analysis of the energy detector.

We summarize the algorithm for the energy detection scheme:

1) First N samples from recorded EMG signal are selected to form a window. All samples in the window are whitened using a pre-whitening filter and a test statistic (8) is formed.
2) Samples from the recorded EMG signal are selected to estimate variance of the noise, i.e., σ_n^2. These are the samples where muscle activity has not yet started, i.e., the recorded signal contains noise only.
3) The threshold $\acute{\gamma}$ is calculated using P_{fa} from (12).
4) Test statistic $T(\mathbf{x})$ is compared with the threshold $\acute{\gamma}$ to mark muscle activity periods; for $T(\mathbf{x}) \geq \acute{\gamma}$, the starting time of the window is marked as starting time for muscle activity, otherwise window is advanced by one sample.
5) Post-processing is applied to remove spurious activities.

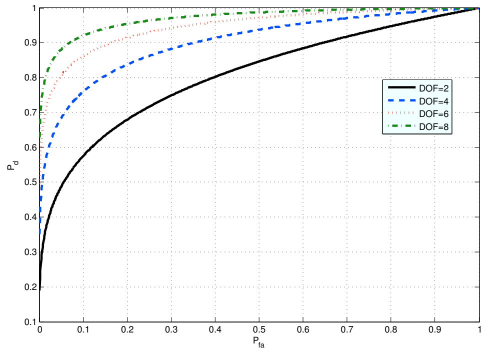

Fig. 1. ROC curves for different DOFs of χ^2 at a fixed SNR=5. More DOFs result in better detection for lower P_{fa}

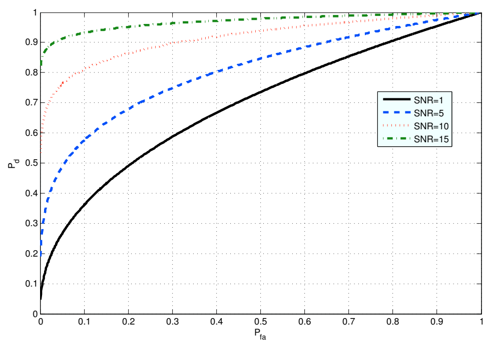

Fig. 2. ROC curves for different SNR values at DOF=2. Better signal SNR results in better detection for lower P_{fa}

B. Performance analysis

We present ROC (Receiver Operator Characteristic) curves using (15) to gain an insight into the performance of the energy detector. Once SNR has been estimated (in the case of observed signal) or fixed (in the case of synthetic EMG signal), we can then draw these curves for range of values of P_d against P_{fa}. ROC curves provide an insight into the detection scheme and highlight the limitations, i.e., trade-off associated with the detection scheme. Fig. 1 shows the effect of increasing number of samples considered for making decision on the detection. These number of samples are the DOF of the χ^2 distribution. As the number of samples (DOF of χ^2 distribution) are increased, we get a higher P_d at lower P_{fa}. Fig. 2 shows the effect of SNR on detection; higher SNR values results in better detection at lower P_{fa} . Moreover, it is evident from Fig. 1 and 2 and that we have limitations on reducing the P_{fa}, as P_d also decreases, meaning that we will have greater probability of miss ($P_{miss} = 1 - P_{fa}$). Therefore, we cannot reduce P_{fa} arbitrarily.

C. EMG signal pre-whitening

A pre-whitening filter based on [7] with the extension of statistical procedure using the Ljung-Box Q-test, is proposed here for the selection of the filter model order. The filter is based upon the idea of fitting autoregressive (AR) model to the recorded EMG signal and then using these AR parameters

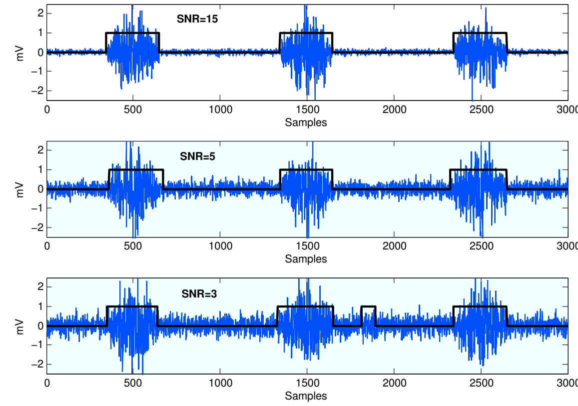

Fig. 3. Detection result on a synthetic EMG signal at different SNR levels.

as moving average (MA) filter coefficients. This procedure can be summarized as follows:

1) Estimate AR parameters by fitting EMG signal to the AR model.
2) Perform the Q-test on residues, that will either fail to reject the null hypothesis, establishing the fact that residuals are un-correlated, or otherwise.
3) In case Q-test rejects the null hypothesis, increase the filter order, i.e, AR model order by one and again perform the Q-test.
4) We observe that in most of the clinical EMG signals, we fail to reject the null hypothesis at AR model order of $p = 30 \sim 40$.

III. Detection Results

We present detection results of proposed scheme on synthetic as well as clinical EMG signals. Before application of the proposed algorithm to the EMG signals, it is important to establish some statistical parameters based on synthetic EMG signals, which may effect the detection results.

A. Detection of synthetic EMG signal

1) Effect of SNR on detection: SNR of the recorded EMG signal influences the performance of the proposed detector. In clinical EMG signals, SNR can be increased by adopting recommended skin preparation and recording procedures. However, to ascertain the performance of energy detector at different SNR levels, it is essential to generate synthetic EMG signals with known SNR values. Multiple realizations of synthetic EMG signal were generated for testing the proposed detection scheme [5]. In Fig. 3, we present detection results on three synthetic EMG signal generated at SNR=15, 5 and 3 with same detection scheme parameters for all three signals as DOF=10 and $P_{fa} = 0.01$. Each synthetic EMG signal contained three activity periods (epochs). The bottom of the Fig. 3 shows that the detection scheme has one Type-I error (false alarm) between 1500 and 2000 samples due to high noise level in the synthetic signal. In such case, reduction in P_{fa} is proposed.

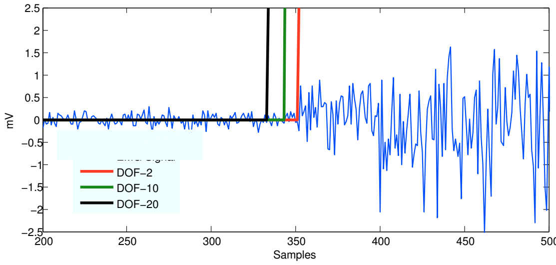

Fig. 4. Detailed view of the effect of different DOFs at the detection of the muscle activity onset.

2) Effect of window size (DOFs) on detection: The proposed algorithm uses a window of EMG samples for making the test statistic $T(\mathbf{x})$, which is also referred to as DOF of the χ^2 distribution. Here, we present the effect of changing DOFs (meaning that we are changing the number of samples selected for making the detection decision) on detection at SNR=10 in Fig 4. Increasing number of DOFs makes detector more sensitive to changes in EMG signal at any specified SNR level. This is due to the threshold $\acute{\gamma}$, which is dependent on the DOFs of the χ^2 distribution (eq. (12)).

B. EMG data collection

The study received prior approval from Institutional Review Board (IRB) of University of Arkansas at Little Rock (UALR). A Noraxon (Noraxon USA, Inc., Scottsdale, AZ) TeleMyo DTS Wireless EMG system was used to record EMG data via the Vicon Nexus 1.7.1 system at sampling rate of 1500 / 3000 Hz. Bipolar, disposable, pre-gelled Ag/AgCl electrodes (dual electrodes with 20 mm inter-electrode distance) were placed on participant's muscle belly. Skin preparation, and all related precautions for recording of EMG data were taken.

C. Detection of clinical EMG signals

Clinical EMG signals recorded from different muscles were used to ascertain the validity of the proposed detection scheme. Fig. 5 presents a typical case of muscle activity onset detection at $P_{fa} = 0.01$ and DOF=10 on two different muscles, i.e., muscle gastrocnemius and tibialis anterior. Figure 5, bottom (tibialis anterior) has relatively high SNR and therefore, the proposed detector is able to identify muscle activity accurately as compared with the gastrocnemius (top figure), establishing the fact that better SNR leads to more accurate detection results.

IV. Conclusion

A new and efficient energy detector for precise detection of muscle activity periods from EMG signal was presented, called the energy detector. The proposed detection scheme exploits the energy information in the myoelectric signal to detect the presence of muscle activity periods. This scheme is robust and efficient for stochastic signals buried in noise (such as the EMG signal). Application of algorithm is computationally less expensive than the double threshold detector and the proposed method can be used to detect muscle activation periods in clinical applications. Detection examples for synthetic and clinical EMG signals were also presented.

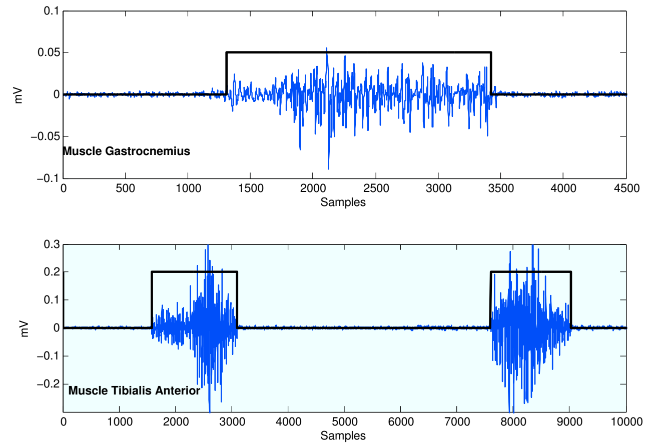

Fig. 5. Detection result for clinical EMG signal recorded from a) top, gastrocnemius muscle; b) bottom, tibialis anterior muscle.

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