A Robust and Adaptive Algorithm for Real-time Muscle Activity Interval Detection using EMG Signals

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Abstract: Detection of Muscle Activity Interval plays a pivotal role in the design and implementation of real-time Myoelectric controlled devices and their applications. This paper presents an algorithm for real-time detection of onset/offset points in the muscles activity by employing adaptive threshold technique on the Correlation Coefficient of Taeger Kaiser Energy Operator using low cost hardware. Performance of the algorithm has also been evaluated through real-time tests carried out under various constrained scenarios and different signal to noise ratios, revealing very promising results with a maximum accuracy of 99.9% using medium or no external forces.

1 INTRODUCTION

In Neuro-rehabilitation, body signals are used as a mean of controlling the assistive devices. The most commonly used body signals for this purpose are obtained through surface Electromyogram (sEMG). In this technique, EMG signals are retrieved from the skin surface using electrodes on the desired muscles (non-invasively), which represent a convolution of the electrical activity of the muscle fibers known as Motor Unit Action Potential (MUAP) (Farina et al., 2014) and are described using eqn. 1.

$$emg(t) = \sum_{i=1}^{N} \sum_{j=-\infty}^{\infty} \psi_i(t)\delta(t - t_{ij}) \tag{1}$$

Where N is the number of active muscle fiber signals known as Active Motor Neurons, $\psi_i(t)$ represents the waveform of the i^{th} motor unit, $\delta(t)$ is the impulse function and t_{ij} is the time delay of the i^{th} motor unit. These signals are generally used to control the speed of a motor or position of an actuator in prosthesis. Therefore, the accurate detection of the points where muscles initiate to move from their relaxed states is of great significance in implementing real-time control of prosthesis. The triggering of the muscular contraction is known as the onset point, while the end point of the contraction is referred to as an offset point. These onset/offset represents the duration of a muscle activity.

For neuro-rehabilitation active control of an external device with maximum precision and minimum processing time is a major requirement. Currently available myo-controlled prosthesis such as *i-limb* and *Ottobock* utilize state machine based controller for selection of movements (Farina et al., 2014). In such systems real-time detection of these onsets/offsets play a vital role. A great deal of work has been carried out in this regard during the past two decades. (Merlo et al., 2003) used amplitude threshold on continuous time wavelet transform for the detection of presence of MUAP . The method proposed is unsuitable for real time activity detection because its accuracy depends upon the shape of window selected which may vary for different movements; in addition, the proposed method is computationally intensive. (Solnik et al., 2010) refer to the use of Teager-Kaiser Energy Operator (TKEO) for the use of EMG detection, which seems to be a very promising parameter . However, they have used a threshold of 3 standard deviations for 25 consecutive samples which makes the overall algorithm non-adaptable especially for scenarios where signal variations due to changes in environmental/physical conditions are experienced; this aspect is further discussed in section (6). The two stage methodology proposed by (Drapala et al., 2010) is based on initial estimation from the entire EMG followed by local estimation. The first stage proposes energy estimation of sEMG signal using the TKEO algorithm. The estimated energy signal acts as input

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to Expectation Maximization (EM) clustering method for the classification of EMG activity region vs. non activity region . Once the active and non-active regions are vividly separated they are further enhanced using a single threshold algorithm. As the algorithm needs complete signal for analysis and comparison, therefore, their work is presented for offline analysis, focusing more on precision as compared to computational complexity. (Xu et al., 2013) present an adaptive approach for onset/offset detection . Their work merges Maximum Likelihood (ML) algorithm with a look-up table, comprising of a set of threshold values based on different Signal to Noise ratios (SNR). The algorithm is not computationally intensive and, therefore, can be adopted for real time signal characterization but the major drawback is the use of simulated data combined with Additive White Gaussian Noise (AWGN) at different SNRs (a mean for generating the look-up table) which cannot be modeled for a real time EMG signal. Further investigations for onset/offset detection have also been carried out using machine learning algorithms such as the use of Gaussian Mixture Model and Hidden Markov Model by (Liu et al., 2015a; Liu et al., 2015b; Naseem et al., 2016). However, all such attempts are limited to offline sEMG and cannot be adopted for real time analysis due to their computational complexity. In this paper, the onset/offset points resulting in the subsequent Muscle Activity Interval (MAI) are determined using temporal and statistical features for the real time sEMG signals. The run-time performance of the proposed algorithm has been evaluated using real-time EMG signals under various constrained scenarios. The algorithm was tested on signals from seven healthy subjects using same experimental procedure as discussed in section (2).

2 EXPERIMENTAL PROCEDURE

2.1 Testing Protocol

Seven healthy subjects volunteered in this study involving three females and four males. All experiments were approved by campus bioethics committee and written consent was also taken from each participant. During these experiments, the elbow joint was fixed while wrist flexion and extension were performed with 0° rest position. In order to check the robustness of the proposed algorithm, three kinds of exercises were performed by each participant.

i. Wrist flexion and extension in the absence of any external force acting on the wrist.

ii. Wrist flexion and extension in the presence of an opposing force acting on the wrist .

iii. Wrist flexion and extension while holding 1 kg, 2 kg, and, 5 kg weights, respectively.

In order to further investigate the accuracy of the proposed algorithm, AWGN was added to the recorded signals to generate different SNRs of 1.25, 3, 6, and 9 dBs. All offline simulations were performed using MATLAB 2015a while all online results were obtained using NI LabVIEW 2015.

2.2 Experimental Setup

Bipolar pre-gelled Ag/AgCl disposable surface electrodes were placed on the left arm at flexer carpi ulnaris and radialis muscles, as shown in Fig. 1, following the recommendations of *Surface Electromyography for Non-Invasive Assessment of Muscles*(SENIAM) (Hermens et al., 2000). The reference electrode was in particular placed on medial epicondyle of elbow joint which was kept at rest during the entire experimentation process. This paper presents results of a pilot study initiated at CASE, Pakistan, to investigate the use of a low-cost hardware for online detection of MAI. For this purpose, a 2 channel *Olimex EKG/EMG bio-feedback shield* was used with *Arduino Uno R3*, despite its lower acquisition signal bandwidth of 0.16Hz to 40Hz which is much less than the required 500 Hz, for sEMG signal. The main idea in this pilot study was to explore the viability / suitability of information contents present in lower frequency components of sEMG signals, for estimation of MAI. sEMG signals were sampled at frequency of 340Hz with 8-bit precision, and the experimental setup was interfaced with LabVIEW using a baudrate of 57,600 bps. The EMG signals were displayed on a real time monitor for visual inspection to ensure quality acquisition.

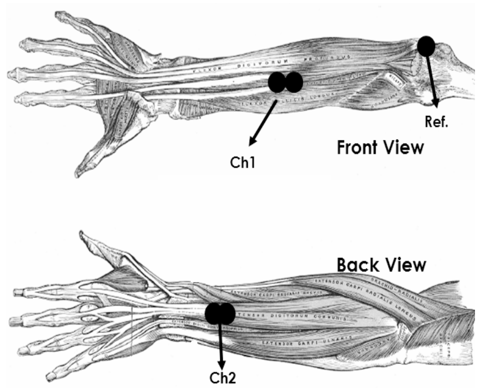

Figure 1: Electrode placement on upper limb for EMG acquisition.

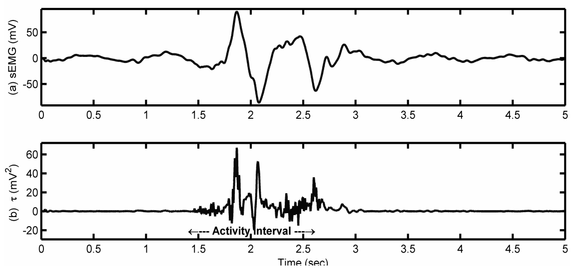

Figure 2: sEMG signal with energy operator (a) sEMG (b) the Energy estimated using TKEO from eqn.2.

3 FEATURES

In order to estimate the onset/offset points following aspects of the sampled sEMG signal have been utilized in the proposed algorithm (discussed in detail in section 4).

3.1 Teager-Kaiser Energy Operator

TKEO is a simple algorithm with two multiplication and a single addition to determine the temporal energy level of a signal at any instant of time as depicted in eqn. 2. It has been used by different researchers for EMG activity analysis with a fixed threshold (Micera et al., 2001) (Xu and Adler, 2004). Fig. 2 presents the Energy calculated using TKEO operator for a sEMG signal.

$$\tau(n) = x(n)^2 - x(n-1)x(n+1) \tag{2}$$

Where, $\tau(n)$ is presents TKEO energy estimator and *x(n)* is the input EMG signal.

3.2 Correlation Coefficient

The correlation coefficient is utilized in order to estimate the change in current state of activity. Correlation between consecutive w samples is calculated if the correlation coefficient of two consecutive windows is approximately 0, it means the behavior in the two windows is changing, referring to a change in current state of the muscles. Thus, the transition points of the correlation coefficient denoted by $\mathbf{ZC\{r(n)\}}$ are the candidate onset/offset points termed as fiducial points, as referred in eqn. 3 below.

$$r(n) = \frac{cov(x(n-w:n-1), x(n:n+w))}{std(x(n-w:n-1))std(x(n:n+w))}$$

$$ZC\{r(n)\} = \begin{cases} 0; & |r(n)| < \varepsilon \\ 1; & Otherwise \end{cases} \tag{3}$$

Where *r(n)*, is the correlation coefficient, *x(n)* is the current n^{th} sample of input signal, w is the size of samples selected for correlation evaluation, which in our case is 30, *cov* is the covariance function and *std* represents the standard deviation; ε is zero crossing threshold and *ZC*{*r(n)*} refers to potential candidate points for onset/offset reference.

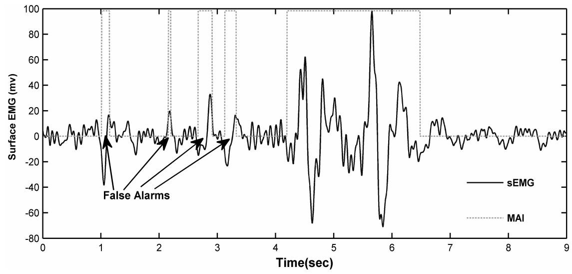

Figure 3: Black solid line presents sEMG signal while grey dotted line show activity region where the small width active regions are false alarms.

3.3 Minimum Activity Length

In order to complete a simple activity such as wrist flexion or extension, it is expected that some definite minimum time duration would be required. In our case, we have assumed it to be around one half of a second, i.e. if *Fs* is the total number of samples per second then an activity interval must be at least *Fs/2* samples long. Therefore, a second threshold based on activity length is incorporated in the proposed algorithm. If the length of the activity region identified is found to be less than *Fs/2*, than the candidate activity region is considered as no activity region and is simply rejected. An example of such false alarms and true activity regions is presented in Fig. 3.

4 ALGORITHM

During all the experiments performed, the hand was initially kept at rest position. For this reason, the algorithm was initialized with *"no activity in progress"*. In order to estimate the onset/offset points, the TKEO parameter for sEMG signal is calculated at every instant, referred to as, $\tau(n)$, followed by correlation coefficient estimation of w consecutive samples. If the correlation coefficient attains a value less than ε, it denotes a change in current state of wrist position, referred as ZC{r(n)}. Once an initial onset point is identified, a record of energy between the current onset points till the next fiducial point is tracked and time interval for maximum energy is estimated. If the energy in current time interval is maximum so far, previous interval is cross examined. If the energy level in the previous interval was at least half of the energy in the current interval, the starting point of previous interval is considered as an onset else the fiducial point of current band is the marked onset. The process continues till an offset is encountered. Once an onset has been found, search for the offset is activated among the subsequent fiducial points. For this purpose, energy of the two consecutive intervals, defined by the subsequent fiducial points, is observed. If the energy level in any two successive intervals falls below a certain threshold, which in our case has been taken equal to 5% of the energy of the onset interval (based on ratio of maximum and minimum power observed), we mark the ending fiducial point of the second interval as the offset. As the level of threshold is not against a hard constant value rather 5% of the energy interval therefore this initial search for onset/offset is referred as the first adaptive threshold.

The candidate MAI from the first adaptive threshold is then evaluated for minimum activity length. It has been observed as well as adopted in different literature that the minimum duration for any hand activity requires at least half a second (Merlo et al., 2003). Therefore, in case the number of samples of the candidate MAI exceeds *Fs/2*, the interval is marked as a valid MAI otherwise rejected as a false alarm. A detailed step-by-step description of the algorithm is provided in Table1 in the form of a pseudo code.

5 RESULTS

This paper presents the implementation of double threshold adaptive algorithm for real time sEMG activity interval detection. The algorithm was tested on real time sEMG signals with three different types of external forces, as discussed in Section 2. All results were tested for both wrist flexion as well as wrist extension and while computing the qualitative measures an average for each scenario using 30 signals for both flexion and extension by each patient were quantified. Performance rating for all scenarios is conducted by comparing the mean error μ, and its respective standard deviation σ. The mean error was evaluated by comparing the estimated fiducial points with visually inspected fiducial points.

5.1 sEMG without Any External Force

Two channel sEMG signals were acquired from upper limb ulnaris and radialus carpi muscles using *Olimex EKG/EMG shield* with a sampling frequency of 340 Hz. The elbow was placed on a wooden table with wrist flexed from 0° rest position and in a similar manner extended from the same rest area. A sample

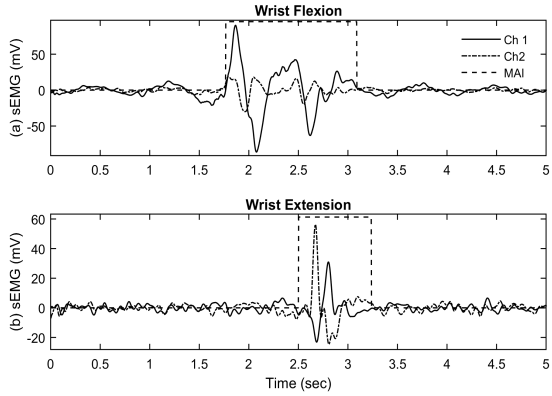

Figure 4: sEMG for wrist flexion and extension without any external force applied.

of the flexion and extension signals acquired without any external force acting on the hand / wrist, as discussed in the above fashion are presented in Fig. 4. Due to negligible external force the MAI from sEMG signal is accurately characterized by the algorithm with an error rate of $0.01 \pm 0.01 msec$ and a maximum accuracy of 99.9%.

5.2 sEMG with Applied Opposing Force (i.e. Frictional Force)

Flexion and extension were performed with a force in the opposite direction of movement of hand acting as a frictional force. The attributes of the acquired sEMG signal with and without external force are same in terms of data variation and other statistical means. However, an evident increase in the time duration of MAI as well as additional harmonics are observed as shown in Fig. 5(a& c). These oscillations appears due to the resistance of the opposing force,

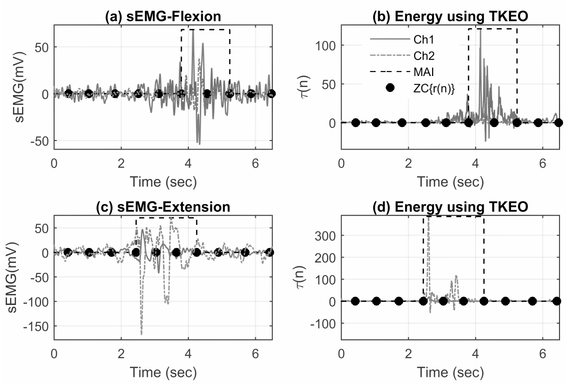

Figure 5: sEMG signals with opposing force applied; (a) wrist flexion and (b) wrist extension, with respective energy signals.

Table 1: Proposed Algorithm.

Input: A matrix $\mathbf{X} \in \Re^{[N\times 2]}$ with **N** representing number of samples and 2 are the number of channels.

$$\textbf{Output}:\mathbf{s} = \begin{cases} 0; If activity in Progress \\ 1; Otherwise \end{cases} \tag{4}$$

1. **Initial Values:** k=1;l=1;w=30; mE=0; onset=0;
2. $\tau(n) = x(n)^2 - x(n-1)x(n+1)$; n=1,2,3,...,N-w //TKEO
3. $r(n) = corr(|\tau(n-w:n)|, |\tau(n:n+w)|)$ //correlation of w consecutive elements, N is the total current length of input samples acquired
4. **if**($|r(n)|$=<0.01) //For any channel using or operator
   on(k)=n;
   if (k == 1) //For initializing onset
   onset=on(k)
   end
   k++;
   if (k > 2) //Estimating the correct onset point using maximum Energy interval

$$\textbf{initial.Energy} = \sum_{\mathbf{u}=\mathbf{on}(\mathbf{k}-\mathbf{1})}^{\mathbf{on}(\mathbf{k})} |\tau(\mathbf{u})| \qquad \textbf{current.Energy} = \sum_{\mathbf{u}=\mathbf{0n}(\mathbf{k})}^{\mathbf{on}(\mathbf{k}+\mathbf{1})} |\tau(\mathbf{u})| \tag{5}$$

   end

5.**if**(max.Energy<initial.Energy)
   max.Energy=initial.Energy //Maximum Energy

$$\textbf{if}(2 \times \sum_{u=on(k-2)}^{on(k-1)} |\tau(u)| < initial.Energy) \tag{6}$$

   onset=on(k-1);
   ty=on(k+1);
   else
   onset=on(k);
   ty=on(k-2);
   end
   s=1;
   end

6. **if**(onset = 0) //If activity is initialized
   if (current.Energy < initial.Energy && current.Energy > max.Energy*0.05)
   offset= on(ii+1);
   s=0;
   end
   else
   off= ty;
   end

7. **if** (s==1 && n-onset > Fs/2)
   Activity In Progress
   elseif (offset-onset >Fs/2)
   x(onset : offset) is the detected Activity Region
   mE=0;k=1;onset=0;
   end //Repeat Step 1 to 5 till the process continues

resulting in an increase in MAI as compared to normal time for the wrist to complete its 90° flexion or extension from rest position. In order to choose the correct onset, it is required to analyze the energy level in the signal continuously. Due to the oscillatory behavior the TKEO based correlation results in multiple closely detected onset candidates as highlighted with black dots in Fig. 5. However, the energy threshold between every two consecutive fiducial points tracks the point from where a consistent increase in energy level is observed, till the maximum energy value is achieved, resulting in the identification of the accurate onset point. It further investigates the existence of offset point and continuously compares the detected MAI with the set sample threshold.

5.3 sEMG with Variable Weights

The same experiment of wrist flexion and extension has been tested with multiple weights in order to investigate the robustness of the proposed algorithm. Multiple alarms are activated in the form of $ZC\{r(n)\}$ which is an affirmation of presence of activity. However, the adaptive threshold is successful in identifying the region of interest. With minimum weights i.e. 1 kg and 2 kg the mean error observed is almost the same as no weight added (0.01 ± 0.01, & $0.01 \pm 0.02 msec$, respectively). With the increase in weight the energy level starts increasing as shown in Fig. 6(b & d). At 5 kg as the weight becomes heavy, there is a continuous pressure on the hand muscles resulting in initial oscillations even when the wrist is at rest position, as can be clearly observed in Fig. 6(f) between 0.5 to 1 sec duration. As the proposed algorithm is based on maximum energy as well as interval length, it selects the second region as muscle activity region and rejects the initial energy band as a false alarm Fig. 6(e & f).

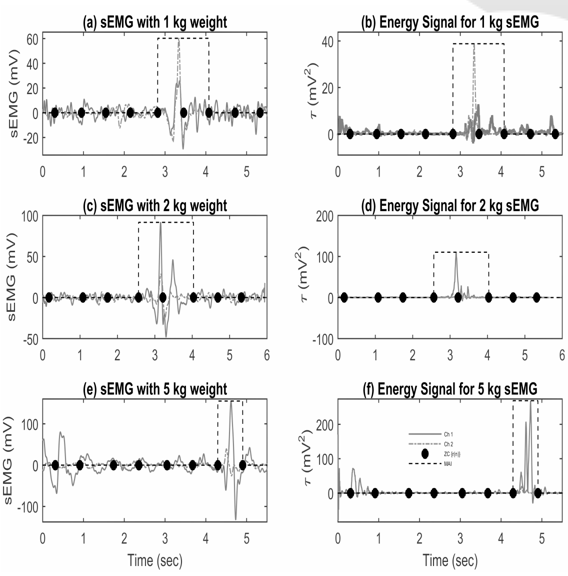

Figure 6: Results of proposed algorithm for sEMG with its corresponding TKEO graph for different weight lifted during wrist extension (a, b) and flexion (c, d, e, & f).

6 DISCUSSION

Muscle contraction or relaxation is responsible for the accurate movement of any limb in human body. In order to estimate muscle activity onset/offset point detection, this paper proposes the use of adaptive threshold based on correlation coefficient of TKEO energy estimator. The proposed algorithm is tested for different scenarios such as free wrist i.e. no external force applied, with an opposing force in the direction of motion, and wrist movement with different weights attached. The results for all above discussed scenarios is presented in Fig. 7. The mean error in case of no external force or 1 kg weight is near to zero, however, when the weight is increased to 2 kg and 5 kg or in case of opposing force, the error slightly increase with a maximum error variation of 270 m sec and provides lowest results with an acurracy of 98.3%. When the hand muscle grasps a weight as heavy as 5 kg pressure is exerted as a result of which additional harmonics are observed in sEMG recorded even at rest position of the wrist. Therefore, the results of MAI is not as high as that in low weight sEMG signals. A comparison with the onset MSE proposed by (Solnik et al., 2010) is also presented in the Fig. 7. The onset detection in no external force, lite weights and opposing

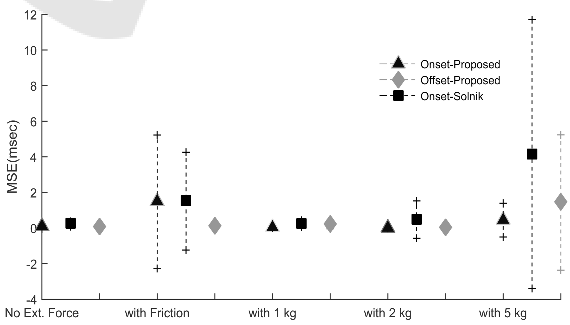

Figure 7: Performace comparison (on the basis of Mean Square Error (MSE) and Standard Deviation values) of the proposed algorithm with the algrithm presented by (Solnik et al., 2010) under various loading scenarios. Bold symbol shapes (i.e. Square, Diamond and Triangle) indicate the Mean Error value while the vertical dotted lines represent the spread of error. Note that the proposed algorithm detects both onset as well as offset points, whereas Solnik algorithm detects onsets ONLY.

Table 2: Mean error and stand deviation comparison of algorithm results for sEMG Onset Detection with constrained and unconstrained environment at different SNRs.

SNRs	No Force		Friction		1 kg		2 kg		5 kg	
(dB)	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
x(t)	0.01	0.01	0.26	0.57	0.01	0.01	0.01	0.05	0.03	0.08
1.25	0.09	0.32	4.72	3.04	0.90	1.76	2.01	3.04	3.21	4.26
3	0.04	0.05	2.89	3.47	0.04	0.07	1.36	1.53	1.23	3.70
6	0.05	0.07	2.09	2.55	0.05	0.06	0.25	0.82	1.85	2.43
9	0.09	0.13	1.18	1.98	0.05	0.05	0.25	0.86	1.47	1.25

Table 3: Mean error and stand deviation comparison of algorithms results for sEMG Offset Detection with constrained and unconstrained environment at different SNRs.

SNRs	No Force		Friction		1 kg		2 kg		5 kg	
(dB)	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
x(t)	0.01	0.01	0.02	0.08	0.004	0.01	0.04	0.01	0.08	0.20
1.25	0.68	2.22	4.77	5.00	1.47	1.13	3.31	2.48	4.75	3.76
3	0.15	0.15	3.93	4.80	0.28	0.22	0.18	2.29	2.85	2.03
6	0.18	0.21	2.50	3.84	0.25	0.24	0.18	0.35	1.30	2.08
9	0.12	0.15	1.50	2.38	0.21	0.26	0.76	0.27	1.30	1.80

frictional force is comparable, where as in case of 5 kg weight the proposed algorithm out performs the other by an onset detection accuracy of 98.3% in comparison with 88.1% achieved by (Solnik et al., 2010).

In order to investigate the performance of algorithm for external interference, AWGN with different SNRs was added to the already acquired EMG signals. The algorithm was run offline on noise added EMG signals to evaluate the performance for onset/offset detection accuracy. The results are summarized in Table 2 & 3, respectively. For 3 and 9 dBs SNR sEMG signals, with no external force, 1 kg, and 2 kg weights the mean error is below 280 msec. But when the signal strength decreases as in case of 1.25 and 3 dB the algorithm has a slight increase in mean error and standard deviation, especially in case of frictional force and 5 kg weights applied. This is due to the fact that when an external force is applied the muscle tries to contract but the external force has a dominant pressure on the muscle, resulting in muscle contraction noise. Further increase in SNR deteriorates the strength of the signal thus an increase in error is observed while estimating the MAI. sEMG acquired in stressful scenarios have a higher frequency as compare to sEMG acquired from wrist with no external interference or lite weights such as 1 kg or 2 kg. The results can be easily improved for such signals if the window length w is increased. However, increase in window length would make the algorithm less suitable for real time applications, therefore, an adaptive window length selection needs to be catered in future.

All sEMG signals evaluated on sEMG focusing easily available low cost equipment targeting lower frequency band of 0.14 Hz-40 Hz. As the lower frequencies provides information about the presence of activity and higher frequencies tends to define the particular movement, therefore, the use of lower frequency range is sufficient for MAI detection. However, it may effect if the same low frequency sEMG signals are used for movement identification.

7 CONCLUSION

The extraction of muscle activity interval can play a vital role for real time Myo-electric controlled devices and other clinical applications. The purpose of the proposed work is to present an algorithm for real time detection of muscle activity using affordable hardware. Although the hardware selected focuses on low frequency sEMG signal only, the detected MAI is considerably accurate and therefore, low cost sEMG acquisition devices such as *Olimex EKG/EMG shield* can be utilized for control of automated prosthesis in order to provide cheaper solutions.

While majority of the methods proposed in literature are limited to offline analysis and onset detection; our proposed methodology is fast and easily implementable for real-time systems as well as handles both activity activation and deactivation regions. The proposed algorithm not only detects the complete muscle activity interval but also provides considerably higher accuracy than other previously proposed algorithms. The methodology presented adopts a double threshold adaptive algorithm for MAI detection. The initial threshold is based on correlation coefficient and percentage of maximum energy providing an adaptive behavior. The use of correlation coefficient provides better performance for different SNRs while the percentage of maximum energy computed over an interval selects the most optimum candidate interval. The experimental results are achieved using real surface EMG signals in different scenarios as well as cross checked with different levels of AWGN. We have shown that the proposed algorithm is robust to estimate the closest correct onset and offset point even with external interference. The proposed algorithm performs best with lite or no external force, achieving an accuracy of 99.9%, and improves performance by 10.2% in worst case scenario in comparison with previously proposed work.

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