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A SNR-Independent Formulation of a Double Threshold Algorithm for the Estimation of Muscle Activation Intervals

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Abstract— **The aim of this work is to propose an improvement to the double threshold algorithm for muscular activation intervals estimation developed by Bonato and his co-workers. The proposed method has been designed in order to be adaptive also when the Signal to Noise ratio (SNR) of the sEMG signal changes during the trial, by re-evaluating the parameters of the algorithm according to the estimated local SNR and the desired detection and false alarm probabilities. This novel implementation is also suitable for working in pseudo real-time since it can give information on burst estimation shortly after the end of the current muscular activity. The proposed method was tested on simulated signals taking into account changes in the SNR during the trial, and results were compared with those obtained with the classical implementation of the algorithm.**

I. Introduction

AMONG the information that can be obtained from the surface electromyographic signal (sEMG), onset-offset timing estimation has been widely investigated in literature in the past two decades. Estimation of sEMG activation timing has been proven to give valuable information both in clinical studies and in other applications: it has demonstrated its usefulness in orthopedics [1][2][3], in the estimation of muscular synergies [4] and in the study and rehabilitation of impairments such as cerebral palsy and paresis [5] [6]. In addition, many sEMG-driven devices and technologies have been developed in the past years, such as rehabilitative orthoses [7], exoskeletons [8] and prostheses [9]. In early studies, estimation of sEMG onset and offset was performed by trained clinicians by means of visual inspection, while, more recently, attention has been focused on the development of automatic computer-based methods. Many algorithms have been developed so far, starting from simple single threshold methods, as in [10], to the double threshold statistical algorithm for muscle activation detection proposed by Bonato and co-workers [11]. Other approaches are based either on time-frequency analysis of the sEMG signal [12][13] or on statistically optimal decision criteria [14][15]. A common limitation of these methods is the reduced ability to accurately detect timings in those conditions where the SNR of the sEMG signal changes during a trial. SNR fluctuations during sEMG recordings are commonly due to changes in the signal power (e.g. changes in the exerted force during isometric trials) or changes in the noise power (e.g. changes in the electrode distance from the muscle, changes in the ground reference level). The second phenomenon in particular can distort the onset-offset estimation of sEMG signal and thus can compromise the validity of an acquisition trial.

In this work a novel implementation of the algorithm proposed by Bonato et al. [11] is presented, in order to overcome estimation errors caused by SNR changes during trials. This implementation is able to adapt, on a burst-to-burst basis, the parameters depending on the desired values of false alarm probability (P_{fa}) and detection probability (P_d), chosen by the user, and on the estimated SNR. Moreover, the implementation of this modified version of the algorithm leads to a pseudo real-time detection (the onset-offset timing of a sEMG burst is provided shortly after the completion of the burst itself), while the original method was intended as an offline procedure. The proposed algorithm has been tested and compared with its classical implementation on epochs of simulated data with SNR varying through time.

II. Materials and Methods

A. Theoretical framework of the algorithm

The detector is based on the assumption that sEMG may be considered as a zero-mean Gaussian process *s(t)* modulated by the muscle activity with a superimposed zero-mean Gaussian noise *n(t)* [16] [17].

According to this hypothesis, the sEMG temporal series $\{x_i\}$ is whitened by means of an adaptive white filter [18] (obtaining the series $\{x_i^w\}$). An auxiliary time series $\{z_i\}$ is then obtained, by summing the square of two consecutive samples of the whitened series. Due to the Gaussianity of both the signal *s(t)* and the sumperimposed noise *n(t)*, successive samples of the whitened series $\{z_i\}$ are independent, thus $\{z_i\}$ can be considered as a χ^2 distribution with two degrees of freedom.

The probability that a specific noise sample of the whitened series is above a threshold *th* can be written as a function of the noise variance σ_{nw}^2 as in equation:

$$P_{th} = P[z > th; x(t) = n(t)] = e^{-th/2\sigma_{nw}^2} \qquad (1)$$

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When both signal and noise are present, the probability that a given sample k is above the threshold th is then given by:

$$P_{dk} = P[z > th; x(t) = s(t) + n(t)] = e^{-th/(2\sigma_{nw}^2+2\sigma_{sw}^2)} = e^{-th/[2\sigma_{nw}\left(1+10^{\frac{SNR}{10}}\right)]} \quad (2)$$

where σ_{sw}^2 is the variance of the signal.

The probability that r_0 successive samples out of m are above a given thresold can be derived from the probability associated to a single sample considering a repetition of Bernoulli trials:

$$P_{fa} = \sum_{k=r_0}^{m} \binom{m}{k} = P_{th}^k (1 - P_{th})^{m-k} \quad (3)$$

$$P_d = \sum_{k=r_0}^{m} \binom{m}{k} = P_{dk}^k (1 - P_{dk})^{m-k} \quad (4)$$

The probabilities expressed in (3) and (4) represent respectively the false alarm probabilty and the detection probability of the algorithm.

B. Standard Implementation of the detector

In the standard implementation, the detector is based on the selection of the desired values for P_{fa} and P_d, and on the setting of the observation window length m and of the second threshold r_0 made before the beginning of the analysis. These values are kept fixed during the trial. The value of P_{th} for the chosen parameters can thus be derived from (3). The value of the first threshold th can be derived from (1) given the noise variance σ_{nw}^2 that can be obtained from the estimation of the SNR of the signal.

A post-processing technique is applied on the output of the algorithm, in order to eliminate short erroneous transitions caused by the stochastic nature of the signal under analysis. These transitions represent false positive and false negative occurrences of limited duration. Given a minimum acceptable duration (that normally can be assumed close to 30 ms) for the voluntary sEMG activity, all the transitions of shorter duration are rejected. Standard parameters for this kind of implementation are $m = 5$ (10 ms of time resolution) and $r_0=1$. P_{fa} and P_d are selected according to the task to be analyzed (typical standard values are 0.95 and 0.05).

C. Novel formulation

In the standard implementation of the algorithm, the SNR estimation regards the whole signal and provides one mean value for the trial. Modifications of the SNR during the recording are not taken into account and affect the results because they prevent the correctness of the threshold th so providing erroneous onset-offset detections.

The novel implementation of the algorithm is based on a preliminary estimation of the noise variance at the beginning of the trial, followed by an update of the SNR estimation for each detected burst. All the parameters of the detector (except the time resolution m that is kept fixed to 10 ms) are updated accordingly to the desired P_{fa} and P_d (namely P_{fad} and P_{dd}) and the current SNR. Specifically:

1) Before the beginning of the analysis the value of m, P_{fad} and P_{dd} are selected (standard values are $m = 5$, $P_{fad} = 0.05$ and $P_{dd} = 0.95$). Also standard values are associated to the SNR and r_0 (SNR = 12 dB and $r_0 = 1$).

2) A buffer (50 ms) of the original signal is whitened by means of an adaptive whitening filter. For every time-step the buffer is updated with the current sample of the original signal.

3) A first-guess estimation of the noise variance is performed on the first 200 ms of the withened signal and the first threshold th is derived from equation (1).

4) A buffer for the analysis is updated every time step with the current sample of the whitened sEMG signal, and the associated χ^2 distribution is estimated. The buffered distribution is then analyzed for burst detection using the current parameters, and post-processed.

5) If the analysis has correctly detected the end of a voluntary sEMG burst, the SNR and the associated noise variance values are updated, while the value of r_0 and th are updated to the optimum values for the estimated SNR and noise variance by numerically solving equations (3) and (4). The analysis is repeated until the SNR estimation converges (the difference between the SNR estimations in two consecutive steps is less than 10^{-3}).

6) Once a burst has been correctly detected the buffer is reinizialized.

In this implementation, the algorithm takes into account changes of the SNR during the analysis and updates the parameters in order to fit the optimal P_{fa} and P_d accordingly to the current SNR and the values of P_{fad} and P_{dd}. Numerical solution of (3) and (4) in fact gives the values of th and r_0 that maximize P_d and minimize P_{fa} for the current value of SNR. If no values of th and r_0 can fit the P_{fad} and P_{dd}, the parameters are selected in order to minimize the false alarm probability with the highest possible detection probability. SNR is evaluated at each cycle of the burst analysis using the estimation of the onset-offset timing. In particular, noise power is the noise of the signal outside the onset-offset timing interval, and the power of the data in this interval is considered as signal power plus noise power.

D. Simulated Signals

The performance of the proposed implementation was tested by using simulated sEMG data. These data were synthesized by using the same sEMG signal model used for the evaluation of the standard approach. The signal realizations were generated by modulating zero-mean Gaussian colored noise (obtained applying the Stulen-De Luca filter [19] to white noise series) with a modulating function (that can be rectangular or Gaussian), truncated on the basis of the desired time support for the burst.

Additive zero-mean white Gaussian noise was added to the modulated signal. Trials were performed in order to take into account changes of the SNR through time. Changes were simulated both as changes in the signal power and in the noise power. The first situation was simulated by constructing trials as a repetition of ten rectangular bursts at different SNR values (random SNR values in a range between 9 and 24 dB). These trials were labeled as Variable Signal (VS) trials.

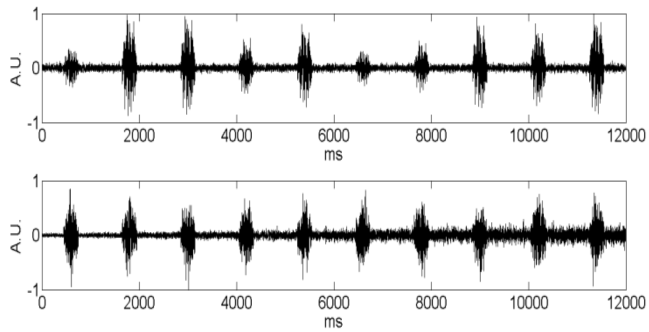

Fig. 1. Example of the two kinds of trials used for the evaluation of the method: top figure shows a trial in which the power of the voluntary burst changes randomly; bottom figure shows a trial in which the power of the superimposed noise changes during the trial.

The second condition was simulated by using Gaussian modulated bursts with different values of the time support. Changes in noise power were simulated by exponentially modulating the power of the superimposed noise in order to provide a SNR degradation of 15 dB during the trial (starting SNR was set at 25 dB). These trials were labeled as Variable Noise (VN) trials. An example of both kinds of signals is shown in Fig. 1.

Detection results were evaluated in terms of: i) bias and standard deviation between estimated and real onset; ii) occurrence of false patterns (either false positive or missed detections). Results were compared with those obtained using the standard implementation of the algorithm. For the VS condition, 100 trials were used for the test.

III. Results and Discussion

Results for VS trials, as presented in Table 1, show that the novel formulation has a lower error in the estimation of the onset (results are similar in the estimation of the offset) and a comparable number of false positive transitions (movements were all detected for both methods) with respect to the standard implementation. Nevertheless the results are both acceptable for clinical use (bias and standard deviation values below 10 ms).

A more marked difference between the two implementations of the algorithm can be noticed in the VN trials, whose results are shown in table 2.

ST	
bias ± std (ms)	-5.9 ± 3.2
FP/Dt	1% / 100%
NV	
bias ± std (ms)	0.1 ± 1.6
FP/Dt	1% / 100%

Table 1. Comparison of results between the standard (ST) and the novel (NV) formulation of the algorithm for VS trials. Results are presented for different time supports and are expressed in terms of bias ± standard deviation, false pattern percentage (with respect of the total number of movements) and detection percentage.

Performance was evaluated for Gaussian modulated bursts with different values of time support $\pm\alpha\sigma$ (with σ being the standard deviation of the Gaussian function and α a multiplicative constant). It can be noticed that, in all the configurations, the standard implementation has a detection performance around 50% only, and detected bursts show a higher error in terms of bias and standard deviation. On the other hand the novel formulation (an example is shown in Fig. 2) has a 100% detection performance and a minimum percentage of false positive transitions with respect to the standard implementation. The main reason for this marked difference in results is related to the fact that the standard implementation of the algorithm estimates a fixed level of noise power for all the trials, while the novel formulation updates the estimation of the noise power and the optimal parameters for the detection for each burst.

	σ = 50 ms		
ST	α = 1	α = 1.5	α = 2
Bias ± std (ms)	- 9 ± 13.8	- 15.2 ± 14	-19 ± 20
FP/Dt	14% / 53%	14% / 50%	5% / 52%
NV	α = 1	α = 1.5	α = 2
Bias ± std (ms)	-0.1 ± 0.7	4 ± 5.3	18.47 ± 20.7
FP/Dt	0% / 100%	0% / 100%	0% / 100%
	σ = 150 ms		
ST	α = 1	α = 1.5	α = 2
Bias ± std (ms)	-24.1 ± 13.1	-25 ± 14.7	-16.8 ± 9.1
FP/Dt	65% / 42%	54% / 41%	22% / 44%
NV	α = 1	α = 1.5	α = 2
Bias ± std (ms)	0.1 ± 0.9	5.8 ± 7.2	49.9 ± 53.6
FP/Dt	0% / 100%	0% / 100%	1% / 100%

Table 2. Comparison of results between standard (ST) and novel (NV) implementations of the algorithm for VN trials. Results are presented for different time supports and are expressed in terms of bias ± standard deviation, false pattern percentage (with respect of the total number of movements) and detection percentage.

This implementation can easily cope with fast changes in the SNR, while abrupt, step-like changes in the power of the superimposed noise may be mistaken for sEMG bursts, thus leading to erroneous detections. Also, this implementation can give information on the estimated onset-offset timing shortly after the completion of the burst under analysis, with a limited time delay depending on the computational complexity of the approach. Preliminary trials on simulated signals showed a response-time of the algorithm well below 500ms, thus not significantly affecting real-time use of the method. A more accurate estimation (in terms of megaflops) of the delay time will be carried out during further testing of the method. Moreover, future developments of this work will be based also on the testing of the proposed implementation on real sEMG signals during exercises specifically designed in order to take into account changes in the SNR during their execution, such as isometric contractions at different levels of force.

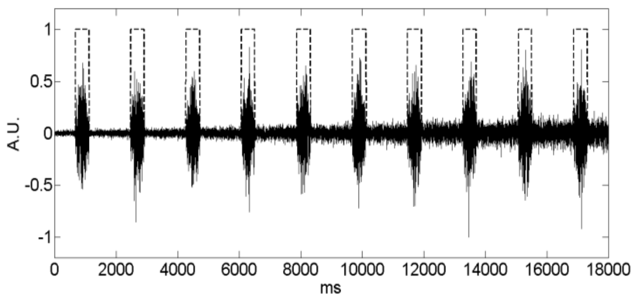

Fig. 2. Example of results obtained with the novel implementation of the algorithm on a VN trial ($\sigma = 150$, $\alpha = 1.5$).

IV. Conclusion

A novel formulation of the algorithm by Bonato and co-workers [11] was proposed and tested. This novel method was designed in order to deal with dynamic situations in which the SNR of the sEMG signal can change due to changes intrinsically related to the task performed or due to disturbances in the recording environment. Moreover, this algorithm can work essentially in real time since it can give information on the estimated burst timing shortly after the completion of the burst itself. Results show that this formulation has a low estimation error when dealing with varying SNR, and provides both a higher detection rate and a lower false positive rate with respect to the classical formulation.

A further advantage is that the algorithm is almost independent of subjective settings of the parameters by the operator.

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