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Adaptive Linear Energy Detector Based on Onset and Offset Electromyography Activity Detection

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Abstract— **This paper describes a new approach for detecting onset/offset electromyography activity. The proposed approach is based on energy analysis which has been widely used in Voice Activity Detection (VAD). A performance analysis has been carried out in order to get the appropriate frame length of EMG signal to adapt within our proposed method. Synthetic and Real EMG signals are used to illustrate us the performance of our proposed method.**

I. Introduction

Surface Electromyogram (sEMG) recording is a widely used approach to obtain physiological or clinical information about nerve and muscle functions [1]. The electromyography is the realm of recording, processing and detecting electrical activity of muscles. The determination of starting and ending times of muscle activity is a critical component of research concerning the analysis of movement patterns, motor control and diagnosis of neuromuscular diseases such as Parkinson's disease.

Several studies on EMG activity detection methods have been proposed such as single-threshold [2], double-threshold [3], Teager Kaiser Energy Operator [4] wavelet-MUAP method [5], sign change [6], and AGLR [7]. In this work, we have proposed the use of the Energy Based method for detecting the onset and the offset times of muscle activity.

The proposed technique is based on an energy detector method named Adaptive Linear Energy Detector (ALED) [8]. This technique is usually used in Voice Activity Detection for identifying the speech and non-speech segments in an audio signal. It has been also employed in VoIP (Voice over Internet Protocol) systems [9], speech recognition [10], voice compression and coding [11], hands-free telephony and audio conferencing.

The energy analysis based algorithms must usually obey to some of the following criteria [12] :

- The use of some physical properties of the phenomenon, such as the signal segments with no EMG activity, for characterizing a good decision rule;
- Providing low sensitivity to non-stationary noise;
- Allowing low computational cost especially for real time applications.

The main contribution of the following work is to adapt the ALED method used in VAD to automatic EMG signal segmentation. This segmentation is necessary to evaluate EMG recording for Parkinson's disease.

The remaining of this paper is organized as follows: section II, describes the system modeling and problem formulation, section III, is dedicated to present a performance analysis and to discuss the obtained results.

II. System modeling and problem formulation

A. Problem formulation

We consider N measurements (*samples*) $\{x(n)\}_{n=1:N}$ of EMG signal. Based on these observations $X = [x(1), x(2), \ldots. x(N)]$, we are interested in determining whether a sample of EMG signal recording x_n contains a signal $s(n)$ embedded in a random background noise $w(n)$ (EMG activity) or, on the contrary, $x(n)$ is just the confusing manifestation of the noise (no EMG activity).

$$\Gamma : \begin{cases} H_0 : \textit{no EMG activity} \\ H_1 : \textit{EMG activity} \end{cases} \tag{1}$$

This task is known as EMG signal segmentation. In this work, the ALED technique has been adapted to resolve the EMG activity detection problem or EMG signal segmentation.

The last issue is an important task. It consists on dividing the EMG signal into activity and non activity regions (segments). In order to do this, many techniques exist. The simplest one compares each signal sample to an appropriate threshold [2]. Other techniques are based on the signal's energy such as [4]. Our method is based on the same representation (signal's energy) where the EMG signal is divided into non-overlapped frames to get the short energy of EMG signal. The last frame is called, in our work, as an analysis frame. The fist problem is how to choose analysis frame length and the background buffer size (v), in order to get a good Onset / Offset EMG activities detection.

B. Adaptive Linear Energy Detector (ALED) technique

Let $x(i)$ be the i^{th} sample of the recorded EMG signal. If the length of the frame is L samples, then the j^{th} frame under consideration can be represented in time domain by a sequence as [9], [13], [14] and [15]

$$frame_j = \{x(i)\}_{i=(j-1)L+1}^{jL} \tag{2}$$

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E_j represents the energy of the j^{th} frame and can be defined as

$$E_j = \frac{1}{L}\sum_{i=(j-1)L+1}^{jL} x^2(i) \quad (3)$$

The choice of the initial value of the threshold E_r is obtained by the baseline recording where we calculate the energy's mean of the v first frames prerecorded ,E_r the threshold is defined as follows

$$E_r = \frac{1}{v}\sum_{j=1}^{v} E_j \quad (4)$$

The frame's energy is a basic feature to detect the EMG activity inside the same frame. The detection rule of the EMG activity is as follows

$$\begin{array}{ll} If\ \mathrm{E}_j > \lambda.E_r\ ,(\lambda > 1) & \text{The frame presents an EMG activity} \\ Else & \text{The frame presents no EMG activity} \end{array} \quad (5)$$

Where, E_r represents the energy of the noise frame, while $\lambda.E_r$ is the threshold value used in the decision making. The scaling factor λ allows a safe band for the adaptation of E_r to the threshold value.

The threshold value is an important parameter to distinguish the no EMG Activity (Noise) from the active signals (myoelectric contraction). The threshold value, in this work, is based on frame's energy estimation. The adaptive threshold detection technique is defined as follows [9], [13] and [14]

$$E_{rNew} = (1-P)E_{rPrevious} + PE_{rCurrent} \quad (6)$$

Where E_{rNew} is the threshold updated value of $E_{r\mathrm{Pr}evious}$ is the previous threshold value, $E_{rCurrent}$ is the energy of the frame's energy being computed currently and P is the step index of the adaptation process (taken from 0 to 1). The adaptive process, given in equation (6), is applied when the no activity is satisfied.

The ALED technique depends on the step index (P) value, and also on the ratio of the energy variance of the actual noise's frames (var_{new}) and the variance of the last processed noise's frames (var_{old}). Step index values are presented in Table I, [9], [10] and [14]:

TABLE I
DETERMINATION OF THE ADAPTATION STEP OF ALED TECHNIQUE
$R = \mathrm{var}_{new}/\mathrm{var}_{old}$

Classification	P
$R \geq 1.25$	0.25
$1.25 \geq R \geq 1.10$	0.20
$1.10 \geq R \geq 1.00$	0.15
$1.00 \geq R$	0.10

III. Application, Results and Discuss

To evaluate our proposed method, we have taken synthetic and real EMG signals segmented manually. Then, the ALED method is applied to segment the EMG signals automatically. The comparison between the manual and automatic segmentation allows us to compute error probability for different frame lengths and different buffer length (v).

Firstly, we have taken a synthetic EMG signal drawn in Fig.1. This signal contains 163097 samples where one activity exists during 81001 samples. The same signal is generated by 100 synthetics MUAPt (Motor Unit Action Potentials train) with $SNR = 10\ dB$ as described in [16]. The sampling frequency is $Fe = 2\ KHz$. The false alarm Probability (P_{fa}), missing Probability (P_{miss}) and error Probability (P_e) are estimated by using the simulated EMG signal with 10^3 Monte Carlos realizations. We have varying the length of background buffer to different frame lengths and we have calculated the P_{fa}, P_{miss} and P_e using following equations (7), (8) and (9) respectively

$$P_{fa} = P(H_1|H_0) \quad (7)$$

$$P_{miss} = P(H_0|H_1) \quad (8)$$

$$Pe = P(H_1).P_{fa} + P(H_0).P_{miss} \quad (9)$$

We assume that $P(H_1) = P(H_0) = \frac{1}{2}$.

Obtained results are given in figures 2, 3 and 4.

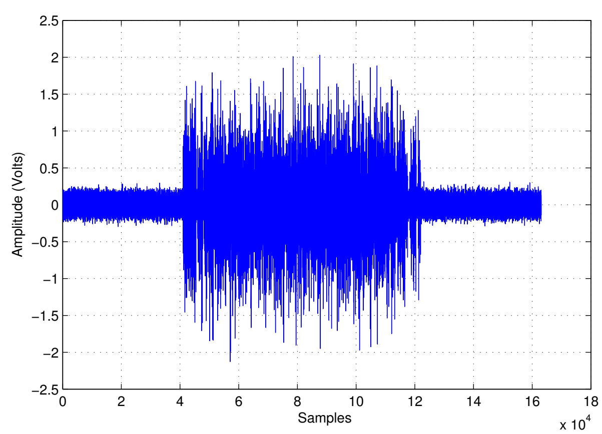

Fig. 1. Synthetic EMG signal .

Note that, as the analysis frame length increases as the probability of miss increases also which is shown in Fig. 3. When the frame's length increases, frames containing few samples of signals plus noise have approximatively the same energy as frames containing only noise without signal. Hence, these few samples of signal are considered as noise which increase the probability of miss.

On the other hand, the more the frame length gets smaller the false alarm probability goes up as shown in Fig.2 And, the analysis frame length is proportional to the frame's energy. Thus, a frame containing non activity samples can be considered as an activity region which increases the false alarm probability.

Then, the analysis frame length has not to be small where the false alarm probability is important and has not to be large where the probability of miss is important. To get the optimal length, the error probability has to be considered.

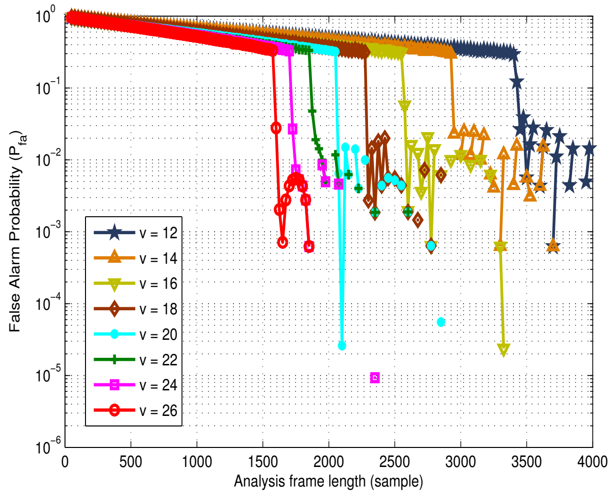

Fig. 2. False Alarm Probability of synthetic EMG signal .

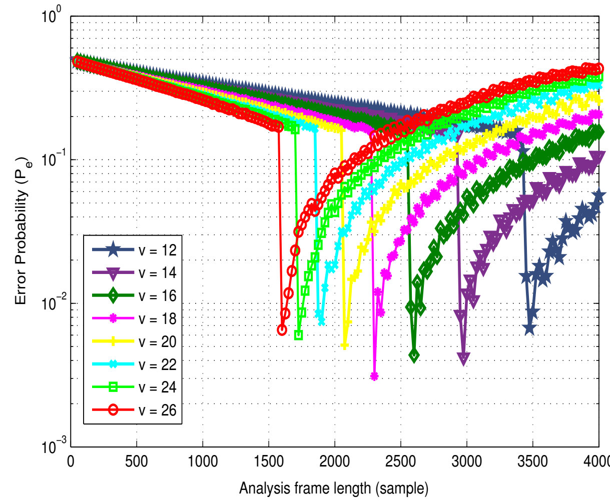

Fig. 4. Error Probability of synthetic EMG signal .

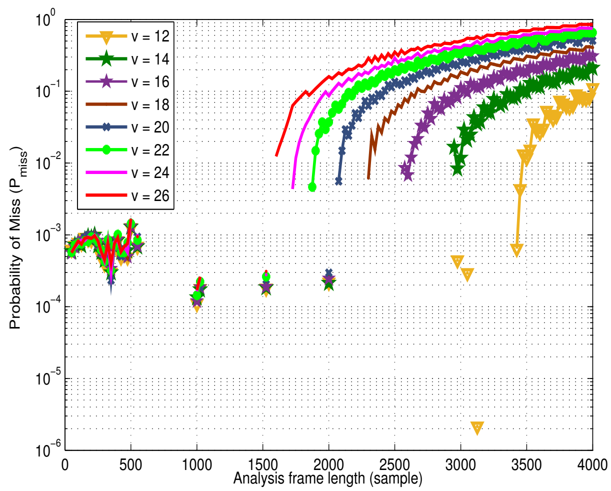

Fig. 3. Probability of Miss of synthetic EMG signal .

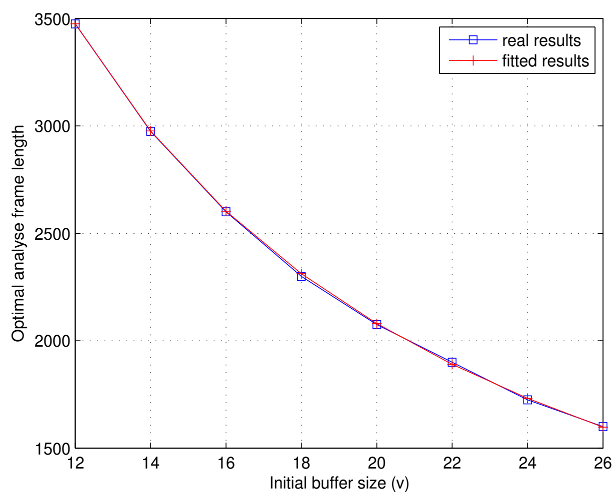

Fig. 5. Analysis frame length versus initial buffer size.

In Fig.4, curves of error probability versus analysis frame length, for each number of considered noise frames (v) given in equation (4), are drawn. For each value of v, an optimal length of analysis frame appears for a minimum of error probability. These results can be summarized in Fig.5 where the relation ship between v and optimal length (T_r) can be fitted by equation (10).

$$T_r = av^b \tag{10}$$

Where $a = 42230$ and $b = -1.005$.

Secondly, ALED technique is applied to real EMG signal . We have recovered one EMG signal of $ABDV muscle$ from a Neurological Exploration of Military Central Hospital of Algiers, Algeria. This signal has several EMG activities and 286301 samples recorded with a sampling frequency $F = 2KHz$. For testing our proposed technique, we have to evaluate its performance for each frame length (T_r) with different buffer size (v). By referring to the plot of Error probability represented in Fig.8, we have chosen the frame length equal to 2500 samples and Buffer size equal to $v = 4$ frames for a minimum of $Pe = 0.03098$, $Pfa = 0.071$ and $Pmiss = 0.017$. The automatically segmentation of real EMG signal is shown in Fig.9

The obtained performance results are given in figures 6, 7 and 8. We observe the same behaviors as in the first application.

Note that, we have taken good onset/offset timing activities detection. Nevertheless, it is necessary to make a compromise between the choice of the initial buffer size (v) and analysis frame length (T_r).

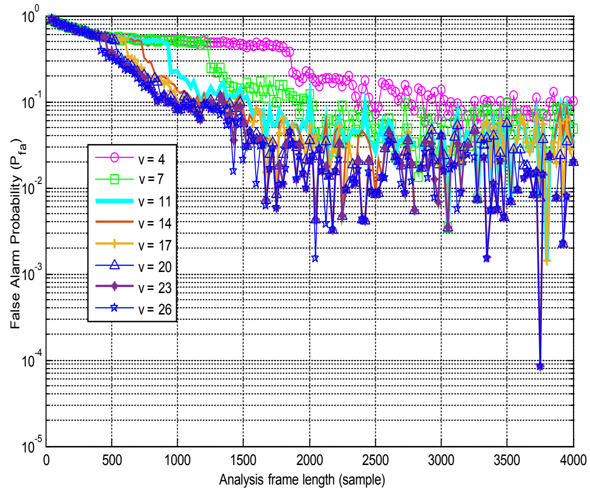

Fig. 6. False alarm probability of real EMG signal.

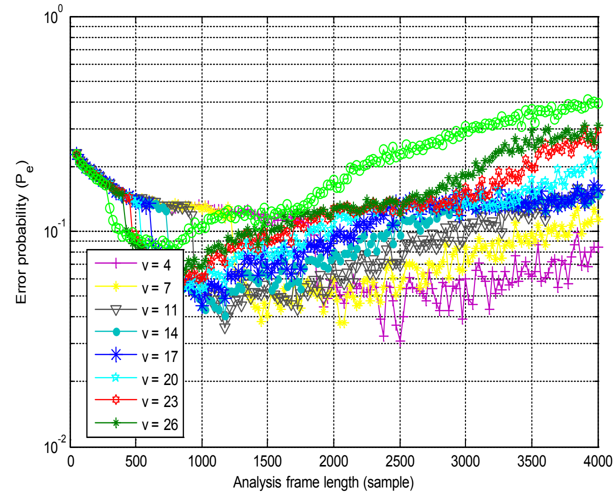

Fig. 8. Error probability of real EMG signal.

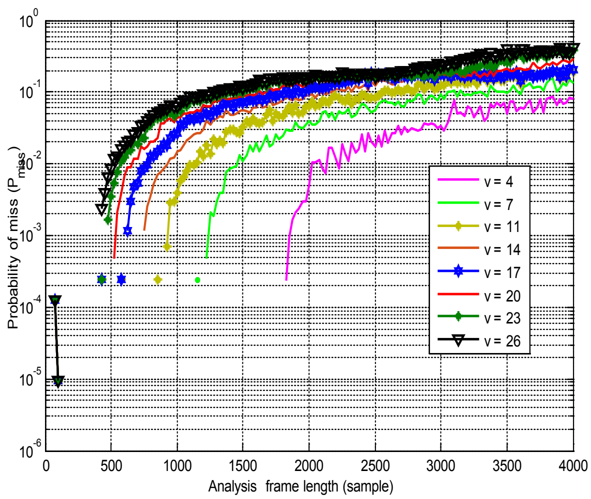

Fig. 7. Probability of miss of real EMG signal.

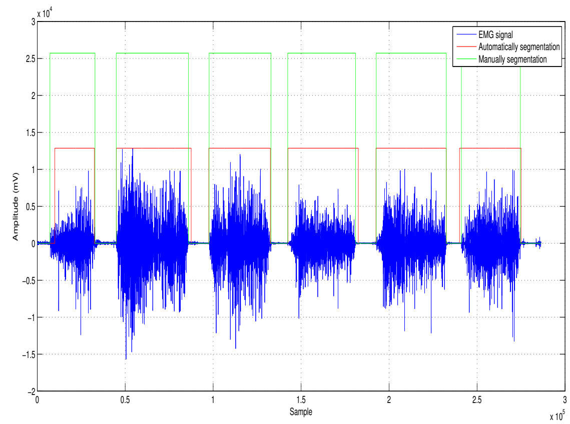

Fig. 9. Automatic EMG segmentation of real EMG signal(with buffer = 4 frames and frame's length = 2500 samples).

IV. CONCLUSION

Electromyography timing activity detection of human skeletal muscle during movement has important clinical applications. The proposed technique for muscle activity detection offers important performances suitable for clinical applications. It may be a useful tool for analysis the EMG signals recorded during the assessment postural adjustment in Parkinsonian patients.

The proposed method shows detection performances of on-off Electromyography activity, especially for the EMG signal that has several activities. We have noted that, the ALED technique can not be applied directly to EMG signal. A learning step is necessary to get an estimation of optimal v and Tr, which are linked to the size and the number of EMG activities.

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