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Novel electromyography signal envelopes based on binary segmentation

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ABSTRACT

In this work, we introduce two novel methodologies to compute the envelope of superficial electromyography signals. Our methods are based on the detection of activation and deactivation patterns using a change-point approach on the variances of the sample. More concretely, an iterative algorithms is proposed to select the change-points between two segments of the signal based on some local statistics introduced in this work. The signal is split up into two segments, and a new search for change-points is recursively conducted in each subsequence. The change-points make possible to calculate local envelopes which reflect the shape of the signal without ignoring the activation and deactivation landmarks. Two methods are proposed in this work, and the improvements with respect to methodologies available in the literature are shown using both synthetic and real data. A thorough analysis of the techniques is performed to that end.

1. Introduction

Electromyography (EMG) signals are an important topic of active research in view of their wide range of medical applications. For example, EMG signals have been classified using different criteria in order to diagnose neuromuscular disorders [1], they have been used as a tool in the evaluation of generalized tonic–clonic seizure semiology [2], in the recognition of emotions using facial recordings and statistical methods [3], in the automatic control of upper limb prosthesis [4], as a criterion to determine the differences in lower-extremity muscular activation walking between older and young adults [5], in the investigation of neck and shoulder muscle activity of orthodontists in natural environments [6] and as a mechanism to measure shoulder muscle fatigue during repetitive tasks [7] among other interesting biomedical applications.

It is important to recall that EMG signals are measurements of the difference of electric potentials between two electrodes. In turn, these measurements are highly correlated to the intensity in muscular activity [8]. There are various well-established procedures to record EMG signals, one of them is called superficial electromyography (sEMG), which consists in placing the electrodes over the skin covering the muscle of interest using a conductive gel to get better data readings [9]. An sEMG signal is essentially a random stationary temporal series in which the activity of the measured muscle is reflected as an increase in the signal amplitude (also called a 'burst' in this work). Muscular activity may be identified by finding the localization, duration, shape and amplitude of those bursts in the electric signal.

Beforehand we must recall that there are various approaches to investigate EMG signals from an automatic point of view. For instance, the recent literature shows progresses on de-noising techniques to remove electric interferences in EMG signals [10], on the efficient decision-tree algorithms for the classification of EMG signals using the discrete wavelet transform [11], on the use of two-directional two-dimensional principal component analysis based on stationary wavelets for EMG signals [12] and on the detection of activation/deactivation patterns in EMG signals with two [13] or more levels of electric activity [14]. However, the methods have sometimes limited applicability, and there are still many

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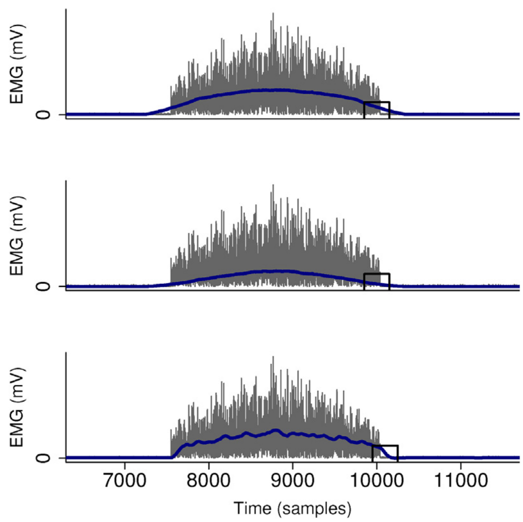

Fig. 1. Envelopes for the same EMG signal calculated using moving averages (top), root-mean squares (middle) and the Butterworth low-pass filter (bottom). The signal is depicted in gray while the calculated envelope is shown as a thick dark blue line. In all three cases, the black rectangles around sample 10,000 show failures of the methods in the detection of the end of a burst. (For interpretation of the references to color in text/this figure legend, the reader is referred to the web version of the article.)

open problems in the development of robust methodologies for the investigation of EMG signals.

As an example on the limitations of some of the methodologies available in the literature, recall that one way to recover the signal burst shape is by computing its envelope. The most common methods to compute envelopes are using moving averages [15,16], root-mean squares [17,18] and Butterworth low-pass filters [19,20]. However, it is important to point out that these methods lack effectiveness in detecting the beginning and the end of the bursts, and that this problem becomes more evident when one tries to obtain a smooth envelope. More concretely, this shortcoming appears when the window size is increased in the case of moving averages or root-mean squares, and when the cut frequency is decreased in the case of Butterworth low-pass filters.

For illustration purposes, Fig. 1 shows the limitations inherent to the calculation of envelopes using moving averages (top), root-mean squares (middle) and the Butterworth low-pass filter (bottom). In that figure, envelopes were calculated for the same EMG signal using the procedures described above. The signal is shown in gray while the envelope is depicted in dark blue. The black rectangles enhance the points of the temporal series where the methods fail to detect correctly the end of an activation period. Obviously, this is a strong limitation of these techniques which merits a closer attention.

In the present work, we will propose two methodologies to compute the envelope of an EMG signal for which the start and the end of the burst do not vanish. As some papers available in the literature [21,22], our approach will be based on the calculation of statistics that are computed 'locally' around the points in the signal. The notion of locality in our context will hinge basically on suitable neighborhoods of points for which the variance has no statistical difference. In order to identify segments in the temporal series with similar variance we will employ an iterative algorithm to detect all the change-points on the variances. Some illustrative simulations will establish the effectiveness of the proposed methodology.

This paper is organized as follows. Section 2 introduces the nomenclature employed throughout this work along with the change-point model proposed and the corresponding statistical hypotheses. In turn, Section 3 will be devoted to develop an iterative algorithm based on the change-point model. In Section 4 we show some illustrative simulations using both experimental and synthetic EMG signals. For the sake of a more objective comparison, we will contrast the performance of the proposed method against others envelope techniques available in the literature. We close this manuscript with a section of final remarks.

2. Mathematical model

Let n be a positive integer. Throughout we let $x = \{x_i\}_{i=1}^{n} \subseteq \mathbb{R}$ be a finite sequence which physically represents a sEMG signal (an EMG for short). More precisely, x_i is a sample of the myoelectric activity of a muscle recorded at the time t_i for each $i \in \{1, \ldots, n\}$. For practical purposes, the sequence $\{t_i\}_{i=1}^{n}$ may represent a uniform partition of the temporal interval $[0, T]$ with $T > 0$. For each $i \in \{1, \ldots, n\}$ let X_i be a normally distributed random variable with mean equal to zero and variance equal to σ_i^2, that is,

$$X_i \sim N(0, \sigma_i^2), \quad \forall i \in \{1, \ldots, N\}. \tag{1}$$

In this work, we will suppose that x is a sample of the sequence of random variables $X = \{X_1, \ldots, X_n\}$.

In this section, we propose a change-point model for the variances of the signal in order to describe different activity levels of x. Our approach hinges on the hypothesis that there exists $M \in \mathbb{N}$ as well as integer numbers

$$0 < k_1 < \cdots < k_{M+1} = n, \tag{2}$$

called *change-points*. Moreover, we will suppose that the variance is constant between two consecutive change-points, and that it changes at each of them. Mathematically,

$$\begin{cases} \mathbf{H}_0: & \sigma_i^2 = \sigma_{k_j}^2, \quad \forall k_j \le i < k_{j+1}, \forall j \in \{1, \ldots, M-1\}, \\ \mathbf{H}_1: & \sigma_{k_j}^2 \neq \sigma_{k_{j+1}}^2, \quad \forall j \in \{1, \ldots, M-1\}. \end{cases} \tag{3}$$

It is worth noting that, in practice, the number of change-points and their locations are not known *a priori*. In order to propose a methodology to determine them, we consider firstly the case of a single point (that is, when $M = 1$) and two possible scenarios: when the location is know or unknown. In a second stage, we will propose an algorithm based on two new local statistics for the general case when $M \in \mathbb{N}$. All of this possibilities will be considered next.

2.1. One change-point with known location

Suppose that there is only one change-point, and assume that its possible location is $k \in \{2, \ldots, n\}$. Throughout we let $\sigma_{k,L}^2$ represent the common variance of the left subsequence $\{X_1, X_2, \ldots, X_{k-1}\}$, and let $\sigma_{k,R}^2$ denote the common variance of the right subsequence $\{X_k, X_{k+1}, \ldots, X_n\}$. In order to determine whether there is a significant change in the variance at the time t_k, the respective set of null and alternative hypotheses is given by

$$\begin{cases} \mathbf{H}_0: & \sigma_{k,L}^2 = \sigma_{k,R}^2, \\ \mathbf{H}_1: & \sigma_{k,L}^2 \neq \sigma_{k,R}^2. \end{cases} \tag{4}$$

The test statistic for the likelihood-ratio test is given by

$$\begin{aligned} D_k &= -2 \ln \Lambda_k \\ &= 2[n \ln(\hat{\sigma}^2) - k \ln(\hat{\sigma}_{k,L}^2) - (n-k+1) \ln(\hat{\sigma}_{k,R}^2)], \end{aligned} \tag{5}$$