An Adaptive Algorithm for the Determination of the Onset and Offset of Muscle Contraction by EMG Signal Processing

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***Abstract*—Estimation of on–off timing of human skeletal muscles during movement is an ongoing issue in surface electromyography (sEMG) signal processing for relevant clinical applications. Widely used single threshold methods still rely on the experience of the operator to manually establish a threshold level. In this paper, a novel approach to address this issue is presented. Based on the generalized likelihood ratio test, the maximum likelihood (ML) method is improved with an adaptive threshold technique based on the signal-to-noise ratio (SNR) estimate in the initial time before accurate sEMG analyses. The dependence of optimal threshold on SNR is determined by minimizing the onset/offset estimate error on a large set of simulated signals with well-known signal parameters. Accuracy and precision of the algorithm were assessed by using a set of simulated signals and real sEMG signals recorded from two healthy subjects during elbow flexion-extension movements with and without workload. Comparison with traditional algorithms shows that with a moderate increase in the computational effort the ML algorithm performs well even for low levels of EMG activity, while the proposed adaptive method is most robust with respect to variations in SNRs. Also, we discuss the results of analyzing the sEMG recordings from the selected proximal muscles of the upper limb in two hemiparetic subjects. The detection algorithm is automatic and user-independent, managing the detection of both onset and offset activation, and is applicable in presence of noise allowing use by skilled and unskilled operators alike.**

***Index Terms*—Adaptive decision threshold, electromyography (EMG) signal, maximum likelihood method, muscle contraction.**

I. Introduction

ANALYSIS of surface electromyographic (sEMG) signals recorded from the skin over the muscles during muscular activity has broad applications for biomechanics, medicine and clinical diagnosis, rehabilitation devices, and so on [1]–[5]. Electromyography (EMG), which mainly reflects the electrical properties of a muscle, has been proven to be a useful tool for interpretation of muscle activities and its varying characteristics in both normal and pathological cases. EMG technique has been widely used as one of the measures for accessing neuromuscular changes of the paretic muscles, including muscle fatigue, in persons after stroke and spinal cord injury (SCI) [6], [7]. Moreover, the evolution of sEMG from single bipolar recordings via a linear array of multiple electrodes to densely packed, multi-channel electrode arrays could in principle extract features of single motor units [8], [9]. Multiple channels arrays (up to 128) with an interelectrode distance of a few millimetres have been used to obtain more spatial information. For some muscles it is now possible to uncover otherwise inaccessible physiological information using multichannel sEMG which conventionally has been the domain of needle EMG [10], [11]. On the other hand, rehabilitation therapy experiment in animal models is a suitable method to evaluate the muscle activation pattern [12]. The topography and temporal course of several sEMG parameters of the triceps brachii muscle in rats during treadmill locomotion has been investigated using an EMG electrode array fixed under the skin [13]. Muscle activation changes after stroke require further investigation in order to design a better training program and to enhance the understanding of the mechanism underlying the rehabilitation. The muscle fatigue dynamics, muscle activation duration in the gait cycle, and the two-side symmetry in the rat model were monitored during a body weight support treadmill running along the rehabilitation program by means of implantable EMG recording electrodes in chronic experiments [14]. Also, the abnormal gait pattern was found to be associated with the electrical activity of the muscles and the muscle fatigue based on the analysis of the EMG changes in SCI rats [15].

For several decades, sEMG signal has been used as a control source in neural prostheses. In current practice, either the position or the speed of a motor in the prosthesis is controlled by the magnitude of sEMG signals recorded from one or two residual muscles. Most commercially available motorized artificial limbs are controlled with sEMG from available muscles of an amputated limb. The device controller is thus engaged in the accurate identification of the time instant when the muscle goes from the relaxed state to the contracted state (onset detection) and pattern classification based on the segmented signals for the control purposes [16], [17]. The determination of the onset and offset times of a muscle contraction is useful for the purpose of

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controlling prosthetic and orthotic devices. In fields such as orthopaedic surgery and rehabilitation, the instantaneous sEMG signal energy serves as a measure of the current level of muscle activation for the motor assessment, whereas the detection of the muscular activation timing in dynamic conditions has a clinical diagnostic impact [18]–[20]. The sEMG signal analysis during rhythmic movements mainly covers activity level and/or activation timing. Generally the sEMG signal variables related to the amplitude of the electrical activity, such as rms or integrated EMG (iEMG), are quantified as activity level. Since different muscle groups have to work in a sequential order to perform a specific physical activity, timing parameters generally determined from the EMG profile includes onset and offset times to identify activation timing in which a certain muscle group participates in the activity [21].

Processing of sEMG can be considered a special field of applied signal processing, with the main focus on extracting specific information from small and often noisy bioelectric signals. Due to the stochastic characteristic of sEMG signals, onset and offset detection is a challenging task, especially in weak sEMG responses. For years the onset detection of muscle contraction has been carried on using a visual inspection or computer-based method by means of a comparison between an arbitrarily chosen value (the threshold) and the raw signal or the sEMG signal energy [22]. When the signal exceeds the preset threshold, a muscular activation is reported. However, the threshold is user-dependent, and is cumbersome to optimize with regards to both the detection bias and the false alarm probability. Generally, purely threshold-based methods represent a tradeoff between detection sensitivity and specificity. High threshold levels will usually lead to delayed or even missed onset detection; a relatively low threshold level results in early onset detection but also raises more false alarms. Thus the freedom of selecting different values may introduce a subjective component in some studies. On the other hand, the implicit assumption underlying most threshold-based methods is that the EMG signal power from a contracted muscle is much greater than that from the same muscle being relaxed. In most cases, sEMG signals have a good signal-to-noise ratio (SNR), so these methods perform well in detecting the onset time when SNR is larger than 10 dB [23]. However, sEMG of small and deep muscles as well as sEMG recorded in patients with neuromuscular diseases may not meet this SNR requirement, which motivates the search for more sophisticated statistical methods.

In order to overcome the aforementioned drawbacks, several statistical algorithms to determine the onset of EMG activity have been developed and published in the literature over the past two decades. An efficient method, known as the maximum likelihood (ML) algorithm, has been introduced to detect the onset of muscle activity from sEMG signals using the generalized likelihood ratio (GLR) test that allows for the detection of abrupt changes of time-varying linear systems [24], [25]. In contrast to commonly used threshold-based estimation methods, ML method proves to be reasonably accurate even for low levels of EMG activity with just a modest increase in the computational complexity. Furthermore, a systematic survey of the state-of-the-art of computerized methods for the onset detection of sEMG signals showed that some of the threshold-based signal-power estimation procedures are very sensitive to signal parameters such as SNR or background activity level, whereas statistically optimized algorithms are generally more robust [26]. In this paper, we address the problem of the onset and offset identification of muscle contraction timing by sEMG signal processing based on statistically optimal decisions. Due to the specific dependence of the detection accuracy on the decision threshold, it is important to determine a proper threshold value for accurate sEMG signal analysis. The proposed statistically optimized method was applied first to simulated signals in a broad interval of SNR to investigate the dependence of estimated error on SNR and decision threshold. Then the new approach, aimed at detecting the muscular activation intervals, was tested on the simulated signals to evaluate its performance and detection capabilities. Results were compared with those obtained by applying two classical threshold-based estimators, referred to as algorithm A and algorithm B to the task of onset and offset detection. Algorithm A starts with estimating the mean μ_0 and the standard deviation σ_0 of the EMG signal in the initial step time when the muscle is relaxed; the onset/offset of contraction is assumed to occur when three consecutive samples are greater/less than a threshold level depending on $\hat{\sigma}_0$. As for algorithm B, the time integral of the full-wave rectified EMG signal is computed over a window of samples and then compared to a suitably chosen threshold, which may be found so that the detection bias is kept within reasonable limits in a broad interval of SNR. Moreover, the proposed method was applied on experimental sEMG signals to discuss its performance and applicability in real contexts.

II. Methods

A. Maximum Likelihood Algorithm

The ML algorithm is based on hypothesis testing to estimate the time instant of muscle contraction onset and offset via sEMG signals. Detecting the contraction onset and offset reflects the existence of two hypotheses, namely the null hypothesis H_0 associated with the relaxed muscle state and the hypothesis H_1 related with the contracted muscle state. A series of observations $y_0^n = [y(0), \dots, y(n)]$ describes the sEMG sample in a fixed-size sliding window that is advanced one sample ahead until the onset or offset is found, while $P_0(y(t))$ and $P_1(y(t))$ denote the probability density functions (PDF) of the observation $y(t)$ corresponding to H_0 and H_1, respectively. The ML test will be used to determine which hypothesis is true for every time instant r from 0 to n. The probability, known as the likelihood function, that the whole sEMG trace responds to hypothesis H_0 is given by

$$L_0\left(y_0^n\right) = p_0\left(y_0^n\right) = \prod_{t=0}^{n} P_0\left(y\left(t\right)\right). \tag{1}$$

The probability that the whole sEMG trace responds to hypothesis H_1 is given by

$$L_1\left(y_0^n\right) = p_1\left(y_0^n\right) = \prod_{t=0}^{n} P_1\left(y\left(t\right)\right). \tag{2}$$

Considering the onset detection for every time instant r, the probability that the sEMG record generated by hypothesis H_0 from time 0 to $r-1$, and by hypothesis H_1 from time r to n is

$$L_1(r, y_0^n) = p_0(y_0^{r-1})\, p_1(y_r^n) = \prod_{t=0}^{r-1} P_0(y(t)) \cdot \prod_{t=r}^{n} P_1(y(t)). \tag{3}$$

Assuming that the offset detection is taken into account for every time instant r, the probability that the sEMG record generated by hypothesis H_1 from time 0 to $r-1$, and by hypothesis H_0 from time r to n is

$$L_0(r, y_0^n) = p_1(y_0^{r-1})\, p_0(y_r^n) = \prod_{t=0}^{r-1} P_1(y(t)) \cdot \prod_{t=r}^{n} P_0(y(t)). \tag{4}$$

Since the EMG signal is generally accepted to be provided with stochastic independence in nature and normally distributed, the likelihood ratios for onset and offset detection become

$$\frac{L_1(r, y_0^n)}{L_0(y_0^n)} = \frac{p_0(y_0^{r-1})\, p_1(y_r^n)}{p_0(y_0^n)} = \prod_{t=r}^{n} \frac{P_1(y(t))}{P_0(y(t))} \tag{5}$$

and

$$\frac{L_0(r, y_0^n)}{L_1(y_0^n)} = \frac{p_1(y_0^{r-1})\, p_0(y_r^n)}{p_1(y_0^n)} = \prod_{t=r}^{n} \frac{P_0(y(t))}{P_1(y(t))}. \tag{6}$$

In order to reduce the computational effort in dynamic conditions, the likelihood ratios for onset and offset detections are recursively calculated by

$$\frac{L_1(r, y_0^n)}{L_0(y_0^n)} = \frac{L_1(r-1, y_0^n)}{L_0(y_0^n)} \cdot \frac{P_0(y(r-1))}{P_1(y(r-1))} \tag{7}$$

and

$$\frac{L_0(r, y_0^n)}{L_1(y_0^n)} = \frac{L_0(r-1, y_0^n)}{L_1(y_0^n)} \cdot \frac{P_1(y(r-1))}{P_0(y(r-1))}. \tag{8}$$

The decision function (DF) is defined as the maximum of the log-likelihood ratio over the possible transition time r. The onset and offset DFs are given separately by

$$DF_1(r, y_0^n) = \max\left\{0, \log\left\{\max_{r\in[0,n]}\left\{\frac{L_1(r, y_0^n)}{L_0(y_0^n)}\right\}\right\}\right\} \tag{9}$$

and

$$DF_0(r, y_0^n) = \max\left\{0, \log\left\{\max_{r\in[0,n]}\left\{\frac{L_0(r, y_0^n)}{L_1(y_0^n)}\right\}\right\}\right\}. \tag{10}$$

Since the exact change time is unknown in a sliding window, it is replaced by its ML estimate. For each candidate time r, the log-likelihood ratio is computed from the observations within the test window. If the maximum of the log-likelihood ratio with respect to all hypothetical change times $0 \le r \le n$ exceeds the onset threshold γ_1 or the offset threshold γ_2, the time r at which the maximum value is obtained serves as the ML estimate of the unknown change time. Each time a new data point $y(n)$ is available, a test window with the upper bound n fixed at the current observation and with its lower bound 0 comprises a series of observations $y_0^n = [y(0), \ldots, y(n)]$ after the hypothetical change time 0.

As far as the likelihood ratios is concerned, the PDFs concerning the null hypothesis H_0 and the hypothesis H_1 in (5) and (6) are separately parameterized in terms of two parameter vector $\boldsymbol{\theta}_0$ and $\boldsymbol{\theta}_1$. The onset and offset DFs can be explicitly specified with the substitution of (5) and (6) into (9) and (10), respectively. It is commonly accepted that the pre-whitened sEMG before the response onset is represented by a sequence of statistically independent zero mean Gaussian random variables with equal variance. Thus, the unknown parameter vector $\boldsymbol{\theta}_0$ is estimated from the first M observations of the sEMG related with the relaxed muscle by ML techniques, resulting in

$$\hat{\boldsymbol{\theta}}_0 = \begin{bmatrix} \hat{\mu}_0 \\ \hat{\sigma}_0^2 \end{bmatrix} = \begin{bmatrix} 0 \\ \frac{1}{M}\sum_{i=1}^{M} (y(i))^2 \end{bmatrix} \tag{11}$$

which is kept fixed throughout the remaining detection procedure. Next, a sliding window of fixed size $n+1$ is continuously shifted along the data sequence. For each possible onset or offset time r in the window, the ML estimate $\hat{\boldsymbol{\theta}}_1$ of the unknown parameter vector $\boldsymbol{\theta}_1$ after or before change is determined from the $n-r+1$ or $r+1$ data points covered by the window, and estimated by

$$\hat{\boldsymbol{\theta}}_{1,on} = \begin{bmatrix} \hat{\mu}_{1,on} \\ \hat{\sigma}_{1,on}^2 \end{bmatrix} = \begin{bmatrix} \frac{1}{n-r+1}\sum_{i=r}^{n} y(i) \\ \frac{1}{n-r+1}\sum_{i=r}^{n} (y(i) - \hat{\mu}_{1,on})^2 \end{bmatrix} \tag{12}$$

or

$$\hat{\boldsymbol{\theta}}_{1,off} = \begin{bmatrix} \hat{\mu}_{1,off} \\ \hat{\sigma}_{1,off}^2 \end{bmatrix} = \begin{bmatrix} \frac{1}{r+1}\sum_{i=0}^{r} y(i) \\ \frac{1}{r+1}\sum_{i=0}^{r} \left(y(i) - \hat{\mu}_{1,off}\right)^2 \end{bmatrix}. \tag{13}$$

Hence, the corresponding maximal log-likelihood ratio is computed and compared with a threshold. After an onset change time has been indicated, the exact offset change time is estimated from all possible candidates in the test window, and vice versa.

B. Selection of Threshold

Both threshold-based approaches and statistically optimized algorithms for onset/offset detection have detection rules and make decision based on the threshold level. Thus, the threshold is a key factor in change detection approaches. It is reported that the detection accuracy depends on the settled threshold for different values of SNR [12], [15]. In particular, the dependence of proper threshold on SNR is studied in this work. Therefore, we need to develop a scheme with synthetic signals generated by models to determine the relationship between the threshold and SNR for an adaptive threshold selection in the ML algorithm.

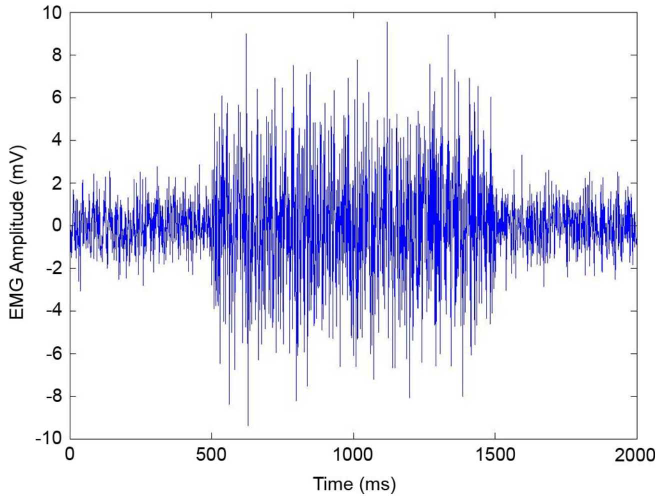

Fig. 1. Simulated sEMG trace with $\mathrm{SNR} = 3$ is synthesized by juxtaposing three signal sequences, lasting $T_1 = 500$ ms, $T_2 = 1000$ ms, and $T_3 = 500$ ms, respectively, when the assumed sampling rate is $f_s = 1$ kHz.

The additive noise in sEMG recordings arises from electronic noise, ambient noise, motion artifacts and inherent instability of the signal. The latter two sources of noise have frequency spectra that contaminate the low-frequency part of the sEMG frequency spectrum [19]. Nevertheless, noise features in the sEMG recording depend also on the analog filters used to detect the signal. The band-pass determination is always a compromise between reducing noise contamination and preserving the desired information from the sEMG signal. Simple models based on the generation of filtered white Gaussian noise have been used to simulate stochastic process with known expected spectra [20]. In this paper, the noise is characterized simply by the SNR, and generated by filtering white noise with a Gaussian distribution of the amplitudes. A set of simulated EMG traces are synthesized by juxtaposing three signal sequences (Fig. 1), lasting $T_1 = 500$ ms, $T_2 = 1000$ ms and $T_3 = 500$ ms, respectively; the assumed sampling rate is $f_s = 1$ kHz. All sequences are obtained by applying white Gaussian noise with zero mean, e.g., $\mu_0 = \mu_2 = \mu_3 = 0$, to FIR filters of the fourth order determined from a representative set of real EMG signals (see next section) using standard techniques of least squares parameter estimation [25]. For the first and third sequences, the modeling is performed when the muscle is in its relaxed state; the standard deviation is then settled to $\sigma_1 = \sigma_3 = \sigma_0 = 1$ mV. The second sequence is intended to simulate the behavior of a contracted muscle. The standard deviation σ_2 of the second sequence is varied in steps, so as to cover a quite broad range of SNRs; the SNR is defined as the quotient of the standard deviation σ_2 of the contraction state and the standard deviation σ_0 of the relaxed state.

The initial time step for all algorithm mentioned in this paper is $D_0 = 50$ ms; the algorithms utilize data samples up to D_0 for estimating the standard deviation $\hat{\sigma}_0$ of the EMG signal in the relaxed state of the muscle. The task of the tested algorithms is to detect the onset and offset change occurring at time $D_1 = 500$ ms and $D_2 = 1000$ ms. The detection accuracy is reported in terms of the error, e.g., the difference between the onset/offset estimates provided by the algorithms and the true onset/offset in milliseconds. For a given SNR, the thresholds γ_1 and γ_2 in the ML algorithm are varied to minimize separately the onset and offset detection error for the determination of the optimal threshold values. Fig. 2 gives the optimal onset and offset thresholds applied for the ML algorithm as a function of SNR between 1.1 to 20. The optimal threshold varies with SNR; for onset detection, the lower noise level results in the larger select threshold. On the contrary, decreasing SNR leads to a larger threshold for offset detection. When the threshold-selection scheme should be applied to the onset/offset ML estimators on real EMG signals, the data samples in the initial time step related to the relaxed and active states of a muscle are used to estimate the SNR of the EMG signal; the threshold selection is adapted to the background activity (noise) based on the predetermined dependence of threshold on SNR by the table look-up scheme or interpolation method.

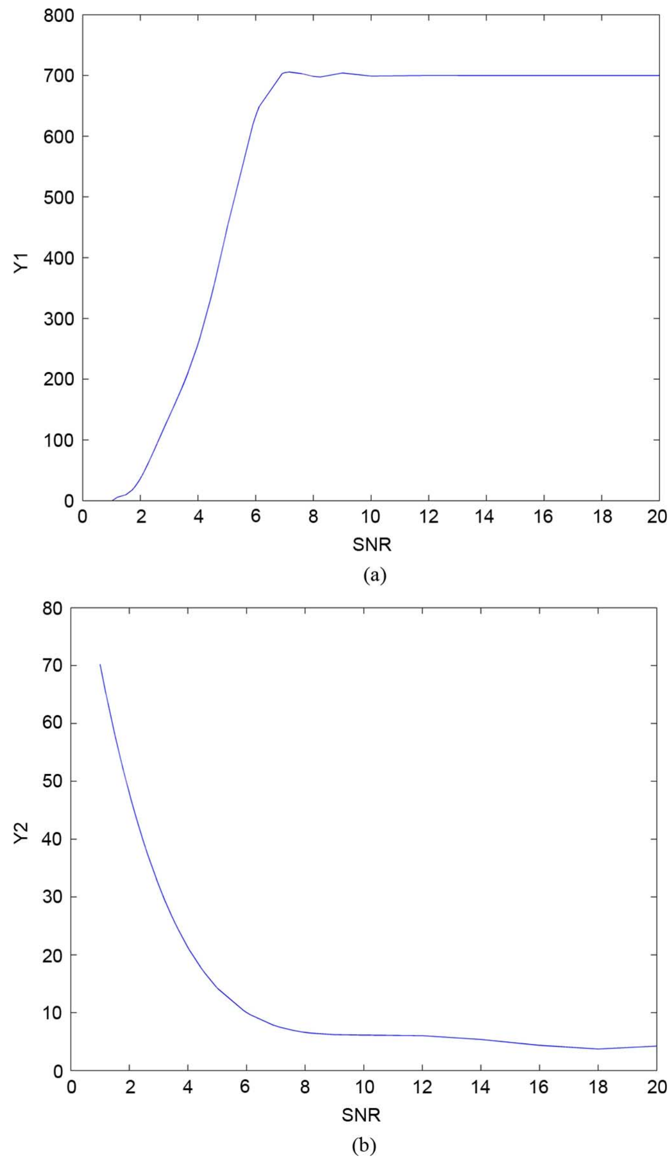

Fig. 2. Optimal threshold in the ML algorithm as a function of SNR, for the (a) onset and (b) offset detection of muscle contraction.

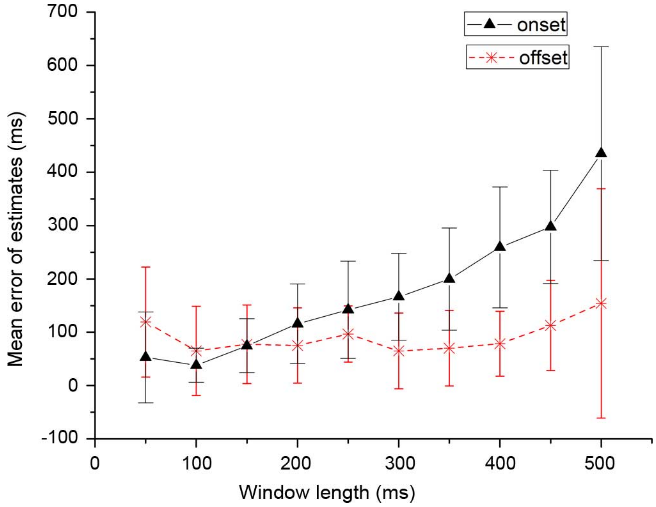

Fig. 3. Effect of the window length on the algorithm performance. The algorithm performance is evaluated by the mean error and error standard deviation of the onset and offset estimates.

III. RESULTS

In this paper, two classical threshold-based estimators (algorithms A and B) and the proposed ML algorithm, referred to as algorithm C, are all tested on large samples of both simulated and real sEMG data. Rating among all methods is performed by comparing their performance, such as mean onset/offset error and error standard deviation.

A. Computer Simulation Experiments

In the simulation experiments, the sEMG trace was generated by adding two uncorrelated realizations of Gaussian white noise with zero mean posing, respectively, as EMG signal and additive noise. The first was obtained by setting the standard deviation to 1 and by band-pass filtering the first Gaussian series of white noise [16]. The cut-off frequencies of band-pass filter were set to 20 and 500 Hz, respectively. The power of the second one, simulating the additive noise, was set to generate sEMG signals with the following SNR values: 1.25, 3, 6, and 9. Thirty epochs, 2 s long, were synthesized, and burst onset and offset time instants were set to 500 and 1500 ms, respectively. The sampling rate was equal to 1 kHz. The detection performance was then assessed with respect to the aforementioned set of 30 epochs of simulated bursts for each SNR value.

The sEMG signal detected during a voluntary muscle contraction is a realization of a nonstationary stochastic process. Any variable of the signal, computed over a sliding window, is intrinsically an estimate of the true value of that variable with an associated variance and bias which depend on the window length. For the ML algorithm, the likelihood ratios are calculated on a sliding window, so the effect of window length on the algorithm performance was investigated on the simulated EMG traces by varying the window length from a minimum value of 50 samples (50 ms) to a maximum value of 500 (500 ms) at steps of 50 ms. Fig. 3 shows the accuracy (mean error) and precision (error standard deviation) of the onset and offset estimates for different window lengths at $\mathrm{SNR} = 1.25$. It is shown that the algorithm performance varies with the window length. The sliding window of 100 ms gave higher accuracy (mean errors of 47 and 65 ms, respectively, for onset and offset estimates) than the others. Moreover, larger time ranges would increase the calculation time of onset and offset detection. Therefore, the likelihood ratios were calculated within a sliding window of 100 ms with acceptable computation cost in this study.

Table I reports the mean error and error standard deviation of onset estimates for each algorithm with the corresponding SNR value; the intervals around the averages given in the table correspond to the standard deviation on either side. Analysis of the mean errors shows that all algorithms show a systematic degradation of detection performance for smaller SNR; the proposed algorithm C with optimal threshold provides estimates closest to the "true" onset when SNR ranges from 1.25 to 9. Above all, algorithms A and B cannot compete with algorithm C for $\mathrm{SNR} = 1.25$ and 3. For $\mathrm{SNR} = 1.25$, algorithm C outperforms algorithm B at the expense of reduced mean error and error standard deviation, whereas algorithm A cannot provide onset detection at all.

Table II depicts mean and standard deviation of offset estimation errors for each algorithm based on simulated EMG traces with different SNRs. When increasing the signal quality of the SNR to no less than 6, all method provided similar results. However, algorithms A and B cannot compete with algorithm C for $\mathrm{SNR} = 1.25$ and 3. For $\mathrm{SNR} = 1.25$, algorithm C outperforms algorithm B at the expense of reduced mean error and error standard deviation, whereas algorithm A is incapable of detecting the offset time. Moreover, analysis of estimate error in SNR ranges from 1.25 to 9 show that algorithm C is most robust with respect to variations in signal properties such as SNR. EMG onsets and offsets were revealed with mean error less than 38 and 50 ms, respectively. Error standard deviations ranged from 3 to 41 ms. In addition, the measured running times of algorithms A, B, and C for onset and offset detection were 3.95 ± 0.47 ms, 5.86 ± 0.61 ms, and 2.47 ± 0.19 s, respectively, at $\mathrm{SNR} = 3$. It is clear that the improved performance of the adaptive ML algorithm comes with just a modest increase in the computational complexity of online analysis.

B. An Experiment Using Real sEMG Signals From Healthy Subjects

A further step in the validation process considered a set of real sEMG signals processed by the ML detection algorithm. Maximal low-speed isotonic elbow flexion-extension movement was performed by two healthy male subjects. Electromyographic activity of brachial biceps muscle was recorded by means of bipolar silver-silver chloride surface electrodes (20 mm in diameter) and using Biotel88 equipment (Gloner Inc., Germany). Raw EMG signals were amplified, filtered (band pass 20–500 Hz) and digitized (sampling rate 2 KHz). The data was exported to technical computing software (MATLAB ver. 2010) for further analysis.

At first, two subjects were seated in front of a height-adjustable table with the hand rested on the table. The sEMG signals with low SNR were recorded when the subjects were instructed to relax or relieve muscular tension in the upper limb and repeat slight elbow flexion-extension movement without workload for five times. In order to increase the SNR of sEMG

TABLE I
COMPARISON OF RESULTS OF THREE ALGORITHMS FOR ONSET DETECTION ON SIMULATED SIGNALS IN DIFFERENT SNRS. MEAN ERROR AND ERROR STANDARD DEVIATION IN MICROSECONDS WERE CALCULATED CONSIDERING A SET OF 30 EPOCHS OF SIMULATED BURSTS FOR EACH SNR CONDITION (1.25, 3, 6, AND 9)

SNR	Algorithm A	Algorithm B	Algorithm C	Optimal Threshold
1.25	—	77±62	38±26	6.26
3	44±34	26±23	16±14	138.71
6	13±12	17±12	12±8	633.09
9	9±7	7±6	5±3	704.42

TABLE II
COMPARISON OF RESULTS OF THREE ALGORITHMS FOR OFFSET DETECTION ON SIMULATED SIGNALS IN DIFFERENT SNRS. MEAN ERROR AND ERROR STANDARD DEVIATION IN MICROSECONDS WERE CALCULATED CONSIDERING A SET OF 30 EPOCHS OF SIMULATED BURSTS FOR EACH SNR CONDITION (1.25, 3, 6, AND 9)

SNR	Algorithm A	Algorithm B	Algorithm C	Optimal Threshold
1.25	—	112±93	50±41	63.95
3	48±51	38±34	13±11	32.04
6	6±6	11±23	8±10	10.03
9	3±3	9±22	6±8	6.19

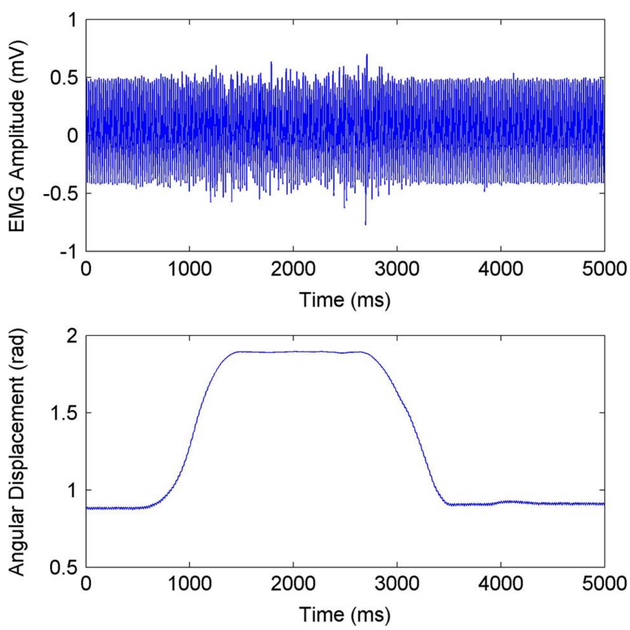

Fig. 4. An example of EMG recording from the brachial biceps muscle and time history of the elbow extension angle without workload (healthy subject 1).

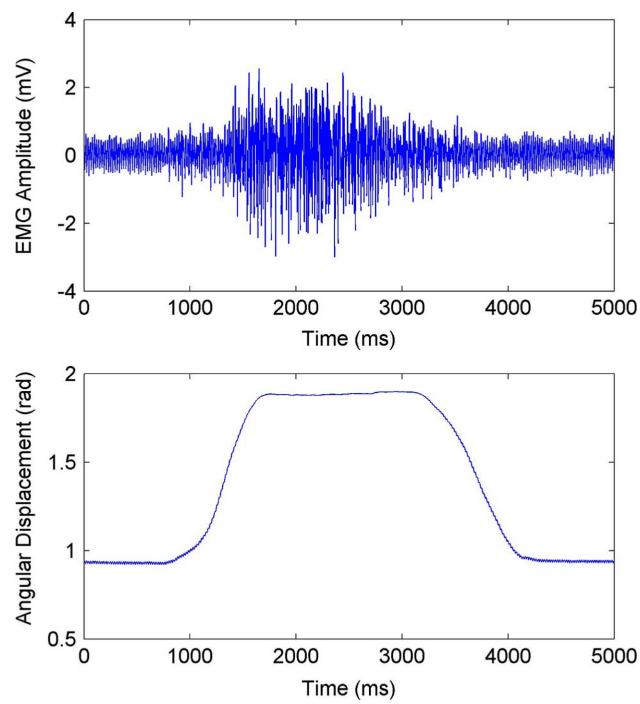

Fig. 5. An example of EMG recording of the brachial biceps muscle and time history of the elbow extension angle with workload (healthy subject 1).

records, each subject was then asked to lift a dumbbell as a workload and repeat the same movement five times. The Biotel system allows the acquisition of arm kinematic trajectories, and provides the information concerning the time instant r_0 when the limb movement effectively switches. Figs. 4 and 5 report the pattern of activation concerning brachial biceps muscle and time history of the elbow flexion angle for healthy subject 1 with and without workload, respectively. It is shown that, for this subject, the state of activation of the brachial biceps is well above the background EMG activity of the same muscle during the limb movement with workload $(\mathrm{SNR} = 2.1)$; on the contrary, the muscle activity is much less pronounced during the same movement without workload $(\mathrm{SNR} = 1.6)$. The data obtained from healthy subject 2 exhibit a similar behavior.

The performance of all algorithms on real sEMG data was expressed by means of mean error and error standard deviation; to this end, the estimate error ε was computed as the deviation between the change time estimates $\hat{r}$ provided by the tested methods and the time instant r_0 determined by an elbow angle variation. Tables III and IV report the mean of the estimated errors for each algorithm and each subject, with the corresponding SNR value; the intervals around the averages given in the tables correspond to the standard deviation on either side.

The ANOVA analysis reveals that, for each healthy subject, the differences between the estimate error produced by algorithm C and the errors produced by its competitors are not statistically significant when the SNR value is high; differences are considered important if the confidence level is greater than 95% $(p \leq 0.05)$. Conversely, the differences between the algorithms at low SNR-value of 1.6 are statistically significant.

TABLE III
PERFORMANCE OF THREE ALGORITHMS EVALUATED BY MEAN ERROR AND ERROR STANDARD DEVIATION IN MICROSECONDS FOR ON/OFF DETECTIONS WITH AND WITHOUT WORKLOAD CARRIED OUT ON HEALTHY SUBJECT 1

Workload	SNR	ON/OFF detection	Algorithm A	Algorithm B	Algorithm C	Optimal Threshold
No	1.6	Onset	529±339	489±200	195±87	12.82
		Offset	909±246	817±226	227±93	55.95
Yes	2.1	Onset	388±219	243±217	185±74	45.23
		Offset	488±259	240±188	205±86	46.03

TABLE IV
PERFORMANCE OF THREE ALGORITHMS EVALUATED BY MEAN ERROR AND ERROR STANDARD DEVIATION IN MICROSECONDS FOR ON/OFF DETECTIONS WITH AND WITHOUT WORKLOAD CARRIED OUT ON HEALTHY SUBJECT 2

Workload	SNR	ON/OFF detection	Algorithm A	Algorithm B	Algorithm C	Optimal threshold
No	3.4	Onset	335±217	340±282	413±129	181.26
		Offset	742±148	669±75	784±379	27.20
Yes	5.1	Onset	453±159	435±451	387±160	468.03
		Offset	688±379	638±153	701±221	13.73

TABLE V
PERFORMANCE OF THREE ALGORITHMS EVALUATED BY MEAN ERROR AND ERROR STANDARD DEVIATION IN MICROSECONDS FOR ON/OFF DETECTIONS CARRIED OUT ON TWO PARALYZED SUBJECTS

Subject	SNR	ON/OFF detection	Algorithm A	Algorithm B	Algorithm C	Optimal threshold
1	1.6	Onset	794±149	351±199	151±92	12.82
		Offset	508±357	681±668	257±213	55.95
2	1.4	Onset	398±306	254±139	119±97	8.08
		Offset	1432±1197	524±619	121±81	60.41

According to the results of the ANOVA analysis, moreover, the performances of algorithms A and B are not statistically significant regardless of the actual SNR value.

C. An Experiment Using Real SEMG Signals From Hemiparesis/Paralyzed Subjects

We illustrated the results of one experiment where the methods are additionally applied to extract reliable information regarding both the sEMG activation and deactivation timing during an elbow flextion or extension of the right upper limb; the movement is performed by two male subjects who are affected by hemiparesis on the right side. The subjects are asked to repeat the same movement five times in response to a bright visual “go” signal displayed at random times. After short practice, each subject produced 20 single responses. The recorded data were visually inspected and only those responses which were definitely between 100 and 400 ms after stimulus presentation were included to the test dataset comprising a total number of 12 responses. Table V reports the mean of the estimated errors for each algorithm and each subject, with the corresponding SNR value; the intervals around the averages given in the tables correspond to the standard deviation on either side. The ANOVA analysis reveals that, for each paralyzed subject, the differences between the estimate error produced by algorithm C and the errors produced by its competitors are statistically significant when the SNR value is low; differences are considered important when the confidence level is greater than 95% $(p \leq 0.05)$.

IV. DISCUSSION

The determination of the exact onset and offset times of a muscle contraction is useful in studies of motor control and performance. In biomechanics, the information extracted from sEMG signals allows for a deeper understanding of muscle functionality during motor tasks as, for instance, gait or orthostatic posture maintenance. In this field, sEMG can furnish at least three major parameters: the duration of muscle activation, the intensity of muscular contraction, and the myoelectric manifestations of muscle fatigue.

The appearance of an automatic and reliable metric of muscular activation timing addresses an urgent need in the field of sEMG research. For years this detection has been carried on by using a visual inspection method or by means of a comparison between an arbitrarily chosen value (the user dependent threshold) and the raw signal. In this study we have developed an algorithm to estimate both the onset and offset time instant of muscle activity from EMG records using the ML method which was originally introduced to study abrupt changes of time-varying linear systems. Moreover, the dependence of the decision threshold on the signal parameter SNR was determined by means of a large set of simulated signals with well-known signal parameters; the threshold for a given SNR was optimized through minimizing the detection error. It is recommended that the decision threshold should be justified based on the SNR estimate in the initial time before detailed EMG signal analyses.

We have shown that for all three algorithms the mean error and error standard deviation of onset and offset estimates on simulated EMG traces is less than that obtained from the real signals. The relatively large discrepancies between simulation results and experimental results can be attributed to the inaccuracy of true onset and offset instants of muscle contraction in real sEMG signals which are determined by the angular signals measured during a flexion-extension movement of the elbow.

Most importantly, results of the computer simulation and real experiments prove that the traditional methods for ON/OFF timing detection of the muscle contraction are comparable to the ML algorithm when the difference between sEMG signal powers in the relaxed and contracted states is salient. On the contrary, the proposed ML algorithm is shown to outperform the classical threshold-based approaches in detecting the onset/offset time when the SNR of EMG signal is near 1, e.g., the sEMG signal is disturbed due to reasons such as baseline noise and movement artifact, or measurement from residual muscles. Nevertheless, it should be noted that the proposed ML method suffers from the possible limitation that the real EMG signal cannot be accurately modeled by Gaussian noise when only a few motor units contribute to the gross EMG signal, e.g., in the important case when SNR is low, or non-Guassian noise sources require the most attention. On the other hand, the ML algorithm can be implemented with ease when the underlying distributions are assumed to be Gaussian.

For specific applications, besides accuracy in onset and offset detection, the speed of the algorithm is of paramount importance. In the past, high accuracy was achieved at the expenses of high computational time, which is unsuitable for online detection [19]. Since the likelihood ratios for onset and offset detections can be recursively calculated, the computational complexity of the ML algorithm is not too high to preclude the opportunity to operate in close to real-time conditions.

V. Conclusion

The detection of muscle activation intervals provides important clinical information, allowing the investigation of the temporal activation patterns of muscle groups. In this paper, an improved ML algorithm with an adaptive threshold technique was devised to face the task of detecting both onset and offset timing of muscle contraction by sEMG signal processing in the case of low SNR. While some of the methods available in the literature are limited to the onset detection, the proposed ML algorithm allowed the extraction of reliable information regarding both the sEMG activation and deactivation timing; relevant performance is better than those obtained using single threshold detectors and are independent of operator subjectivity. Moreover, the likelihood ratio was recursively calculated for a complete real-time implementation and implies that the ML method may be appropriate for routine clinical applications.

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