# A Fast and Reliable Technique for Muscle Activity Detection From Surface EMG Signals

Andrea Merlo, Dario Farina, *Member, IEEE*, and Roberto Merletti*, *Member, IEEE*

***Abstract*—The estimation of on–off timing of human skeletal muscles during movement is an important issue in surface electromyography (EMG) signal processing with relevant clinical applications. In this paper, a novel approach to address this issue is proposed. The method is based on the identification of single motor unit action potentials from the surface EMG signal with the use of the continuous wavelet transform. A manifestation variable is computed as the maximum of the outputs of a bank of matched filters at different scales. A threshold is applied to the manifestation variable to detect EMG activity. A model, based on the physical structure of the muscle, is used to test the proposed technique on synthetic signals with known features. The resultant bias of the onset estimate is lower than 40 ms and the standard deviation lower than 30 ms in case of additive colored Gaussian noise with signal-to-noise ratio as low as 2 dB. Comparison with previously developed methods was performed, and representative applications to experimental signals are presented. The method is designed for a complete real-time implementation and, thus, may be applied in clinical routine activity.**

***Index Terms*—Continuous wavelet transform (CWT), gait analysis, movement analysis, muscle activation intervals, muscle timing, surface electromyography.**

## I. INTRODUCTION

THE estimation of on–off timing of human skeletal muscles during movement has important clinical applications [1], [2]. Several methods to address this issue are proposed in the literature. The techniques referred to as "single-threshold methods" are based on the comparison of the rectified raw signals and an amplitude threshold whose value depends on the mean power of the background noise [3]. Other methods compare a lowpass filtered version of the rectified signal (the signal envelope) with a threshold based on the noise related envelope [4]. Different types of filters have been proposed leading to noncomparable results; furthermore, usually, no compensation for the time delay introduced by the filter is performed, resulting in a bias in muscle activity detection [5]. These methods are not based on the physiological origin of the signal and, consequently, they are not tuned on surface EMG signal characteristics, such as the motor unit action potential (MUAP) shapes. Due to the high signal-to-noise ratio (SNR) required for accuracy in estimation, single-threshold methods are suitable only for coarse on–off detection. They are usually unable to recognize a correct timing with slowly increasing muscle activity, that is, with low SNR at the beginning of the contraction, while performing better if an abrupt change of the signal power occurs.

In order to improve accuracy within the single-threshold detection scheme, methods based on the envelope time evolution, rather than on its instantaneous value, have been proposed. With these techniques, onset is detected when a weighted average of $N$ consecutive samples overcomes a given threshold [6], [7]. A similar method, based on two contiguous windows, was developed in [8].

A more advanced approach has been recently proposed in [9], where two thresholds are applied on whitened data with the possibility of setting the probabilities of occurrence of false positives and of correct detection. This approach leads to a bias on onset estimate lower than 10 ms with a standard deviation lower than 15 ms on phenomenologically simulated signals with 8-dB SNR [9], [10]. Maximum-likelihood methods, such as cumulative sum, approximated generalized likelihood ratio [11], [12], and approximated cumulative sum [13] focus on abrupt changes of the variance of the whitened EMG signal by using, respectively, no windowing, a sliding window, and two contiguous sliding windows. The higher the *a priori* knowledge of the underlying process, the better is the performance of such methods.

A common evolution of the techniques proposed to detect EMG activity is in the direction of a local analysis of the signal. Global properties are replaced by local properties, whose degree of change is measured on the basis of their recent values. This approach leads to an increase of accuracy, since the threshold level can be more precisely and adaptively set, and to a decrease in computational effort with respect to maximum likelihood methods, since only a segment of signal is processed [13].

In this paper, we propose a novel approach for estimating muscle on–off timing, based on a physical model of muscle activation rather than on a phenomenological one. Muscle activity is recognized on the basis of the presence of MUAPs in the surface EMG signal.

## II. METHODS

### A. Simplified Model of Signal Generation

Surface EMG signal is the summation of MUAP trains. A basic function $f(t)$ can be assumed to approximately describe the shape of a generic MUAP detected on the skin surface, so that an MUAP train (MUAPT) is analytically described as follows:

$$\mathrm{MUAPT}_j(t) = \sum_i k_j \cdot f\left(\frac{t-\theta_{ij}}{\alpha_j}\right) \quad (1)$$

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A. Merlo and D. Farina are with the Centro di Bioingegneria, Department of Electronics, Politecnico di Torino, 10129 Torino, Italy.

*R. Merletti is with the Centro di Bioingegneria, Department of Electronics, Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129 Torino, Italy (e-mail: merletti@polito.it).

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where $j$ indicates a specific MU, $k_j$ is an amplitude factor, $\theta_{ij}$ are the occurrence times of the MUAPs of the MU, and $\alpha_j$ is a scaling factor [14]. The amplitude and scaling factor depend mainly on the depth and size of the MU. The EMG signal $s(t)$ can be expressed as

$$s(t) = \sum_j \mathrm{MUAPT}_j(t) + n(t) = \sum_j \sum_i k_j \cdot f\left(\frac{t - \theta_{ij}}{\alpha_j}\right) + n(t) \tag{2}$$

being $n(t)$ additive noise.

### B. Matched Continuous Wavelet Transform (CWT)

In the case $\alpha_j = \alpha_0, \forall j$ and $n(t)$ being white noise [see (2)], one single event is repeating in the signal with a known shape and unknown amplitudes and times of occurrence. In this case, the matched filter [15] is the optimal filter for detecting the presence of a MUAP. If, as it happens in real cases, different MUs have different distances from the recording electrodes, that is if $\alpha_j$ (2) is different for different MUs, a unique filter is not optimal for all the events present in the signal. In the assumption made in (2), the different MUAPs have the same shape but different width and amplitude, being the scaled versions of the prototype function $f(t)$. The application of the CWT may, thus, be a useful tool. CWT is defined as [16]

$$\mathrm{CWT}(a, \tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} s(t) \cdot w^* \left(\frac{t - \tau}{a}\right) \mathrm{d}t \tag{3}$$

where $s(t)$ is the signal to be analyzed, $w(t)$ is a prototype function called *mother wavelet*, $\tau$ is a translation index, and $a$ is a scale parameter $(a > 0)$ related to the frequency content, where $\Im\{g(t/a)\} = aG(af)$ is the Fourier transform of the function $g(t/a)$. At a particular scale, the CWT acts as a filter whose impulse response $h(t)$ is equal to $w(-t)$. If the mother wavelet is matched to $f(t)$ [17], the CWT is a bank of filters matched to the MUAP shape. The CWT can therefore be used to extend the fixed event detection, performed by the matched filter, to a scale varying (but fixed shape) event detection, with different MUAPs having an optimal matching at different scales. The better the matching, the higher the output peak corresponding to the MUAP identification with respect to the filtered noise. In case of single differential recording, the first order Hermite–Rodriguez (HR) function $\mathrm{HR}_1(t)$ has been used in the past to describe the basic MUAP shape [18]

$$\mathrm{HR}_1(t) = k_{n,1} \cdot H_1\left(\frac{t}{\lambda_n}\right) \cdot e^{-t^2/\lambda_n^2} \tag{4}$$

where $n$ is the scale factor, $k_{n,1}$ is a constant that normalizes the function at unitary energy, $H_1(t)$ is the Hermite polynomial of order one [18], and $\lambda_n$ determines the function duration.

In general, the mother wavelet $w(t)$ should be chosen according to the EMG detection modality. The range of the scale parameter $a$ [see (3)] is chosen in order to obtain wavelet durations within the physiological MUAP durations (5–40 ms). For each scale, CWT performs a subband analysis of the original signal.

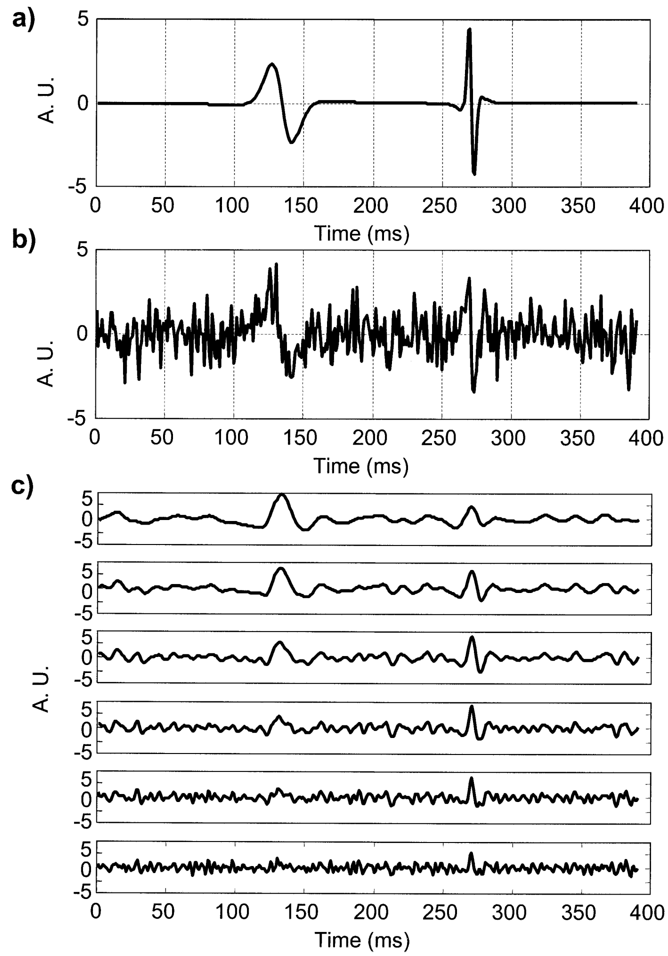


Fig. 1. (a) Two simulated single differential MUAPs at different depths in the muscle and with different conduction velocities, appearing in a composite signal at two different instants of time. (b) Same MUAPs as in (a) corrupted by colored noise (0 dB SNR). (c) Output signals from the bank of filters with different scale factors.

By sampling the CWT on a few scales, we obtain the output of a bank of filters with a specific degree of matching with a selected MUAP. Fig. 1 shows two simulated single differential MUAPs embebbed in colored noise at 0-dB SNR and the output of the bank of filters with different scale factors. The optimal filters to detect the two MUAPs (highest peak in correspondence to the MUAP relative to the peak value without the MUAP) are different, as expected.

### C. Detection Scheme

A classic event detection scheme is applied to the filter outputs. A function $\eta(t)$ is defined as

$$\eta(t) = \max_a \{\mathrm{CWT}(a, t)\} \tag{5}$$

An amplitude threshold, defined on the basis of the noise level (see later), on the function $\eta(t)$ is then applied to detect the presence of MUAPs. Fig. 2 shows an example of simulated single differential signal [19] (see later for details on signal simulation) and the corresponding function $\eta(t)$.

The threshold on the function $\eta(t)$ is selected considering an initial period $(0 < t < T_{\mathrm{noise}})$ in which EMG activity is not

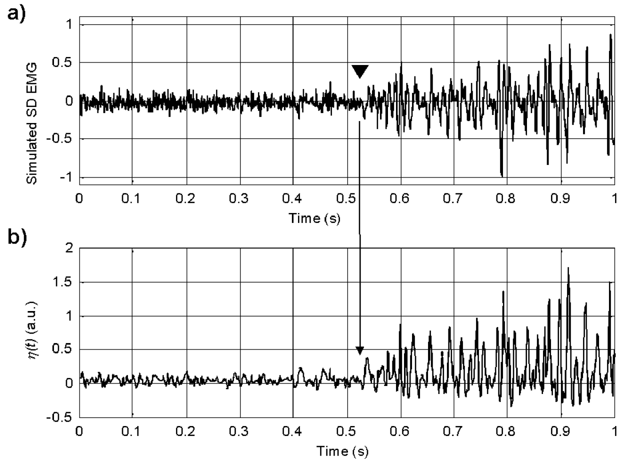


Fig. 2. (a) Synthetic single differential EMG signal generated with the model described in [19] and corrupted by colored noise (4-dB SNR), simulating an increasing muscle activation (see text for details). (b) Testing function $\eta(t)$ (see text for details) computed from the signal shown in (a). HR function of order one was used as mother wavelet [18]. The arrow indicates onset of muscle activity.

present. The amplitude $M$ of the maximum of the test function $\eta(t)$ within this interval is used to set the threshold value $th$ as

$$\begin{aligned} M &= \max\{\eta(t)\}, \qquad \text{for } 0 < t < T_{\text{noise}} \\ th &= \gamma \cdot M \end{aligned} \tag{6}$$

where $\eta(t)$ is defined in (5) and $\gamma > 1$.

The revealed vector is set at one for the time periods during which $\eta(t)$ exceeds the threshold $th$ and zero, otherwise. If the SNR is high, the choice of the value $\gamma > 1$ is not critical, due to the great amplitude difference between EMG signal and noise. If the SNR is low, a low value of $\gamma > 1$ becomes a conservative choice.

### D. Postprocessing

After the detection process, events identified and separated by a temporal distance smaller than 125 ms are considered as belonging to the same contraction and merged. This value (125 ms) corresponds to a global muscular firing rate of eight pulses per second (pps), which is arbitrarily assumed as the lowest effective muscle activity. After the merging of activity bursts closer than 125 ms, the detected events shorter than 5 ms are attributed to either isolated MUAPs or noise related spikes and disregarded.

### E. Simulation Procedure

The theoretical bases of the method do not allow the use of a phenomenological model for testing performance. A structure-based model is necessary. For this purpose, the model proposed in [19] was used in this study. The model simulates synthetic MUAPs generated by finite-length fibers and detected by surface electrodes with physical dimensions. The volume conductor is an anisotropic and nonhomogeneous medium constituted by muscle, fat, and skin tissues [20].

The simulated signals were detected by a single differential detection system, with interelectrode distance 20 mm and circular electrodes with radius 5 mm. The detection probe was located at the middle between the innervation zone and the tendon region of a number of MUs having mean semilength (in either directions) of 65 mm. The detection volume of the system has been defined as the region of space in the muscle in which a single fiber produces a potential at the skin surface (detected in single differential configuration) with energy higher than 1/100 of the energy of a fiber placed below the electrodes at 1-mm depth in the muscle. The number of fibers of each MU varied between 50 and 450 and the MU fiber density was 20 $\text{fibers/mm}^2$ [21], [22]. The territory of the MUs was assumed circular and the fiber density in the muscle was 200 $\text{fibers/mm}^2$. Sixty-five MUs have been simulated in each trial. The recruitment pattern has been assumed as suggested in [21] and [23] with an exponential recruitment of MUs. The firing rate of each MU was increased linearly in time after recruitment with a slope of 10 pps/s (pps = pulses per second). The minimum firing rate was 8 pps (firing rate at the recruitment) and the maximum was 35 pps with interpulse interval variability of 20%. The CV distribution was Gaussian with mean 4 m/s and standard deviation 0.7 m/s. Other parameters of the simulations were fixed as in [23]. Each simulation set consisted of 50 synthetic signals with the 65 MUs placed randomly in the detection volume. Since the purpose was to test onset estimation and the proposed method is local, the critical part of the signal (lowest SNR) was at the beginning of activation, with a few MUs with low firing rates.

For each SNR value, 20 independent noise realizations were generated and added to each of the 50 synthetic signals (thus, 1000 synthetic signals for each SNR value were generated). The added noise was generated by filtering white Gaussian noise with a bandpass filter with cutoff frequencies 10 and 400 Hz, which is typical of surface EMG amplifiers. SNRs equal to 2, 4, 6, and 8 dB were tested. SNR was defined on the first 100 ms of muscular activity, as suggested in [9]. True onset of simulated signals was defined as the energy centroid of the first MUAP appearing in the signal. Sampling frequency of the simulated signals was 1024 Hz. This simulation procedure is similar to that described in [23], to which the reader can refer for details.

### F. Comparison With Other Methods

On the same simulated signals, the performance of two methods previously proposed—the single-threshold [3] and the double-threshold [9] approach—was tested. In the single-threshold method, the mean value $x_N$ and the standard deviation $s_N$ of the signal in the interval with only noise were computed. The rectified signal was then compared with a threshold $th = x_N + \gamma s_N$; typical values for $\gamma$ are $\gamma = 2$ and $\gamma = 3$. We applied the single-threshold algorithm varying $\gamma$ from one to three at steps of 0.2, in order to assess the best performance of the method on our simulated signals (the results shown in the following are the best in the range of $\gamma$ tested). A revealed vector is set at one when the rectified signal overcomes the threshold and zero, otherwise. The use of the postprocessor leads to the final revealed vector and, consequently, to the activation instant estimate.

For the double-threshold approach, data were whitened and assumed Gaussian distributed. Consecutive pairs of samples were then squared and summed, leading to a random process with a $\chi^2$ distribution. With this approach, the user can select the probability of false alarm $P_{fa}$ (typical 0.05) [9]. A first

TABLE I
BIAS AND STANDARD DEVIATION OF ONSET/OFFSET ESTIMATE. ONE-THOUSAND SYNTHETIC SIGNALS CORRESPONDING TO DIFFERENT NOISE REALIZATIONS AND LOCATIONS OF THE MUs IN THE MUSCLE HAVE BEEN GENERATED FOR EACH SNR VALUE. POSITIVE BIAS MEANS ANTICIPATED DETECTION; NEGATIVE BIAS MEANS DELAYED DETECTION OF ONSET/OFFSET. THE RESULTS FROM THE THRESHOLD VALUE RESULTING IN THE MINIMUM STANDARD DEVIATION FOR SNR HIGHER THAN 2 dB ARE SURROUNDED WITH BOLD LINES

| | SNR (dB) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 2 | | 4 | | 6 | | 8 | |
| **Threshold coefficient γ** | Bias (ms) | Std (ms) | Bias (ms) | Std (ms) | Bias (ms) | Std (ms) | Bias (ms) | Std (ms) |
| 1.2 | -18 | 45 | -8 | 45 | 1 | 46 | 4 | 37 |
| 1.4 | -37 | 29 | -24 | 27 | -15 | 22 | -8 | 19 |
| 1.6 | -39 | 26 | -22 | 25 | -12 | 22 | -3 | 17 |
| 1.8 | -58 | 24 | -42 | 26 | -28 | 24 | -17 | 19 |
| 2.0 | -69 | 29 | -51 | 24 | -35 | 25 | -22 | 21 |
| 2.2 | -80 | 37 | -60 | 23 | -42 | 26 | -28 | 23 |
| 2.4 | -95 | 53 | -68 | 25 | -50 | 25 | -33 | 25 |

threshold is computed on the basis of this probability value and of a noise power estimate, which is carried out when only noise is present and EMG signal is absent. The second threshold works as follows: If at least $r_0$ (typical value one) samples within a sliding window of $m$ (typical value five) samples overcome the first threshold, then the revealed vector is set at five in correspondence to that window position. A postprocessor joins bursts separated by less than 30 ms. When tested on synthetic signals generated by a phenomenological model, as described in [9], the implemented algorithm produced results comparable with those reported in [9].

In addition to the single- and double-threshold approaches, we tested the application of a single matched filter to the signal, followed by a threshold. All the filters used in the multiscale approach were applied separately with the same postprocessor, as previously described. The initial time interval, with colored noise realization required to define the threshold value, was set to 200 ms for all the methods.

### *G. Detection and Processing of Experimental EMG Signals*

Surface EMG signals were detected by adhesive electrodes (diameter 20 mm, interelectrode distance 22 mm) from the rectus femoris, vastus medialis, biceps femoris, and semitendinosus muscles of one healthy subject during gait. For each muscle, the location of the innervation zone was identified by using a 16-channel electrode array [24], [25]. The electrode pair was then placed between the most distal (or proximal) innervation zone and the distal (or proximal) tendon region. Signals were acquired with a 16-single differential channel portable EMG system (LISiN, Torino Italy—Ottino Bioelettronica, Rivarolo, Italy—PRIMA Biomedical & Sport, Mareno di Piave, Italy), sampled at 2 kHz, converted in 12-bit digital format, and bandpass filtered (3-dB bandwidth: 30–300 Hz). Power line interference (50 Hz) was removed offline by adaptive filtering [26]. A four-level coded basography (foot-flat FF, push-off PO, swing SW, brake BR) was also acquired during gait using two foot switches placed under the heel and the first metatarsal head.

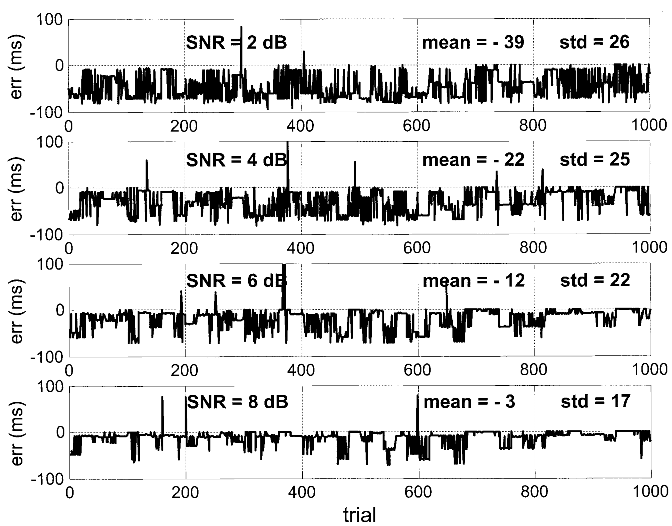


Fig. 3. Error (difference between the real and estimated onset/offset) of onset/offset detection for the 1000 simulated signals at 2, 4, 6, and 8 dB SNR. A positive error corresponds to an anticipated detection due to noise, a negative error corresponds to a delayed estimate due to a missed MUAP. Twenty independent noise realizations for 50 different anatomical conditions are investigated, thus resulting in 1000 simulated signals for each SNR value.

In addition, signals detected from one patient with orthostatic, essential, postural, and Parkinsonism tremulous movement were also used to test the method. SensorMedics miniature skin electrodes were used in this case, with pick up area 2.5 mm in diameter, interelectrode distance 15 mm, in single differential configuration. Data were sampled in this case at 1 kHz.

Representative results of the application of different algorithms to experimental signals are shown in the following. The method proposed in this paper and that proposed in [9] are qualitatively compared. Moreover, we also computed the signal

TABLE II

COMPARISON OF RESULTS OBTAINED BY THREE ALGORITHMS FOR ACTIVATION INSTANT DETECTION ON SIMULATED SIGNALS (SEE TEXT FOR DETAILS ON THE SIMULATION MODALITY). THE BIAS AND STANDARD DEVIATION OF ONSET/OFFSET ESTIMATE IS REPORTED. AS FOR THE RESULTS REPORTED IN TABLE I, 1000 SYNTHETIC SIGNALS HAVE BEEN GENERATED FOR EACH SNR VALUE. POSITIVE BIAS CORRESPONDS TO ANTICIPATED DETECTION, NEGATIVE BIAS TO DELAYED ONSET DETECTION. THE METHOD PROPOSED IN THIS PAPER (MFM), THE ONE PROPOSED IN [9] (BO), AND THE SINGLE-THRESHOLD APPROACH (ST) ARE TESTED. VALUES OF THRESHOLD COEFFICIENT $\gamma$ BETWEEN 1.0 AND 3.0 IN STEPS OF 0.2 WERE USED, AND THE BEST RESULTS (MINIMUM STANDARD DEVIATION) ARE REPORTED FOR EACH METHOD. THE POSTPROCESSING SCHEME USED IN THIS PAPER THAT JOINS REVEALED BURSTS CLOSER THAN 125 ms AND REMOVES ISOLATED SPIKES SHORTER THAN 5 ms WAS APPLIED TO THE SINGLE-THRESHOLD METHOD WHILE THE DOUBLE-THRESHOLD METHOD WAS IMPLEMENTED WITH THE POSTPROCESSOR PROPOSED IN [9]

| | SNR (dB) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 2 | | 4 | | 6 | | 8 | |
| **Method** | Bias (ms) | Std (ms) | Bias (ms) | Std (ms) | Bias (ms) | Std (ms) | Bias (ms) | Std (ms) |
| **MFM** | -39 | 26 | -22 | 25 | -12 | 22 | -3 | 17 |
| **BO** $P_{fa} = 0.05$ $P_d = 0.99$ | 41 | 68 | 21 | 69 | 12 | 47 | 0 | 53 |
| **ST** | 55 | 154 | 67 | 147 | 62 | 135 | 72 | 139 |

envelope in some experimental cases. The envelope of the rectified signal was obtained in these cases with a Butterworth low-pass filter of the fourth-order whose cutoff frequency was set at 10 Hz, and phase compensation was used. The threshold value on the envelope to assume the presence of activity was obtained multiplying by $\gamma$ the peak value of the envelope in the interval with only noise. A postprocessing similar to that applied for the method proposed in this paper was applied to the results from the envelope analysis.

## III. RESULTS

### A. Performance With Synthetic Signals

Table I reports the bias and standard deviation of onset estimate for all the cases tested and for different choices of the threshold value. A bias of 22 ms with a standard deviation of 25 ms is achieved with SNR equal to 4 dB for $\gamma = 1.6$ [see (6)]. The choice of the threshold $\gamma$ is not critical in the range 1.4–2.0; with 8 dB SNR, a bias lower than 5 ms with a standard deviation lower than 20 ms can be achieved.

Being the method local, its performance on onset detection strongly depends on the local SNR of the first MUAP. Thus, different simulated MU distributions in the detection volume lead to rather different errors, as depicted in Fig. 3. Within a single anatomical case, the variance of the estimate of the onset time may be much lower than the global variance and the bias higher than the average one. The results provided in Table I are an average indication that takes into account a large variety of MU spatial distributions.

### B. Comparison of Different Methods on Simulated Signals

On the same set of simulated signals, we tested the performance achieved by using a single filter in the detection phase. All the filters used for the filter bank in the multiple scale approach described were tested separately. With a single filter, at 4-dB SNR, the standard deviation of onset/offset estimation was 30 ms in the best case. In the worst case, the standard deviation approached 300 ms.

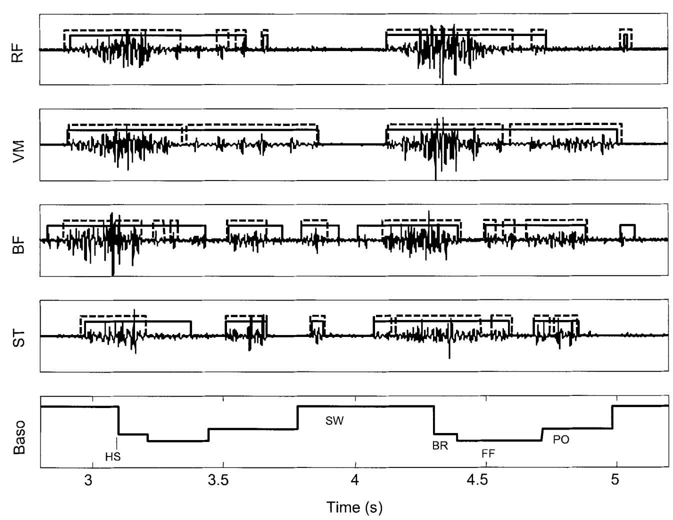


Fig. 4. Surface EMG signals detected during gait from the rectus femoris (RF), the vastus medialis (VM), the biceps femoris (BF), and the semitendinosus (ST) muscles of a healthy subject during gait. A four-level coded basography (Foot-Flat, Push-Off, SWing, BRake) was also acquired using two foot switches HS = (heel strike). Activation intervals estimated using the proposed method with $\gamma = 1.6$ (solid line) and using the method proposed in [9] (dotted line) are shown. See text for further details.

The comparisons of the present method with the single and double-threshold approaches are summarized in Table II. The single-threshold approach (best case) leads to a standard deviation of onset estimate always greater than 130 ms and results in the worst performance. The standard deviation of the double-threshold method is around 50 ms with a SNR of 6 and 8 dB. With the method proposed in this paper the standard deviation of onset estimate reduces from 26 to 17 ms when the SNR varies from 2 to 8 dB.

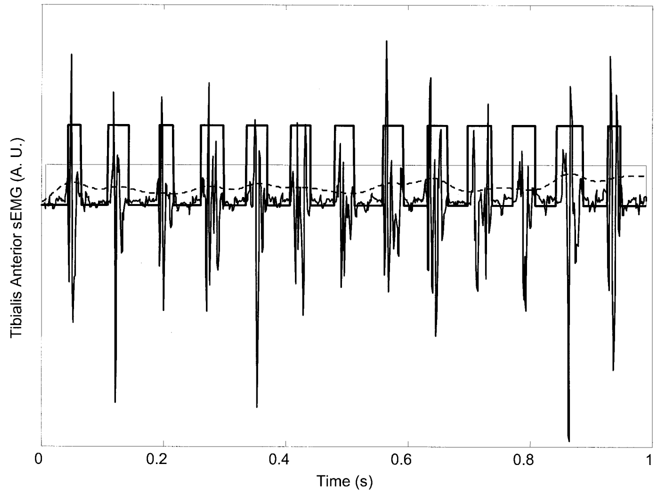


Fig. 5. Surface EMG signal detected from the tibialis anterior muscle of a subject with pathological tremor. Envelope based on fourth-order Butterworth filtering of the rectified signal (dashed line), envelope-based onset estimate (solid line), and onset detected with the method proposed in this paper (heavy solid line) are shown. The noise part of the recording used to set the thresholds is not shown.

### C. Applications to Experimental Signals

Fig. 4 shows a representative result of the application of the technique to experimental signals detected, as described above, during gait of a healthy subject. A representative stride of the subject is reported. The figure compares the method presented in this paper with the technique proposed in [9] and based on a different signal model. The two methods provide similar indications with small differences due to the different postprocessor. The algorithm described in this study joins together bursts separated less than 125 ms, while the algorithm depicted with dotted line in Fig. 4 joins together bursts separated less than 30 ms. For this reason, the activation intervals depicted with solid line are longer. These parameters can, of course, be changed on the basis of experience. The activity of the knee flexors shown in Fig. 4 (semitendinosus and biceps femoris muscles) detected during the push-off phase is reported in previous works [1], [27], while it is not observed in other studies [28].

A surface EMG signal detected from the tibialis anterior muscle of a parkinsonian patient is reported in Fig. 5. Envelope, envelope-based onset, and onset detected with the method proposed in this paper are shown. It is evident that the envelope of the signal results in poor indications about the intervals of muscle activity when close bursts are present in the signal.

## IV. Discussion

The detection of muscle activation intervals (muscle on or muscle off) provides important clinical information since it allows the investigation of the temporal activation pattern of muscle groups, for example during gait [29]. From the signal processing point of view, the problem is that of detecting the presence of signal in a noisy recording. This problem can be addressed with different approaches. For the specific application, besides the accuracy in the detection, the speed of the algorithm is of paramount importance. In the past, high accuracy was achieved at the expenses of high computational time [9], which is unsuitable for online detection.

A new method is proposed in this paper for the detection of muscle activation intervals, which is based on more detailed *a priori* information about surface EMG. Most previous approaches were based on the separation between noise and EMG signal on the basis of their respective power. The basic idea of the present study is to progress from a purely phenomenological EMG generation model to an approximated structure-based model. The resultant algorithm is conceptually simple (it is an extension of the classic matched-filter/threshold detection scheme) and may be implemented in real time.

A proper standardization of electrode placement procedures (electrode location, interelectrode distance, electrode size), as suggested for example by the recent European recommendations for surface EMG signal detection and processing [30], is required. The performance may indeed decrease if the electrodes are not properly placed, in particular if they are close to the innervation zone or tendon regions where the MUAP shape can change significantly. Thus, the technique is less generally applicable with respect to other methods, which are not based on strong *a priori* assumptions [5]. Since correct electrode placement is necessary for reliable assessment of EMG amplitude and frequency content [31], [32], this limitation of the approach is acceptable both in research and clinical environments.

It is worth noting that the method can be extended to the case of multi-channel detection, i.e., by recording EMG signals with linear arrays of electrodes [24], [25], and by applying the detection algorithm to a single channel and checking for the propagation of the detected MUAPs, as suggested in [14], thus decreasing the probability of false positive occurrences. In this case, the electrode placement and the necessary recording instruments may be more complex and, probably, not yet suitable for clinical applications. The proposed method is a good tradeoff between complexity of signal recording, performance, and speed of the algorithm. Moreover, the structure of the algorithm (basically a bank of digital filters) allows online implementation on digital signal processor (DSP)-based systems.

Since the comparison of different techniques strongly depends on the signal model used, performance evaluation should be based on a preliminary discussion on the way of simulating surface EMG signals. A phenomenological model, generating a stochastic signal, is a rough way to interpret surface EMG; on the other hand, the described simulation method, which is based on a physical and physiological model of the muscle [19], may not meet the assumptions made by other researchers for developing their algorithms. For example, the performance of the double-threshold method appear worse (bias and standard deviation of onset estimates of the order of 50 ms at 8 dB SNR) than reported previously for other signal models [9]. The reason is that the signals simulated in this study do not meet the assumption of colored Gaussian noise, especially at the beginning of the activation, when a small number of MUAP spikes are present. At the activation and deactivation instants, the synthetic signals used are almost deterministic (summation of a few MUAPs). These considerations highlight the importance of the simulation method adopted for testing performance.

In the representative experimental signals reported (Fig. 4), where the SNR is high, the present approach and the two threshold method proposed in [9] perform in a similar way, but the comparison can be only qualitative. The envelope based method appears, on the contrary, not suitable for signals with contiguous short bursts (Fig. 5).

## V. Conclusion

The proposed method for muscle on–off detection offers performance suitable for clinical applications and is completely automatic without any intervention required by the operator. Moreover, its computational time is limited, with the possibility of real-time implementation. Thus, it may be a useful tool for the analysis of surface EMG signals recorded during movement, especially when the computational time should be limited.

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**Andrea Merlo** graduated in electronics engineering from Politecnico di Torino, Torino, Italy, in May 2000.

From 2000 to 2001, he was a Fellow of the Laboratory for Neuromuscular System Engineering, Politecnico di Torino, where he focused his research on standardization of surface EMG recordings from muscles of upper and lower extremities and during gait. Currently, he is working as a Bioengineer with Movement Analysis Laboratories within the Neurology Department of three hospitals in Italy and Switzerland. His main interests concern the transfer of signal processing techniques and statistical methodologies to the daily clinical routine.

Dr. Merlo is a Registered Professional Engineer.

**Dario Farina** (M'01) graduated *summa cum laude* in electronics engineering from Politecnico di Torino, Torino, Italy, and received the Ph.D. degree in electronics engineering from Politecnico di Torino and at the Ecole Centrale de Nantes, Nantes, France, in 1998 and 2001, respectively.

During 1998, he was a Fellow of the Laboratory for Neuromuscular System Engineering, Politecnico di Torino. Since 1999, he has been involved in teaching activities in electronics and mathematics at Politecnico di Torino and, since 2002, he has been a Research Assistant Professor at the same university. His main research interests are in the areas of signal processing applied to biomedical signals, modeling of biological systems, and basic and applied physiology of the neuromuscular system. He acts as referee for approximately ten scientific international journals and is on the Editorial Board of the *Journal of Electromyography and Kinesiology*.

Dr. Farina is a Registered Professional Engineer.

**Roberto Merletti** (S'71–M'72) graduated in electronics engineering from Politecnico di Torino, Torino, Italy, and received the M.S. and the Ph.D. degrees in biomedical engineering from The Ohio State University, Columbus.

Since 1984, he has been Associate Professor of biomedical instrumentation with the Department of Electronics of Politecnico di Torino. From 1989 to 1994, he was Associate Professor with the Department of Biomedical Engineering, Boston University, Boston, MA, and Research Associate at the Neuromuscular Research Center of the same university. Since 1996, he has been the Director of the Laboratory for Engineering of the Neuromuscular System at Politecnico di Torino, where he is coordinator of a project sponsored by the European Community and of a project sponsored by the European Space Agency. His research focuses on detection, processing and interpretation of surface EMG, electrical stimulation, and neuromuscular control.