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Amplitude independent versus amplitude dependent muscle activity detection algorithms: a comparative study

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ABSTRACT

The amplitude dependent muscle activity detection algorithms of the surface electromyography (sEMG) signals are very sensitive to the changes in the background noise levels and the performance of these amplitude-based methods is highly deteriorated when the Signal to Noise ratio (SNR) of the sEMG signal is low. sEMG signals of deep and small muscles as well as sEMG signals recorded from patients that have neuromuscular diseases may not meet this SNR requirement which motivates the need for amplitude independent algorithms that can detect weak muscle activities. Moreover, the sEMG signal amplitude is not constant during the recording time due to the variation in the characteristics of the electrode-skin interface and due to the changes in the ground reference level. Therefore, the performance of the muscle activity detection algorithms should not be affected by the involuntary amplitude variations of the sEMG signal in order to achieve reliable control of robotic devices intended for disabled people. To accentuate the importance of the amplitude independent muscle activity detection methods over the amplitude dependent detection methods, a comparative study has been conducted in this paper between the performance of an amplitude independent muscle activity detection algorithm (FLA-MSE algorithm) and three amplitude dependent algorithms with respect to the detection capability of weak muscle activities and with respect to the immunity against false alarms. The results have showed that the performance of the amplitude independent algorithm outperformed the performance of the amplitude dependent algorithms for detecting weak muscle activities and for robustness against false alarms.

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1. INTRODUCTION

Because of the stochastic characteristic of sEMG signals, muscle activity detection is a challenging task, especially in weak sEMG signals due to the gradual increase of amplitude and frequency, artefacts noise, spurious background spikes, and random variations in the background noise (usually introduced by electrode movement over the skin) [1]. Many algorithms have been developed in the literature to detect muscle activities from the sEMG signal. The conventional algorithms compare the amplitude parametrs such as the envelope, the average rectified value, the root mean square value of the signal with a predefined threshold value, this threshold must be determined according to the amplitude of the measured signal during no activity period and must be modified whenever the amplitude changes due to many factors. The threshold is user dependent and is cumbersome to optimize with regards to both the detection bias and the false alarm probability, where high threshold levels will usually lead to delayed or even missed onset detection; a relatively low threshold level results in early onset detection but also introduces more false alarms [2, 3]. These methods are very popular because of easy implementation, but achieve satisfactory results only when the SNR of the signal is sufficiently high.

Various methods for muscle activity onset detection have been proposed, in which the majority of the used parameters are related to the amplitude of the sEMG signal. For example, wavelet template matching [4, 5] was proposed for sEMG muscle activity onset detection by comparing the shape of the surface motor unit action potentials with the appropriate wavelet functions, where good performance can be achieved only when the shape of surface action potentials matches well with the selected wavelet template. However, for experimental sEMG signals, such ideal condition cannot always be guaranteed which may result in a less precise onset detection of muscle activity. Moreover, this detection approach requires large computational power, mainly due to the calculation of the continuous wavelet transform. Qi Xu et al. [2] have developed a detection algorithm based on the maximum likelihood method improved by an adaptive threshold, but the performance of these statistical methods mainly depends on the correct estimation of a priori information of the sEMG signal. Moreover, in statistical detection methods, cumulative sum method requires information about the probability density function which is not available in most real-life problems. Since the firing of action potentials increase the signal amplitude of sEMG signal, the Teager-Kaiser Energy (TKE) operator [6-9] was proposed to highlight this increase and to achieve good performance for the detection of muscle activities especially for sEMG signals that have low SNR. However, the detection methods based on TKE operator was mainly limited to the background noise with Gaussian distribution and they are very sensitive to the spurious background spikes. The authors in [10] have developed a statistical method based on unsupervised learning to model the sEMG signal distribution in the frequency domain; however, this method require intensive computational efforts to process the signal. Vaisman et al. [11], have developed a muscle activity onset detection method based on singular spectrum analysis, but this method need computer to implement the algorithm due to high computational power needed to calculate the expectation– maximization clustering. Furthermore, this method assumes that sEMG signal must have pre-contraction, contraction and post-contractions parts. Xu and Ping [12] have developed a muscle activity detection algorithm against spurious background spikes by using sample entropy analysis of the sEMG signal, but this method needs high computation efforts and therefore it is difficult to be implemented in real time. Jie and Qiuping [13] have developed a detection algorithm by employing the integrated profile of the sEMG signal in the presence of the spurious background spikes for the spinal cord injury patients, this method depends on the changes in the amplitude of the sEMG signal to report the muscle activities. Severini et al. [14] have improved the Bonato double threshold detection method [15] by making the decision threshold value adaptive to the changes in the sEMG signal to noise ratio. Most of the aforementioned methods require either prior knowledge about the EMG generating model or intensive calculations making them impractical for real-time applications because many of them are not intended to control robotic devices but for other applications like neurological diagnosis or sports medicine. Moreover, statistically optimal decision, frequency domain analysis, and machine learning detection methods need heavy computational requirements that would impose burdens on real time implementation especially for embedded systems, while real-time system demands fast algorithms having low computational complexity.

In order to emphasize the importance of employing amplitude independent muscle activity detection algorithms to control hand robotic devices used for disabled people, a comparison has been made in this paper between the performance of the amplitude independent muscle activity detection algorithm presented in [30, 31] (FLA-MSE algorithm) and three amplitude dependent algorithms (Rectified and filtered sEMG, Teager Kaiser Energy Operator, Integrated Profile). All the four algorithms have low computational efforts and can be implemented in real time. The comparison has been conducted with respect to the ability of detecting weak muscle activities and with respect to the immunity against false alarms caused by involuntary amplitude variations in the sEMG signals (false alarms cause unintended movements of the robotic devices).

2. THE FLA-MSE ALGORITHM

The FLA-MSE algoritm is an amplitude independent muscle activity detection algorithm developed by *Husamuldeen et al.* [30] and it was successfully employed to control the movement of a soft robotic glove. The algorithm employs the First Lag Autocorrelation (FLA) and the Modified Sample Entropy (MSE) to detect weak muscle activities from sEMG signals. The algorithm is also immune against spurious background spikes that may contaminate the sEMG signal and degrade the performance of the amplitude dependent muscle activity detection methods. Moreover, the algorithm is computation efficient to enable real time implementation and can distinguish between two types of muscle activities “hand close” and “hand open” by using single sEMG channel without the need to apply the classification algorithms.

The distinguishing procedure of the FLA-MSE algorithm is illustrated in Figure 1, Figure 2 shows a sample of the performance of the algorithm to detect and classify two muscle activities “hand close” and “hand open” from real sEMG signal obtained from the forearm muscles of a healthy subject.

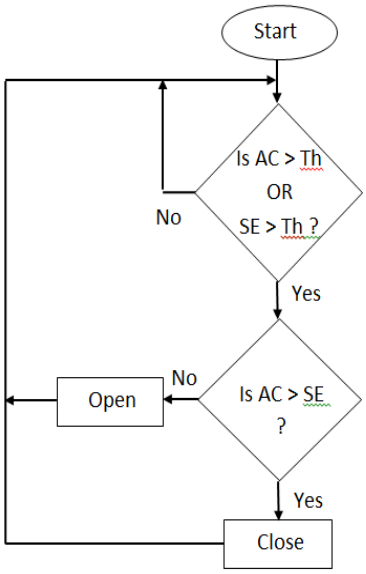

Figure 1. Muscle activity distinguishing flow chart

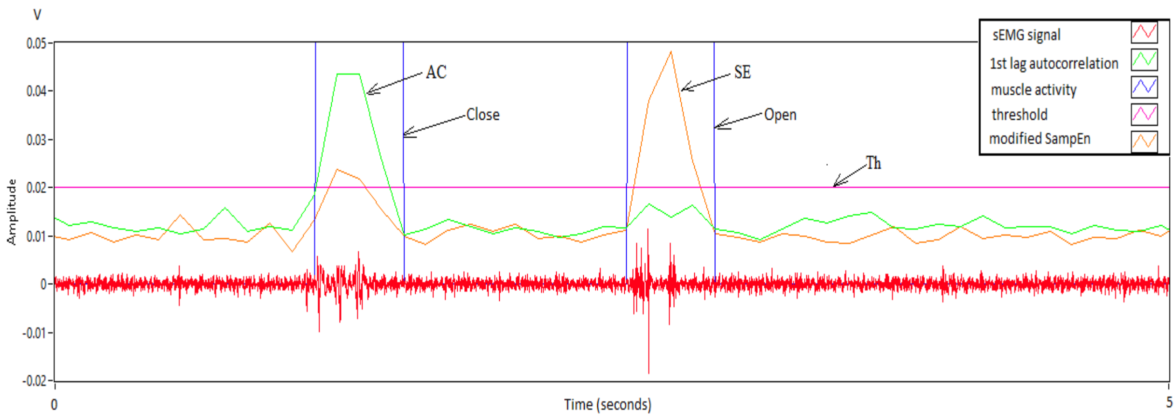

Figure 2. sEMG signal with one “close” and one “open” activity

3. PERFORMANCE COMPARISON BETWEEN THE FLA-MSE ALGORITHM AND THREE AMPLITUDE DEPENDANT MUSCLE ACTIVITY DETECTION ALGORITHMS

To evaluate the performance of the amplitude independent muscle activity detection method against amplitude dependent detection methods, a comparison has been conducted between the performance of the amplitude independent FLA-MSE algorithm and three amplitude dependent detection methods. The first method is the classical detection method which compares the rectified and filtered sEMG signal with a predefined threshold, where this method was used in most of the practical implemented hand robotic devices [16-25]. The second method is the Teager Kaiser Energy Operator (TKE) [7-10, 26] and the third method is the Integrated Profile (IP) [13, 27] of the sEMG signal. These three methods were chosen because they can be implemented in real time and have low computational efforts. The comparison was done with respect to the ability of detecting weak muscle activities and with respect to the immunity against false alarms, where these two parameters are the most important parameters that a muscle activity detection algorithm must have for reliable control of hand robotic devices intended for disabled people.

For the first method, each sEMG signal segment was full wave rectified and filtered by a 4th order Butterworth IIR low pass filter with a cutoff frequency of 10Hz as was used in [17] and as suggested by International Society of Electrophysiology and Kinesiology (ISEK) guidelines [28]. The rectified and filtered sEMG signal was compared with a threshold value which is three times standard deviation of the sEMG signal during no activity period as suggested in [29], a muscle activity is reported when the signal exceeds the threshold value. For the second method, the TKE operator was computed for each sEMG segment and the result was compared with a threshold of eight times standard deviation of sEMG signal during no activity period as suggested in [9]. For the third method, the integrated profile algorithm [13] was applied for each sEMG segment.

3.1. Comparison with Respect to the Detection Capability

The hardware setup shown in Figure 3 was used to conduct a comparison among the four algorithms (FLA-MSE algorithm, rectified and filtered, TKE, IP) according to the flow diagram illustrated in Figure 4 to test the ability of detecting weak muscle activities. A healthy subject wearing soft glove on his left hand has generated ten weak ‘close’ muscle activities from his Flexor Carpi Ulnaris (FCU) muscle as suggested in [30]. The amplitude independent FLA-MSE algorithm has managed to detect all the ten muscle activities as illustrated in Figure 5, while the IP method has detected six muscle activities, rectified and filtered method and TKE method both have detected four muscle activities. Figure 6 shows a zoomed sEMG signal of Figure 5.

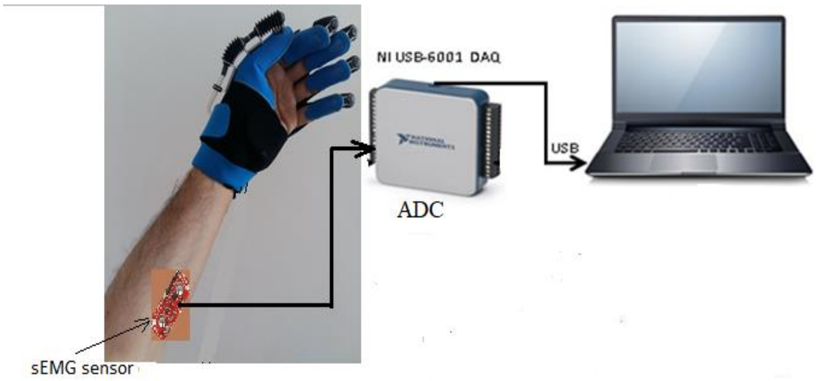

Figure 3. The hardware setup used in the experiments

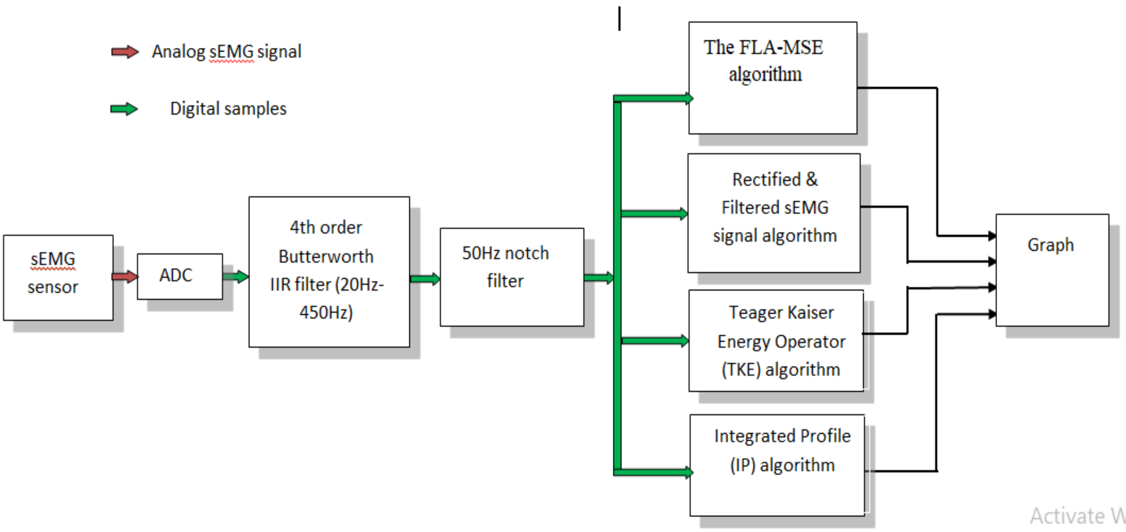

Figure 4. Flow Diagram used for the comparison among the four algorithms

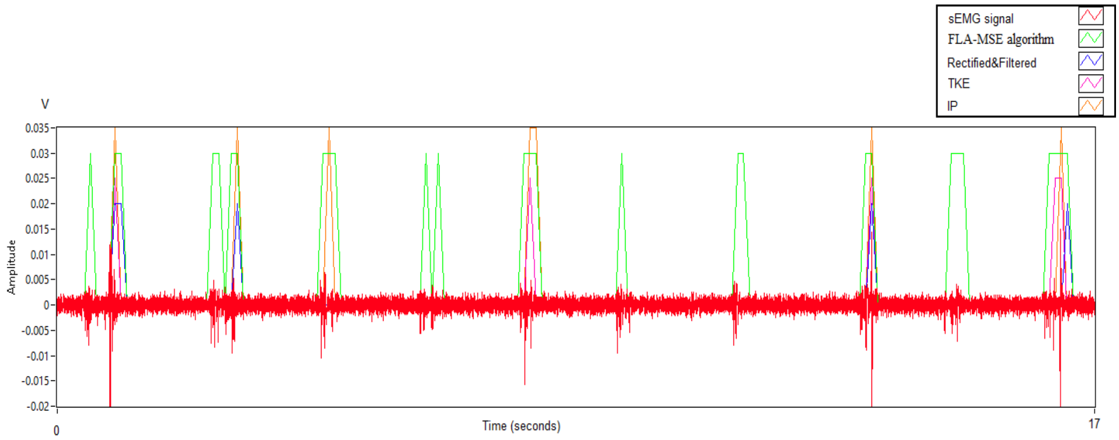

Figure 5. sEMG signal with ten muscle activities. Comparison among the four algorithms with respect to the ability of detecting weak muscle activities

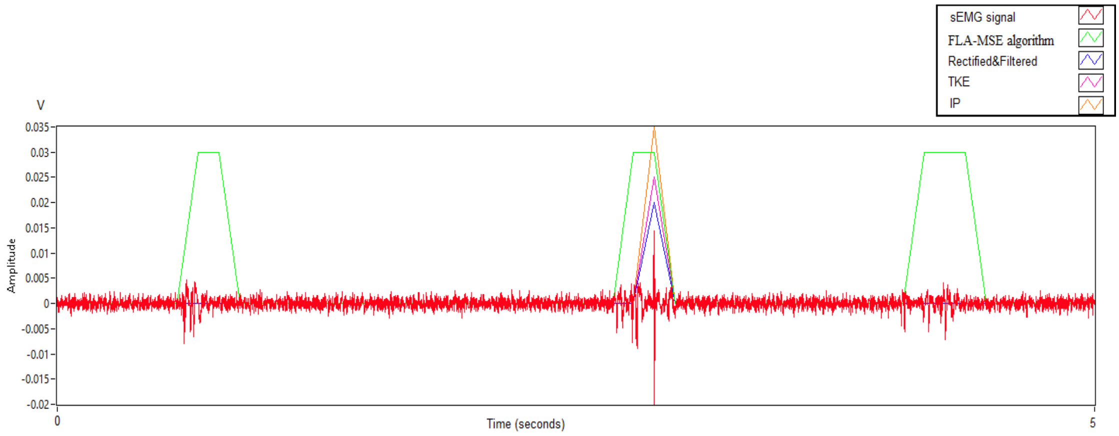

Figure 6. sEMG signal with three muscle activities. Zoomed sEMG signal of Figure 5

To test the reliability and robustness of the detection capability of the amplitude independent FLA-MSE algorithm with respect to the inter-experimental variations, three rounds were conducted in different times with new doff and don of the sEMG channel for each round. Each round was including a generation of 25 weak 'close' muscle activities by a healthy subject wearing soft glove on his left hand. The sEMG channel was located on the Flexor Carpi Ulnaris (FCU) muscle of the forearm. As shown in table 1 and Figure 7, the FLA-MSE algorithm has succeeded to detect all the muscle activities. There was no difference of the outcomes for experiments conducted on different times, indicating that there was no impact of inter-experimental variations on the efficacy of the amplitude independent method to detect weak muscle activities. In contrast, the amplitude dependent methods have given different performance for each round because the amplitude of sEMG signals was different in each round due to the reinstalling and installing of the sEMG channel and consequently changing in the electrode-skin interface characteristics.

Table 1. Numbers of the Muscle Activity Detections for the Three Rounds

Round No.	No. of true detected muscle activities out of 25 activities			
	FLA-MSE algorithm	Rectified and filtered sEMG	Teager Kaiser Energy operator (TKE)	Integrated Profile (IP)
1st	25	2	10	4
2nd	25	1	1	1
3rd	25	7	7	7

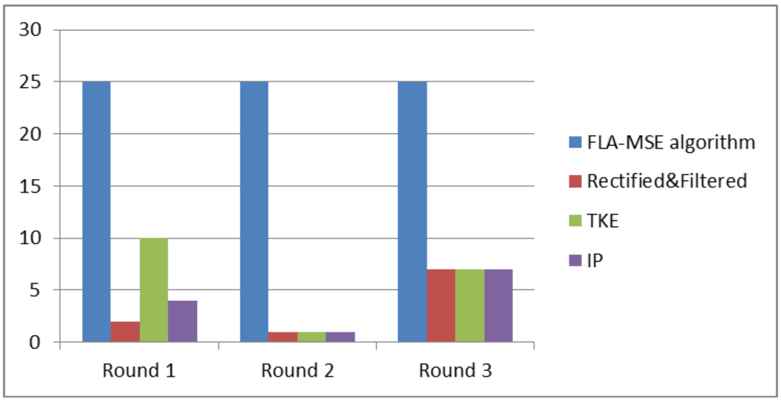

Figure 7. Numbers of true detected muscle activities by the amplitude independent FLA-MSE algorithm compared to the other amplitude dependent algorithms

Figures 8, 9, and 10 with 5 seconds window span show samples of the muscle activity detections for the three rounds, where round 1 was with noisy sEMG signal and round 2 was with very weak muscle activities. The difference among the three rounds with respect to the sEMG signal was due to the changing in the electrodes contact with the skin caused by don and doff of the sEMG channel.

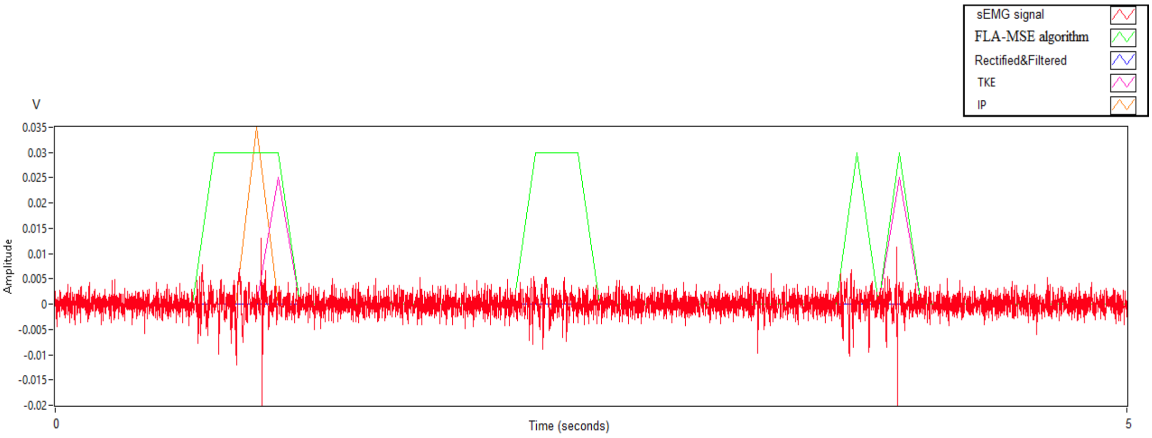

Figure 8. sEMG signal with three muscle activities from the FCU muscle for round 1

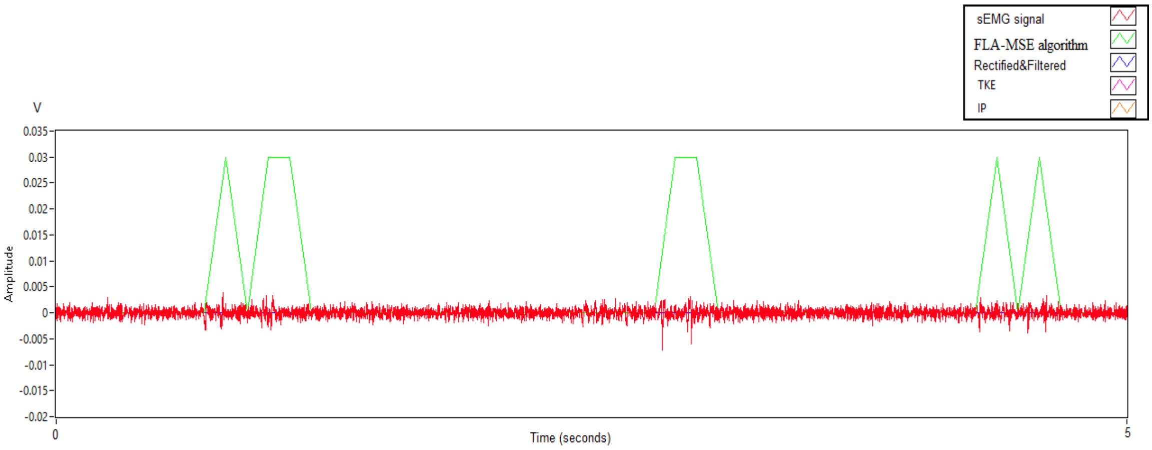

Figure 9. sEMG signal with three muscle activities from the FCU muscle for round 2

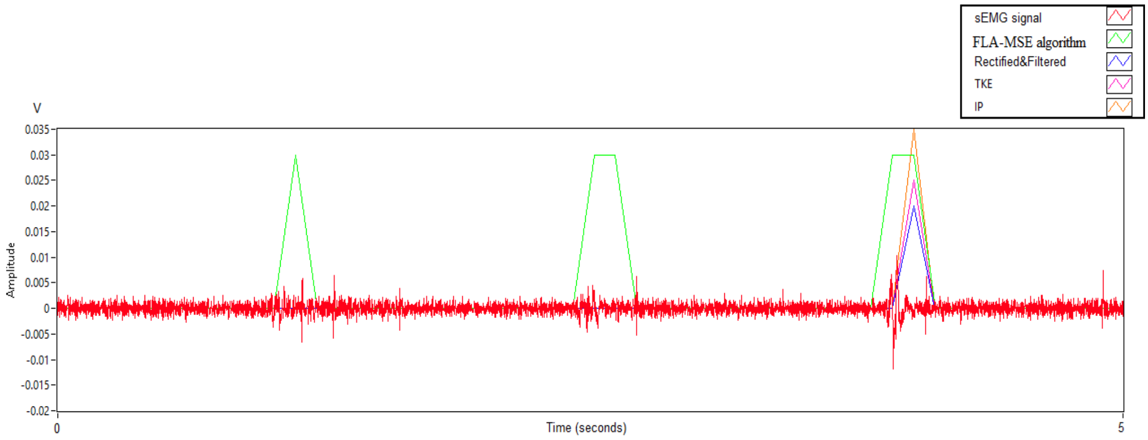

Figure 10. sEMG signal with three muscle activities from the FCU muscle for round 3

To compare the performance of the four algorithms for detecting (not distinguishing) different types of muscle activities like “Close” and “Open” from the Flexor Carpi Ulnaris (FCU) muscle, twenty “Close” activities then twenty “Open” activities were generated by a healthy subject wearing soft glove on his left hand. The numbers of the detected “Close” and “Open” muscle activities by the four algorithms are shown in Table 2 and Figure 11.

Table 2. Numbers of the Detected “Open” and “Close” Muscle Activities by the Four Algorithms

Muscle activity from FCU muscle	No. of the detected muscle activities out of 20 activities			
	FLA-MSE algorithm	Rectified and filtered sEMG	Teager Kaiser Energy operator (TKE)	Integrated Profile (IP)
“Close”	20	8	12	9
“Open”	20	6	20	8

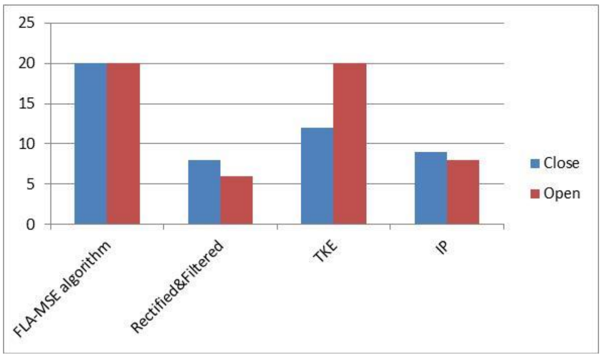

Figure 11. Detected “Open” and “Close” muscle activities by the four algorithms

The amplitude independent FLA-MSE algorithm has succeeded to detect all the “Close” and “Open” activities which is not the case for the other three amplitude dependent algorithms (keeping in mind that just the FLA-MSE algorithm can distinguish between “Close” and “Open activities). With respect to the “Close” activities, the other three algorithms have failed to detect many of them due to the low SNR of this activity. With respect to the “Open” activities, the TKE algorithm has managed to detect all of them due to the good SNR of this activity from the FCU muscle, whereas the “Rectified & Filtered” and the “Integrated Profile” algorithms have failed to detect many of them due to the nature of this activity which is composed of sharp pulses. Figure 12 and Figure 13 show samples of the sEMG signal that was used to do the comparison, where sEMG signal with four detected “Close” activities and four detected “Open” activity are appeared in a 5 second window span.

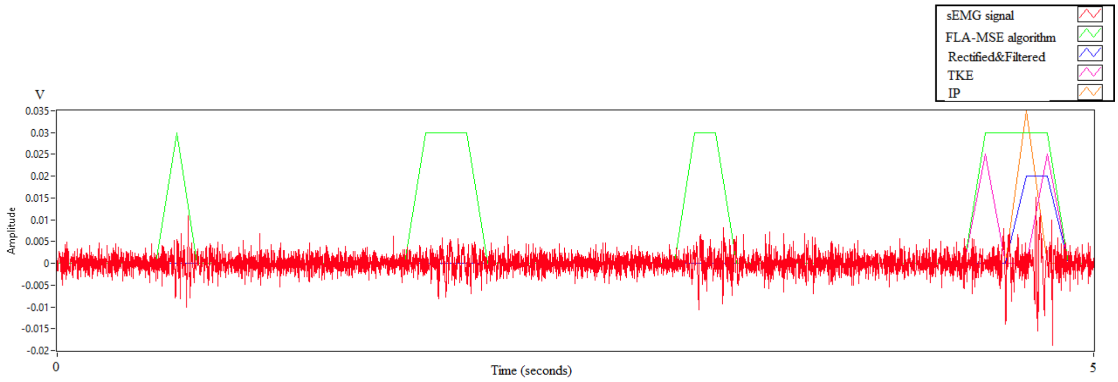

Figure 12. sEMG signal with four "Close" muscle activities from the FCU muscle

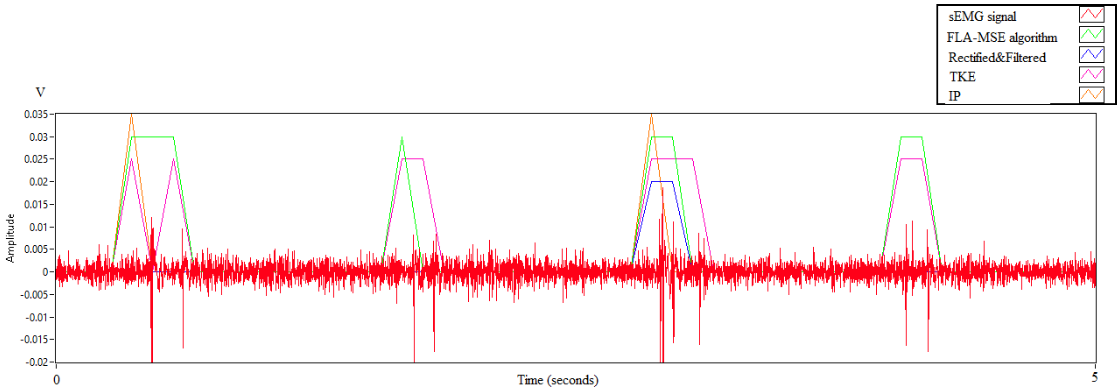

Figure 13. sEMG signal with four "Open" muscle activities from the FCU muscle

3.2. Comparison with respect to the immunity against false alarms

To compare the robustness of the four algorithms against false alarms caused by amplitude variation of the sEMG signal, an Additive White Gaussian Noise (AWGN) with a standard deviation of 5 mV was added to a real sEMG signal. A real sEMG signal without muscle activities was obtained from the Flexor Carpi Ulnaris muscle of a healthy subject and the AWGN was added five times to the signal to simulate an amplitude variation for the sEMG signal. As shown in Figure 14, the amplitude independent FLA-MSE algorithm was immune against amplitude variation and there is no false alarm, while the other algorithms have produced false alarms for each amplitude variation.

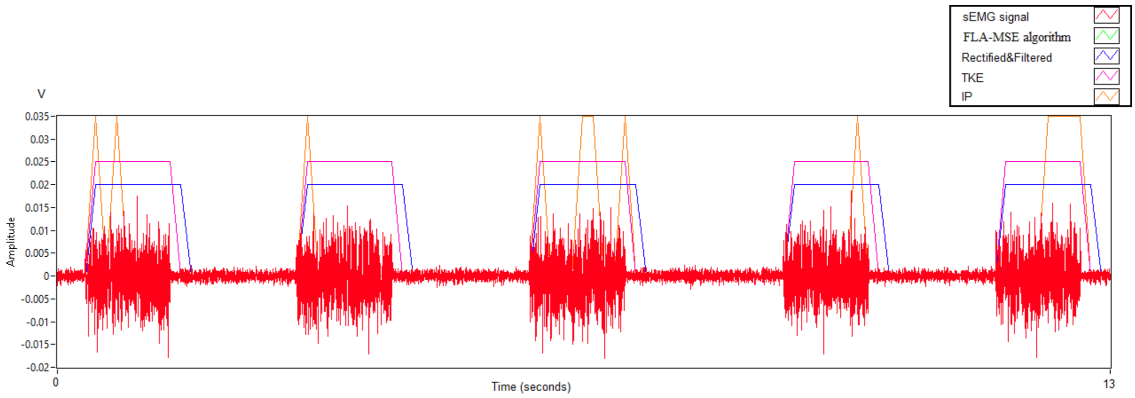

Figure 14. sEMG signal without muscle activities and with five AWGN. Comparison among the four algorithms with respect to immunity against false alarms

4. CONCLUSIONS

The sEMG signal amplitude characteristics differ from one person to another and from time to time according to many factors like the electrode location, sweat, fatigue, blood circulation, the electrical impedance of the skin, the thickness of adipose tissue, and body temperature. Moreover, it is found in previous studies that motor unit over activity in stroke patients are sometimes present as a background signal that may contaminate the voluntary sEMG signal of the impaired muscles and make it difficult to use the conventional amplitude dependant methods for detecting muscle activities of neurological injury patients. In this paper, a comparison has been conducted between the performance of the amplitude independent FLA-MSE algorithm presented in [30] and three amplitude dependent muscle activity detection algorithms with respect to the ability of detecting weak muscle activities and with respect to the immunity against false alarms caused by involuntary amplitude variations. The sEMG signal was obtained by using single channel from the forearm muscles of a healthy subject wearing soft robotic glove in his left hand. First of all, ten weak musle activities were generated from the Flexor Carpi Ulnaris (FCU) muscle and a comparison among the four algorithms was done with respect to the detection capability, where the amplitude independent algorithm has detected all the ten activities. To test the reliability and robustness of the detection capability of the amplitude independent algorithm with respect to the inter-experimental variations, three rounds were conducted in different times with new doff and don of the sEMG channel for each round, 25 muscle activities were generated for each round. The results have revealed that the detection capability of the amplitude independent algorithm outperformed the amplitude dependent algorithms with respect to the detection of weak muscle activities. To compare the performance of the four algorithms for detecting different types of muscle activities, 20 hand "Close" activities and 20 hand "Open" activities were used in the comparison. The FLA-MSE algorithm has succeeded to detect all the muscle activities which is not the case for the other algorithms. Finally, a comparison has been conducted among the four algorithms to test the robustness against false alarms caused by involuntary amplitude variations. The result has confirmed the robustness of the amplitude independent method against false alarms in contrary to the amplitude dependent methods. Employing amplitude independent muscle activity detection methods for controlling hand robotic devices intended for disabled people makes these devices more reliable to be used in daily basis.

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