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Detection of Tremor Bursts from the sEMG Signal: an Optimization Procedure for Different Detection Methods.

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Abstract—**Two different detection techniques for EMG burst detection are here used to reveal tremor in both a set of synthetic data and in a small sample of experimental trials. An optimization procedure that employs the minimization of a cost function to provide the parameter set characterizing the two techniques is here presented and its performance assessed. The results obtained with the optimization procedure are satisfactory and suitable for practical use: the values for both bias and standard deviation in the estimation of both onset and offset time instants are lower than 10 ms, and the sensitivity and positive predictive value in the detection of tremor bursts are > 96% for SNR levels higher than 6 dB.**

I. INTRODUCTION

Surface electromyography (sEMG) is widely used in many fields such as sport medicine, clinical research and rehabilitation. Many studies aimed at processing the sEMG signal in order to extract information related to relevant variables such as the amplitude of the muscular activation [1], [2], or the electrical signs of muscular fatigue [3]. The timing of the muscle activation is among the most monitored variables and a number of computer-automated algorithms have been developed to estimate it [4]. Traditional techniques are based on the rectification and low-pass filtering of sEMG data followed by a threshold, to discriminate muscle activation from the noisy background [5], [6]. Even if this approach is computationally parsimonious, it is affected by the subjective choice of the parameters set. Model-based algorithms override this limitation thanks to a more robust mathematical approach [7], [8], [9], which is suitable for a wide class of voluntary muscular activations.

However, to the best of our knowledge, little is known about the applicability of the standard methods for the detection of a specific rhythmic activity such as the involuntary muscular activation that drives the oscillatory movement known as tremor. Tremor is defined as a roughly sinusoidal oscillation of a body part driven by a rhythmic muscle contraction, and it is commonly related to the manifestation of some kind of neurological disorder, such as Parkinson's disease, essential tremor and multiple sclerosis, besides the more common physiological tremor [10], [11], [12]. The detection of tremor bursts could provide a useful insight into the mechanisms underlying the generation of pathological or physiological tremor, either by defining the phase relationship between antagonistic muscle pairs [13] or by studying the relationship between electrical and mechanical tremor manifestations [14]. Moreover, the timely and accurate detection of tremor bursts could help in increasing the effectiveness of tremor-related assistive technologies: for instance, if Functional Electrical Stimulation (FES) is employed to reduce tremor, the sEMG burst detector may help triggering the suppression device that stimulates out-of-phase the trembling muscles [15], [16]. Up to now, the only attempt aimed at the proper detection of tremor bursts has been proposed in [17], where a non linear analysis technique based on the calculation of a running Second Order Moment Function (SOMF) is used to detect parkinsonian tremor bursts.

In this study, two traditional techniques, respectively the single threshold detector (STh) proposed by Hodges et al. [6] and the statistical double threshold detector (DTh) proposed by Bonato et al. [7], are taken into account, with the specific aim of tracking tremor from the sEMG signal. In particular, we will present an optimization procedure able to look for the optimal set of the parameters under different tremor conditions, through the minimization of a cost function that takes into account the algorithm's detection ability. This optimization procedure is applied on a dataset of synthetic tremor sEMG signals with different levels of Signal to Noise Ratio (SNR). Once optimized, the behavior of the algorithms is then assessed on tremor sEMG signals obtained experimentally.

II. MATERIALS AND METHODS

Signals used as a benchmark in this study were simulated according to the model of muscle contraction described in [18]: a realization of White Gaussian Noise (WGN) was band-pass filtered using a filter with the power spectral response defined in the following:

$$P(f) = \frac{F_h^4 f^2}{(f^2+F_l^2)(f^2+F_h^2)^2} \quad (1)$$

where $P(f)$ is the power spectrum, F_l is the lower cut-off frequency and F_h is the higher cut-off frequency. Values for

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F_l and F_h were chosen randomly for each simulated signal respectively in the range [40-60] Hz and [100-120] Hz. The presence of muscle contraction was simulated through amplitude modulation by a train of gaussian functions with a standard deviation randomly variable in the range [20-30] ms, in order to model a single tremor burst as a fast muscle contraction with energy distribution concentrated in a short time interval. An uncorrelated realization of WGN was superimposed to the signal realization in order to model background noise activity; noise variance was chosen in order to provide the desired level of SNR. Realizations of tremor sEMG signals were generated with tremor frequencies spanning in the typical range of pathological tremor [4–10] Hz, and with SNR levels in the range [2 – 20] dB.

A. Experimental Signals

Experimental sEMG signals were recorded from one patient affected by Essential Tremor (ET), by using patches composed by a 8x8 array of electrodes similar to the one presented in [20]. The patches were positioned over biceps, triceps, flexor and extensor muscles of the upper limb. sEMG signals were acquired using 2 OT Bioelettronica EMG-USB amplifiers, and each channel was band-pass filtered in the [10-750] Hz band, sampled at 2048 Hz and digitized at 12 bit. Data were recorded while the patient maintained the arm outstretched in front of the body against gravity.

B. Optimization Procedure

The optimization was carried out by defining a cost function T representative of the overall detector performance, which takes into account the following detection performance measures: sensitivity (*S*) and positive predictive value (*P*) in the detection of the single tremor bursts, standard deviation (σ) and bias (μ) in the estimation of the onset and offset time instants of the tremor bursts. For the definition of the cost function we firstly introduce a vector *V* in the space (*S,P*):

$$|V| = \sqrt{\frac{S^2+P^2}{2}} \tag{2}$$

whose amplitude approaches unity as the detection performance increases. Once |*V*| is calculated, a modulation parameter *M* is introduced, which is related to the performance of the detector in terms of σ and μ, as follows:

$$M = 1 - \frac{1}{2}\sum_i \sqrt{\frac{(\mu_{N\,i}^2+\sigma_{N\,i}^2)}{2}} = 1 - \frac{1}{2\sqrt{2}}\sum_i \rho_{N\,i} \tag{3}$$

where the notation *i* refers to either onset or offset, μ_N and σ_N refer respectively to the normalized values of μ and σ with respect to the maximum acceptable value for the error - set at 50 ms for both the onset and offset estimation - and ρ_N denotes the corresponding normalized root mean square error. *M* approaches unity as the estimation of the transition instants improves. The cost function is then defined by:

$$T = 1 - |V|M \tag{4}$$

where the amplitude of the vector *V* is multiplied by the parameter *M*. Since the overall detector performance improves as *T* goes towards 0, the aim of the optimization procedure is the minimization of the cost function T defined in (4), which corresponds to find the set of parameters that leads to an increase of *S* and *P*, and to a reduction of ρ at the same time.

C. Single Threshold detector (STh)

Single threshold algorithms employ a decision function with reference to a window sliding over the sEMG signal that is full-wave rectified and low-pass filtered: muscle active state at the time instant t_i is identified when the value of the decision function exceeds a user-predefined threshold. We considered the method described in [6] as representative of the class of single threshold algorithms. This method takes into account the first *K* samples of a signal where no muscle activity is supposed to be present, and determines the mean value *m* and the standard deviation *s* of the values in this interval; then the decision function is computed sample by sample as the mean of the samples inside the sliding window *W*, and the muscle active state is indicated if this value exceeds the threshold *m+hs*, being *h* a real positive multiplying value. For our purposes, we set the cut-off frequency of the low-pass filter at 50 Hz, as indicated in [4], and the values of *m* and *s* were calculated inside the first *K = 300* samples. Then the algorithm is completely characterized by the pair {*W-h},* being *W* the window width and *h* the multiplicative value defining the threshold. The optimization was thus performed by varying the parameters *W* and *h* and calculating the cost function *T* for different *SNR* levels. The parameters *W* and *h* were chosen respectively from *W = {10,20,30,40,50,60,70}* ms and *h = {3,4,5,6}*, thus leading to 28 different algorithm configurations. For each level of *SNR* ([2-20] dB), each pair {*W-h*} was tested on 100 sEMG realizations with tremor frequency varying randomly in the previously defined range. A post-processor was applied to the raw output of the algorithm in order to eliminate inconsistent transitions: in particular the post-processor merges multiple transitions if they are less than 10 ms apart, because they are considered as representative of the same tremor burst, and rejects isolated bursts lasting less than 10 ms since they are considered as physiologically inconsistent with a tremor event. The resulting values of *S*, *P*, μ and σ were used to calculate the cost function *T* for that level of *SNR*.

D. Double Threshold detector (DTh)

The statistical double threshold detector [7] is based on the assumption that a sEMG signal $\{x_i\}$ can be modeled as described in [19]. The series $\{x_i\}$ is whitened and used to construct a series defined as:

$$z_i = x_{2i}^2 + x_{2i-1}^2 \tag{5}$$

that has a χ square distribution with 2 DOF, and is used to define the algorithm decision function. The decision rule says that if at least r out of n successive samples lie above a predefined threshold value th, the muscle active state is detected. Therefore, r works as a second threshold of the algorithm, while the value of the first threshold th depends on the estimated *SNR* and is related to the user desired false alarm probability. The optimization is performed by keeping the parameter n fixed at 5, so that the algorithm is completely characterized by the pair $\{P_z\text{-}r\}$, where P_z is the probability that a noise sample is above the threshold th. The algorithm parameters were chosen in the following sets: $P_z = \{0.005\text{-}0.1\}$ with steps of 0.005 and $r = \{1,2,3,4,5\}$, leading to 100 different configurations. In the optimization phase, the same sEMG signal dataset described for the STh was used, and the post-processor described in [7] was limited to 10 ms since, besides a tremor event with a duration lower than 10 ms being not plausible, the low duration of the inter-burst distance at higher tremor frequencies could affect the detector output.

III. RESULTS

The optimization for the two algorithms led to the optimal parameters set shown in figure 1, in the space $\{W\text{-}h\}$ and $\{P_z\text{-}r\}$ for the STh and DTh respectively.

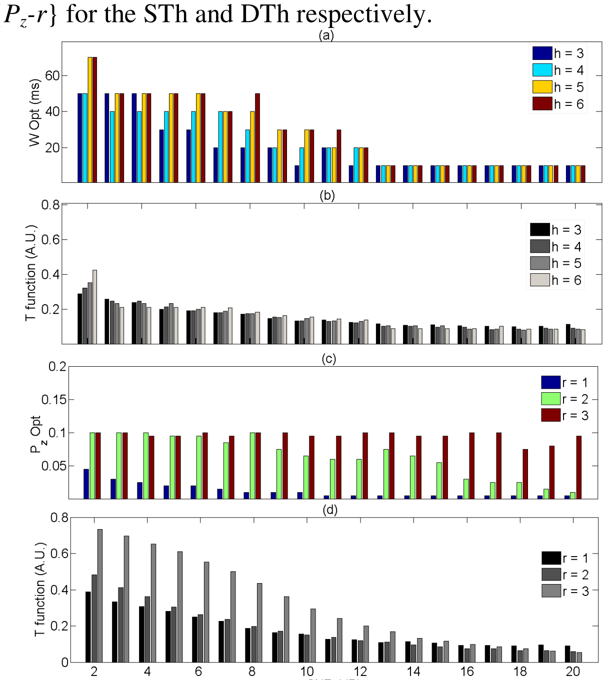

Figure 1: Optimal values of the algorithm parameters when varying SNR: (a) optimal W values of the STh, corresponding to different levels of the multiplicative threshold h, and (b) the corresponding cost function T values; (c) optimal P_z values of the DTh corresponding to different levels of the second threshold r, and (d) the corresponding cost function T values.

When varying the *SNR* level, a general pattern in the data is present: for STh, the optimal configuration of the parameters seems to be related to *SNR* only through the window width W, since it decreases when *SNR* increases, while the multiplicative threshold h shows little influence on the T function (fig. 1-b). For DTh, the optimal configuration shows a decreasing trend for the optimum value of P_z, with the second threshold r fixed to 1, while for $r = 2$ the decreasing behavior starts from 8 dB (fig. 1-d). Nevertheless, both detectors show an optimal configuration that depends on the current *SNR* level (fig. 2), and this may not be suitable when working with real tremor conditions, as the *SNR* can vary with time (and thus may bring to the need of estimating sample by sample the local *SNR* in order to properly detect tremor activation patterns).

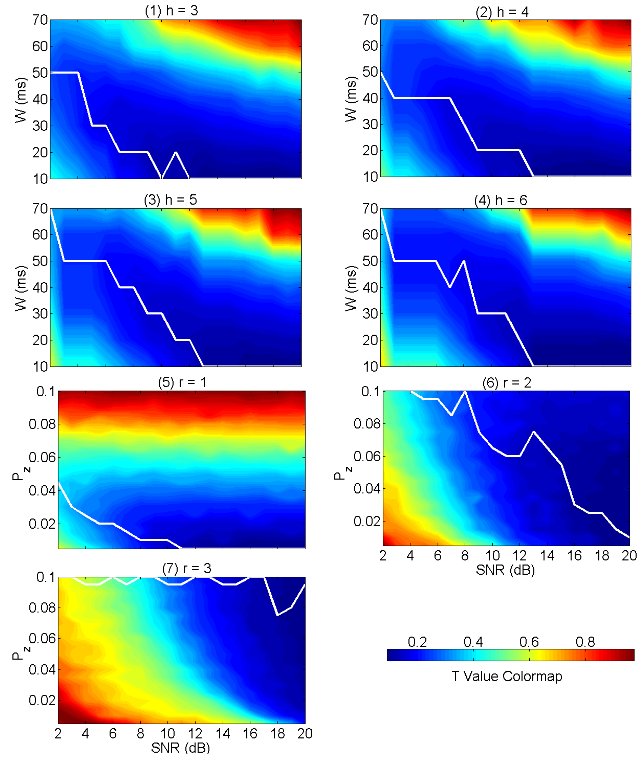

Figure 2: Mesh depicting T as a function of parameters W (meshes 1-4), or P_z (meshes 5-7), and *SNR*. Different meshes correspond to different value of the second parameter (h in meshes 1-4, and r in meshes 5-7). The white line shows the trajectory of the minimum value of T, as a function of *SNR*.

In order to make the detector less sensitive to the variations in the local *SNR*, a general configuration for the algorithms can be found, able to provide a T value lower than a given threshold for a range of *SNR* levels. In this way we can define a criterion of acceptability by thresholding the T function and thus choosing the best configurations for muscular timing detection. With a threshold value equal to 0.25, no configurations with SNR lower than 6dB were found for DTh, and were thus discarded from the analysis.
In DTh, the set $\{P_z = 0.02,\ r = 1\}$ provides T values under the threshold for every considered SNR; the corresponding set for the STh ($\{W = 30\ ms,\ h = 4\}$) leads to a T value always lower than 0.23. The corresponding values of S and P are higher than 0.96, with σ and μ constantly below 10 ms and then comparable with the ones commonly accepted in literature. However, besides the optimal configurations, from the comparison between the map of the T cost functions for the two analyzed methods (fig. 1) it emerges

that the behavior of STh is less sensitive to the variations of parameters, as shown by the wider extension of the zone with low *T* values.

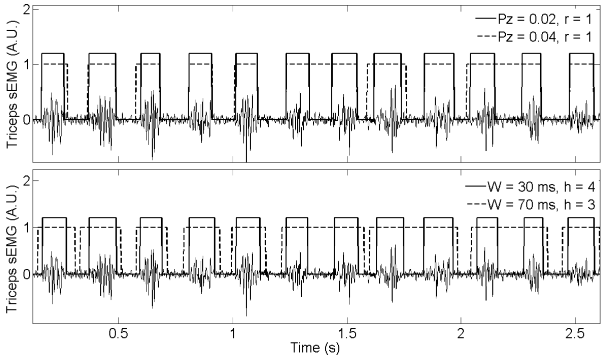

Figure 3: Real tremor sEMG signal recorded on the triceps muscle during an arm outstretching task: the output of both the algorithms (upper panel: DTh, lower panel: STh) with the optimal and a non-optimal parameter set is showed.

In figure 3, the output of the two algorithms on a real tremor sEMG signal recorded from the experimental trials described in the previous section is shown (triceps muscle during an Arm Outstretching task). Both algorithms are able to properly detect tremor bursts when the optimal set is used.

IV. Discussion and Conclusions

Two traditional algorithms for the detection of muscle activation intervals, respectively the STh detector proposed by Hodges and colleagues, and the DTh detector proposed by Bonato and co-workers, were analyzed when applied to tremor sEMG signals. With the optimization procedure presented in this work the optimal parameter set for the detection and timing of muscular tremor bursts was found for both the detectors. The STh detector presents lower sensitivity to the variations of the cost function with respect to changes in the parameters than the DTh. In order to make the parameters of the two algorithms as independent as possible from the current *SNR* and then applicable to tremor data series, a general set providing a value of the cost function as low as possible was found. The results obtained with the optimal parameter sets (*{W = 30 ms - h = 4}* for STh and *{Pz = 0.02 and r = 2}* for DTh) are comparable with those commonly accepted in literature, and they are thus suitable for use in clinical practice. Compared to the technique proposed in [17] where computational simplicity is accompanied by a parameter set that is chosen empirically across trials, the analyzed methods are able to provide the on/off timing of the single tremor bursts with an optimized parameter set that does not depend on tremor frequency and SNR.

Limitations of the analyzed method could rise when variations in the background noise or tonic muscle activity are present: this may lead to equivalent changes in the *SNR* that would decrease the accuracy in the detection for both methods. Further studies may address this issue, by proposing *SNR*-adaptive methods for tremor burst detection.

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