Detection of sEMG Muscle Activation Intervals Using Gaussian Mixture Model and Ant Colony Classifier

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***Abstract*—A new efficient and user-independent technique for the detection of muscle activation (MA) intervals is proposed based on Gaussian Mixture Model (GMM) and Ant Colony Classifier (AntCC). First, time and frequency features are extracted from the surface electromyography (sEMG) signals. Then, GMM is used to cluster these extracted features into burst & non burst. Those features with their class name are then used as the input for the AntCC algorithm in order to derive classification rules. Finally, the obtained rules are used to detect sEMG activation timing of human skeletal muscles during movement.**

The performance of the proposed technique is demonstrated by means of synthetic simulated sEMG signals and real ones. The proposed technique is then compared to two previously published techniques: wavelet transform-based method [1] & double threshold-based method [2]. It is concluded that our technique outperforms those methods and significantly improves the accuracy of good MA timing detection. Moreover, to our knowledge, the proposed technique is the first user-independent one since no tuning parameters are required. Our findings show that the proposed method is convenient for automatically processing large amounts of sEMG signals with performance beyond that of the state of the-art methods.

***Index terms*—** Activation Timing Detection, Onset detection, Timing Off Detection, Ant Colony Classifier (AntCC), Gaussian mixture model (GMM).

I. Introduction

Surface electromyography (sEMG) is a non-invasive technique for measuring muscle electrical activity that occurs during muscle contraction. sEMG can provide different information about the neuromuscular control and muscle activity such as the level and timing of the muscle activation MA [3], [4] or the level of fatigue [5], [6]. Thus, sEMG is a useful tool of biomechanical studies [7], [8].

Temporal analysis and detection of the MA timing has widely been used to study human motion for healthy and unhealthy people [9], [10]. However, abnormal timing of sEMG that can occur during gait cycle, and especially with Parkinson's Diseases (PD) patients [11], makes the automatic and efficient detection of MA timing being a challenging problem. Most of published methods of MA timing [12], [13], [14], [15], [16] have focused only on onset detection and few have addressed off-timing and activation interval detection [1], [2], [17], [18], [19]. All these methods could be classified into two main approaches: (i) visual inspection and (ii) computer-based algorithms. The first approach is strongly depending on the experience of an expert [20]. Obtained results are not repeatable, neither accurate to be applied in healthcare applications. The second approach is a computer-based algorithm and several techniques have been proposed including: single & double threshold-based methods [2], [14], statistical optimal decision-based methods [12], [15], [17], probabilistic-based methods [21], wavelet transform-based methods [1] clustering and classification-based methods [18], [16] and energy operator-based methods [19]. The performance of these cited methods considerably varies as they have different properties, computational complexity and accuracy. They all need either a systematic preprocessing or/ and a postprocessing step to achieve accurate results. All these methods are user-dependent, since at least one of their tuning parameters must be set by the user for each considered sEMG signal thus making them time consuming.

Our purpose is to propose an efficient and user-independent method in order to improve the detection of sEMG onset, offset and MA timing with respect to reproducibility of detectable events. The most original part of this method is to use GMM clustering and Ant colony classifier (AntCC) to automatize the processing of a large amount of sEMG signals. We propose a method based on four stages which are (i) features extraction, (ii) features clustering, (iii) features classification and (iv) post-processing. This method will be applied to simulated and real sEMG from PD patients and healthy control subjects. The method proposed will be compared to the double threshold-based method [2] and the wavelet transform-based method [1].

The present paper is organized as follows: section II presents the four stages of our proposed approach. Section III presents the results obtained from simulated signals with different signal to noise ratio (SNR) (10 dB and 20 dB) and real sEMG signals in order to ascertain the performance of the proposed algorithm. The comparison with previously published methods is also provided. Finally, section IV concludes this paper.

II. Proposed method

Our proposed method consists of the following 4 stages: (i) feature extraction, (ii) feature clustering using the Gaussian Mixture Model, (iii) feature classification using AntCC and (iv) post-processing. The complete procedure is e is presented in the block diagram in figure 1 and described in algorithm 1. Details of each stage are provided in the following.

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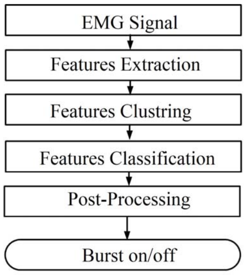

Fig. 1. Proposed approach

A. Feature extraction

We propose to use both time and frequency domain features as input for GMM and AntCC to detect sEMG activation timing.

1) Time domain features: thanks to their computation simplicity, we propose to use the 4 most commonly-used time features extracted by using the same window length $N_w = 8$ as proposed in [22]. These features are the maximum amplitude ($A_n = \max|x(i)|$), minimum amplitude ($a_n = \min|x(i)|$), where $i \in [n - N_{\frac{w}{2}} : n + N_{\frac{w}{2}}]$ and n is the discrete time, the mean ($\mu_n = \frac{1}{N_w}\sum_{i=n-\frac{N_w}{2}}^{n+\frac{N_w}{2}} x(i)$) and standard deviation ($\sigma_n = (\frac{1}{N_w}\sum_{i=N_w-\frac{w}{2}}^{N_w+\frac{w}{2}}(x(i)-\mu_n)^2)^{\frac{1}{2}}$).

2) Frequency domain features: we employ two easy-to-use features the median frequency (MDF) and the energy ratio. MDF is the one of the most examined frequency feature defined as the frequency value at which the sEMG power spectrum is divided into two regions with an equal integrated power [23]:

$$\sum_{j=1}^{MDF} p_j = \sum_{j=MDF}^{M} p_j = \frac{1}{2}\sum_{j=1}^{M} p_j. \tag{1}$$

where p_j is the sEMG power spectrum at the frequency bins j, $M = 64$ being the length of frequency bins. The energy ratio is obtained using the Discrete Wavelet Transfom (DWT) [24]. DWT of the signal provides a set of coefficients called wavelet coefficients [25]. The key feature of DWT is the time-frequency localization which means that most of the energy of the wavelet is restricted to a finite time interval. The signal can be partitioned at different resolution levels and an energy can be calculated from the discrete wavelet coefficients at each decomposition level.

3) The matrix input for GMM: At the end of the feature extraction stage, we obtain a matrix of extracted features F from the signal during N sliding windows. We denote by $f_{m,n}$ the m^{th} feature recorded at time instant n. F is given by the following equation:

$$F = \begin{array}{c} \begin{matrix} F_1 & F_2 & \cdots & F_n \end{matrix} \\ \begin{pmatrix} f_{1,1} & f_{1,2} & \cdots & f_{1,n} \\ f_{2,1} & f_{2,2} & \cdots & f_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ f_{m,1} & f_{m,2} & \cdots & f_{m,n} \end{pmatrix} \end{array} . \tag{2}$$

This matrix will be used as input for GMM to conduct the clustering stage. Figure 2 shows an example of simulated signal with $SNR = 20$dB and its extracted features, the sampling frequency being $F_s = 1024$ Hz.

B. Gaussian Mixture Models (GMM)

GMM is used to model an unknown probability density function by a weighted mixture of J Gaussian distribution [26]:

$$p(F_n) = \sum_{z=1}^{J} P_z.\mathcal{N}(m_z, \Sigma_z). \tag{3}$$

where $\sum_{z=1}^{J} P_z = 1$,m_z and Σ_z represent the mean and the covariance matrix respectively, and P_z is the probability that data vector F_n is generated by the component z.

According to [30], the distribution of the logarithmic power of sEMG signal is characterized by a two component GMM (J=2) in each frequency band. These two components correspond to the posterior distribution of sEMG burst (MA) and non-burst logarithmic powers, respectively. We then use the iterative generalized mixture decomposition algorithm [26], which adjusts the parameters m_t, Σ_t and P_t with respect to an initial estimate, and terminates when no significant change occurs in these values between two successive iterations. It returns the posteriori probability that the vector F_n stems from the distribution associated with the cluster. To obtain a hard clustering, we use the maximum value of the cluster probability $Class = max(cp_k)$.

To sum up, the GMM stage clusters the recorded features previously extracted into two different classes (on: burst and off: no-burst). This binary clustering will be added as a last row in F (2).

$$F = \begin{array}{c} \begin{matrix} F_1 & F_2 & \cdots & F_n \end{matrix} \\ \begin{pmatrix} f_{1,1} & f_{1,2} & \cdots & f_{1,n} \\ f_{2,1} & f_{2,2} & \cdots & f_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ f_{m,1} & f_{m,2} & \cdots & f_{m,n} \\ \boldsymbol{class_1} & \boldsymbol{class_2} & \cdots & \boldsymbol{class_n} \end{pmatrix} \end{array} . \tag{4}$$

This matrix will be used as input for AntCC to conduct the classification stage.

C. Ant Colony Classifier

Ant colony classifier is inspired from ants' social behavior. Ants use pheromones as a communication medium when searching for the shortest paths to food sources [22], [28]. In swarm intelligence, AntCC is applied over labeled data in order to detect the classification rules, so that each detected path by the artificial ants represents one candidate classification rule. These rules are of the form: if "rule antecedent" then "rule consequent". The condition "rule antecedent" stands for a conjunction of terms (F1 & F2 & . . . & Fn), where each term is a condition (Fi, operator, value) [22]. An example of a term is (MDF < value). The "rule consequent" is the detected class

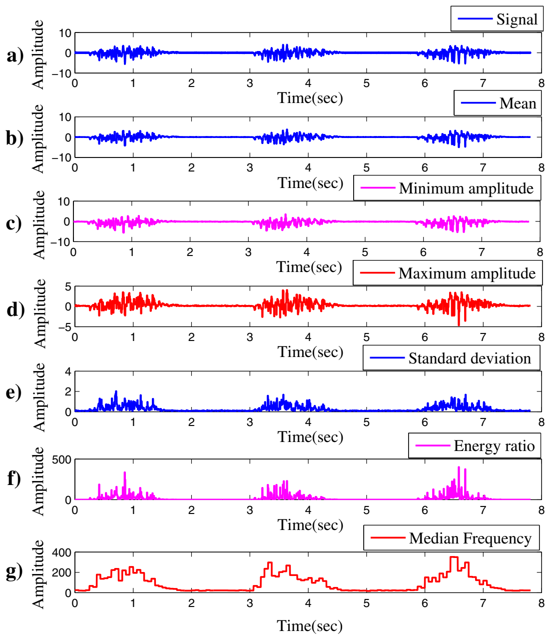

Fig. 2. Feature extraction: (a) simulated signal which is generated using the sEMG generator described in [27] with $F_s = 1024$ Hz and $SNR = 20$ dB, (b) extracted mean, (c) extracted minimum amplitude, (d) extracted maximum amplitude, (e) extracted standard deviation, (f) extracted retained energy, (g) extracted median frequency.

where their attributes satisfy all the terms in the "antecedent rule". Based on obtained labeled data, AntCC will discover the set of classification rules, which will be used to detect the on & off timing of sEMG signal. All the stages included in the algorithm proposed for sEMG activation timing detection are summarized on the algorithm 1.

Algorithm 1 sEMG timing detection

$i = 0$
Set the window No.1 size $N_w = 8$;
for $i \leq$ length of signal - N_w **do**
  Calculate time features in the sliding window
  Decompose signal into 4 levels by DWT
  Calculate Retained energy
end for
Set the window No.2 size $z = 64$;
for $i \leq$ length of signal - z **do**
  Calculate Median Frequency
end for
Features clustering by GMM
Derive Classification rules by Ant colony
$j = 0$
for $j \leq n$ **do**
  Calculate the Lower Bound (LB_j)
  Calculate the Upper bound (UB_j)
end for
if $(((LB_1 \leq y_{j,1} \leq UB_1)\ \&\ \ldots\ \&(LB_n \leq y_{j,n} \leq UB_n))$ **then**
  $Class =$ Burst off
else
  $Class =$ Burst on
end if
Calculate the Activation period
for $i \leq$ length of Burst on **do**
  Activation period-= Offset(i)-Onset(i)
end for
Post-processing as in [1]

D. Post-processing

To cancel the erroneous transitions of the detector output, we consider the same postprocessing as in [1] for sake of comparison with wavelet-based method [1] and double statistical threshold-based method [2]. The basic idea is to merge activity bursts closer than 125 ms and disregard detected events shorter than 10 ms. We however point out that a previously comparison of these two methods was conducted in [1] but using two different post processing steps which in our opinion is not objective since postprocessing step can significantly affect the resulting performance.

III. Results and Discussions

In this section, we first apply the proposed algorithm to synthetic signals. Then a comparison with existent techniques is performed on both synthetic and real sEMG signals.

A. Synthetic sEMG signal processing

Simulated sEMG signals are generated at 1024 Hz sampling rate (F_s) with the simulator described in [27]. The mean conduction velocity was fixed to 4 ms^{-1} with minimum firing rate$=$ 8Hz, the maximum recruitment ratio was 79%, the inter-electrode distance was 5 mm. Monte-Carlo simulations were conducted with two different values of the SNR $(10$ and 20 dB$)$. Each simulation set consisted of 100 synthetic signals.

Our proposed technique is compared to the wavelet-based method [1] and the statistical double threshold-based method [2]. The tuning parameters of the former are threshold=1.6 while for the later the tuning parameters are w=5, r_0=1. Figures 3 and 4 show the obtained results using the three considered methods for an SNR=20 dB after and before post processing, respectively. From, figure 3, we can clearly see that the proposed algorithm has similar performance as the two others for SNR=20 dB but it outperforms the two others for 10 dB. The obtained onset, offset, MA timing is the closest one to the true onset and MA timing. As one can notice from figure 4, the proposed algorithm presents the lowest number of erroneous transitions which occur only at the end of the burst on.

Figure 5 shows a comparison of the detector performance on simulated signals using receiver operating characteristic (ROC). In general, ROC curves of the proposed algorithm outperforms the other detectors, with accuracy equal to 80.4%for 20 dB and 76.08% for 10 dB. Table I summarized a comparison of the root mean square error (RMSE) of the three considered methods measured in millisecond.

Table II shows the probability of false alarm and false negative rate of the three compared methods. A false positive error indicates the presence of burst when in reality is not, and a false negative indicates the presence of non-burst when in reality is not. The statistical double threshold-based method has the best results with 0 false burst & 0 false non-burst. We however note that if the post-processing only cancels the events shorter than 5 ms instead of 10 ms (see section II-D), the false positive alarm and the negative rate will slightly degrade.

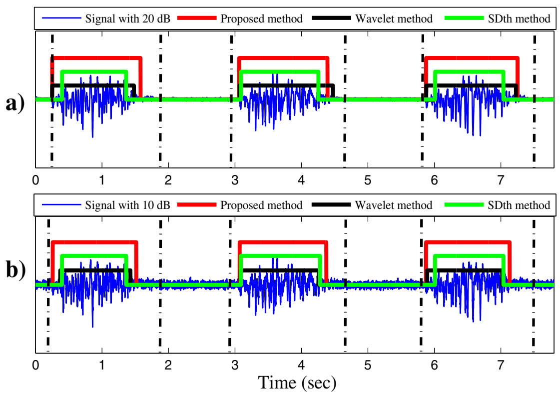

Fig. 3. MA timing estimated using the proposed method (red line), the wavelet-based method (black line) and the statistical double threshold-based method (SDth)(green line) superimposed to the simulated sEMG signal for: a) SNR = 20 dB, and b) SNR = 10 dB. Dot vertical line represents the true timing.

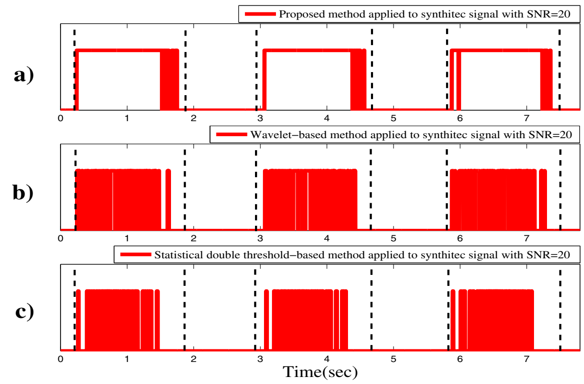

Fig. 4. Detected activation timing using the three compared algorithms applied to synthetic signals of figure 3with SNR=20 dB without postprocessing: a) Activation timing detected by AntCC, b) Activation timing detected by the wavelet-based method [1] c) Activation timing detected by the statistical double threshold-based method [2]. Dot vertical line represents the true timing.

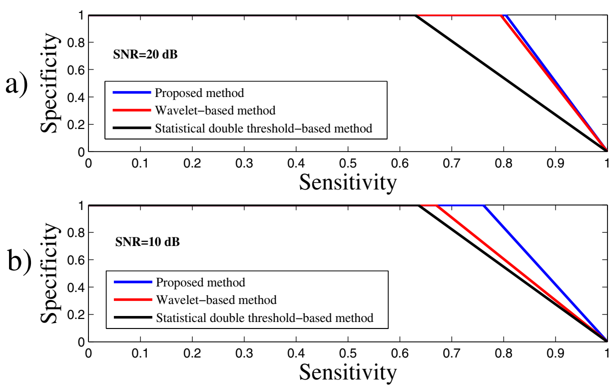

Fig. 5. Performance comparison of the three methods: the proposed method, the wavelet-based method (tuning parameter: threshold = 1.6) & the statistical double threshold-based method (tuning parameter: w=5, r0=1) using roc curves. (a) ROC curves for the SNR equal to 20 dB, (b) ROC curves for the SNR equal to 10 dB.

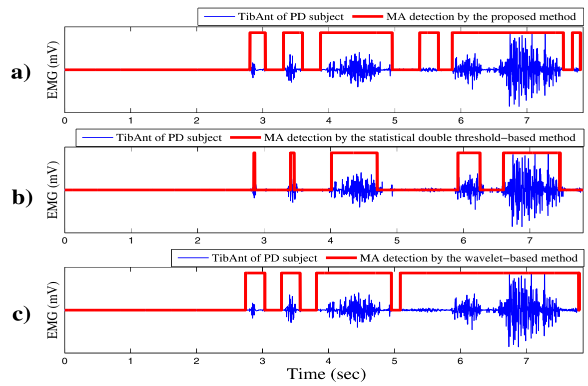

Fig. 6. sEMG signal detected during gait from right Tibialis Anterior TA on PD subject. Activation intervals estimated using (a) the proposed method (b) statistical double threshold-based method [2] (tuning parameter: w=5 & r0=1), (c) wavelet-based method [1] (tuning parameter: threshold = 1.6)

TABLE I
ROOT MEAN SQUARE ERROR (MEASURED IN MILLISECOND) OBTAINED BY THE THREE ALGORITHMS FOR ONSET, OFFSET AND ACTIVATION TIMING DETECTION ON SIMULATED SIGNALS WITH SNR =(10 & 20 DB). 100 SYNTHETIC SIGNALS HAVE BEEN GENERATED FOR EACH SNR VALUE. THE PROPOSED METHOD (ANTCC), STATISTICAL DOUBLE THRESHOLD-BASED METHOD [2] AND WAVELET-BASED METHOD [1] ARE TESTED.

		Proposed approash			**Wavelet-based method**			**Statistical double threshold-based method**		
		1st Burst	**2nd Burst**	**3rd Burst**	**1st Burst**	**2nd Burst**	**3rd Burst**	**1st Burst**	**2nd Burst**	**3rd Burst**
Onset	**10 dB**	98.2	187.6	204.7	127.2	199.6	113.7	168.8	171.4	324.1
	20 dB	47.3	340.7	304.1	16.5	176.7	288.5	169.8	158.5	188.1
offset	**10 dB**	394.4	284.4	370.6	466.4	415.5	482.0	500.2	391.3	468.0
	20 dB	263.6	359.0	404.1	395.3	236.3	269.4	520.3	407.6	472.1
activation	**10 dB**	481.2	468.5	531.9	585.3	610.4	585.2	668.6	558.8	683.6
	20 dB	299.2	385, 6	371.8	411.7	364.1	407.3	690.0	564.5	660.3

B. Real sEMG signal processing

Figure 6 shows the results obtained by applying the three considered methods on sEMG signal recorded on a PD patient from the tibialis anterior muscle wih five bursts the sampling frequency was equal to $1999 Hz$. We can see that the proposed method was able to identify small bursts in between whereas the other detectors fail at doing it.

TABLE II
PROBABILITY OF FALSE ALARM & FALSE NEGATIVE FOR THE THREE COMPARED METHODS ON ACTIVATION DETECTION FOR SIMULATED SIGNALS WITH SNR =(10 & 20 DB).

	False Positive		False Negative	
	10 dB	20 dB	10dB	20dB
Proposed approach	18	0	6	0
Wavelet-based method	4	53	0	0
SDth	0	0	0	0

IV. CONCLUSION

In this paper, we proposed a new and user-independant method for the detection of onset, offset & activation timing in sEMG. The proposed approach is based on Gaussian mixture decomposition and Ant Colony Classifier. GMM is used to cluster the data into burst & non-burst. Based on these labeled data, AntCC derives the classification rules for classification. We applied our proposed approach on real sEMG & synthetic signal to evaluate the performance of the detector. Our experimental results proved that the performance of our proposed approach outperforms the wavelet-based method [1] and the statistical double threshold-based one [2] with accuracy equal to 80.4%for 20 dB and 76.08% for 10 dB. Moreover, the method proposed can be used in real-time & clinical applications as it is completely automatic without any need for intervention by the operator.

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