

IMPLEMENTATION OF A REAL-TIME AUTOMATIC ONSET TIME DETECTION FOR SURFACE ELECTROMYOGRAPHY MEASUREMENT SYSTEMS USING NI myRIO

by

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For using the surface electromyography (sEMG) in various applications, the process consists of three parts: an onset time detection for detecting the first point of movement signals, a feature extraction for extracting the signal attribution, and a feature classification for classifying the sEMG signals. The first and the most significant part that influences the accuracy of other parts is the onset time detection, particularly for automatic systems. In this paper, an automatic and simple algorithm for the real-time onset time detection is presented. There are two main processes in the proposed algorithm: a smoothing process for reducing the noise of the measured sEMG signals and an automatic threshold calculation process for determining the onset time. The results from the algorithm analysis demonstrate the performance of the proposed algorithm to detect the sEMG onset time in various smoothing-threshold equations. Our findings reveal that using a simple square integral as the smoothing-threshold equation with the given sEMG signals gives the best performance for the onset time detection. Additionally, our proposed algorithm is also implemented on a real hardware platform, namely NI myRIO. Using the real-time simulated sEMG data, the experimental results guarantee that the proposed algorithm can properly detect the onset time in the real-time manner.

Key words: *surface electromyography, smoothing, onset time detection, NI myRIO*

Introduction

The movement of muscles is controlled by the electric signals generated from the brain, called electromyography (EMG). Since the signal is detected using a surface electrode, it is then called surface electromyography (sEMG). The sEMG signal gives benefits in many applications, such as robotic control [1, 2], patient rehabilitation [3], Parkinson's disorder recognition [4], and prosthesis devices controlling [5, 6] to improve the quality of life for the disabled and elderly people [7].

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Three main methods to process the sEMG data consist of onset time detection, feature extraction and feature classification. The first important part is the onset time detection because this part is used to determine the first peak of sEMG signals. Although we have the best feature extraction and the classification algorithms to interpret the signals, the inefficient onset time detection may give the erroneous results in automatic systems. However, from several literatures [5, 8, 9], most works consider only the feature extraction and the feature classification parts; the onset time detection process is not studied. Moreover, using the manual onset time detection is not appropriate for the automatic sEMG measurement systems.

According to the literature review, some works proposed the onset time detection techniques. For example, the Teager-Kaiser energy operator was applied for locating the onset time of a muscle activity [10]. The work in [11] developed a new algorithm to determine the onset time for measuring the sEMG signals in an inspiratory event. In [12], an autoregressive-generalized autoregressive conditional heteroscedastic (AR-GARCH) model was used to detect the onset and the offset times, and it also gave the better performance than a double-threshold detection technique. The work in [13] proposed a novel algorithm for the real-time onset time detection using the quasi-tension technique to detect wrist movements. In [14], the P&WND method was compared with the traditional Di Fabio's method to detect the EMG signals for a segmentation process. Finally, in [15], the maximum likelihood method was applied with an adaptive threshold technique to estimate the onset and the offset times of muscle contraction. Nevertheless, all onset time detection algorithms for finding the first sEMG signals from those research works as described above were evaluated on the computer. The complicated algorithms which are not suitable for an embedded system were used in those methods. Therefore, the simple algorithm which fits to be implemented in an embedded hardware is required.

This paper introduces a simple algorithm for detecting onset times of sEMG signals. There are two main processes in the proposed algorithm: the smoothing process for reducing the noise of the measured sEMG signals and the automatic threshold calculation process for determining the onset time. In addition, the proposed algorithm is implemented and tested using the LabVIEW program on the NI myRIO FPGA.

The proposed algorithm was analyzed in the MATLAB with measured sEMG data sets and the six statistic equations including standard deviation (STD), root mean square value (RMS), mean average value (MAV), waveform length (WL), simple square integral (SSI) and integrated EMG (IEMG). The algorithm analysis results demonstrate that using the SSI for both smoothing and thresholding (notation: SSI-SSI equation) with the 50-point window size gives the best result for detecting the onset time of the given sEMG data. Then, the SSI-SSI equation based algorithm was implemented on NI myRIO to detect the sEMG in real-time. The test results also show that using the proposed algorithm to detect onset times of the sEMG signals on NI myRIO gives the same results as the analysis.

Preliminaries

Data acquisition

To use the sEMG signals, the process starts when the sEMG is detected by the surface electrode. In this work, ten sEMG data sets were gathered from each hand motion. We used Ag/AgCl surface electrodes (*i. e.* 3M Red-Dot Solid Gel 2237) [16] to acquire the sEMG signals from both muscles, Flexor carpi radialis and Extensor carpi radialis longus. Two pairs of bipolar electrodes were placed lengthwise on the same muscle. One pair was placed on the

Flexor carpi radialis, and the other was placed on the Extensor carpi radialis longus. Both electrode plates were pasted on the skin surface of the right forearm of the volunteer. The displacement from the center to the center between each one is 20 mm. The reference electrode (*i. e.* ground electrode) was placed on the other wrist as shown in fig. 1(a). All sEMG signals were recorded by using Mobi6-6b (TMS International BV, Netherlands) [17] and stored in a text file. The band-pass filter in the range of 10-500 Hz was used to remove the motion artefact frequency and the random interference frequency. The sampling frequency was set to 1,000 Hz. The hand motions consist of one motionless (*i. e.* rest) and six types of the movements (*i. e.* wrist flexion (WF), wrist extension (WE), hand close (HC), hand open (HO), pronation (PN), and supination (SN)) as shown in fig. 1(b). Each movement was performed for 0.5 second and rested for 4 seconds in the duration. The process was repeated for ten times. An example of sEMG data from both muscles is shown in fig. 2.

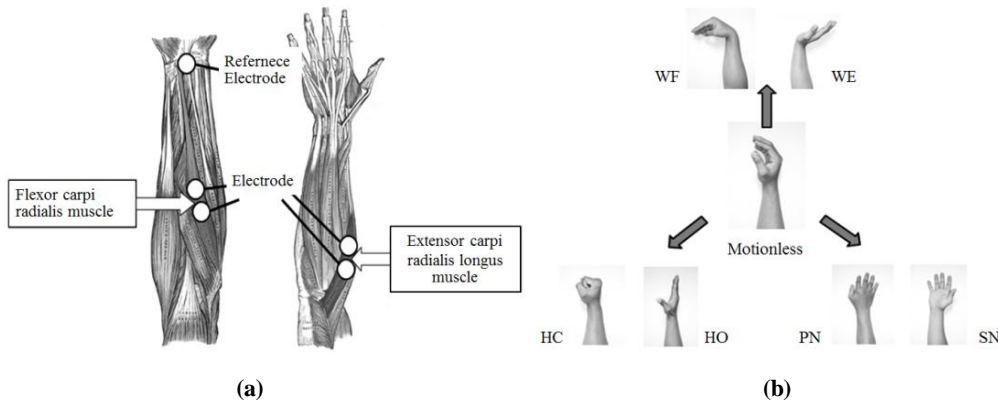


Figure 1. (a) Target muscles and electrode placement positions; in our experiment, the reference electrode is placed on the left wrist [18, 19]; (b) seven types of hand movements [20]

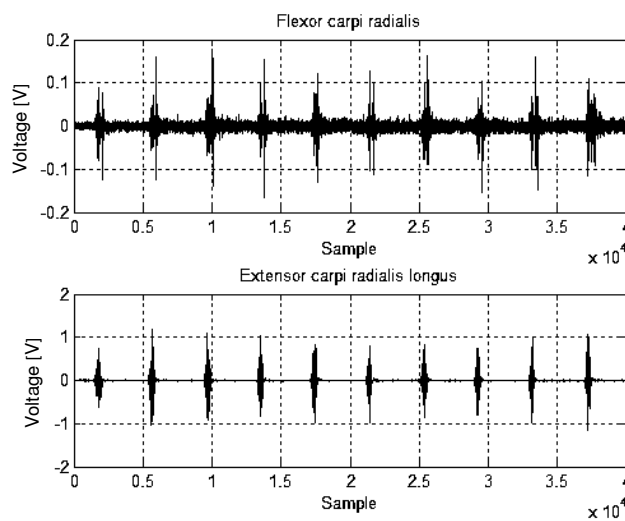


Figure 2. The sEMG signals from both muscles

Statistic equations

Many statistic equations are used as feature extraction for extracting the hand movements from the sEMG data [5, 8, 21]. Six equations which have provided the good result in the feature extraction [8, 21] are selected to represent smoothing and threshold calculations. Six gathered statistic equations used in this work are shown as follows:

$$\text{STD} = \left(\frac{1}{N-1} \sqrt{\sum_{n=1}^N (x_n - \bar{x})^2} \right) \quad (1)$$

$$\text{RMS} = \left(\frac{1}{N} \sqrt{\sum_{n=1}^N (x_n - \bar{x})^2} \right) \quad (2)$$

$$\text{MAV} = \frac{1}{N} \sum_{n=1}^N |x_n| \quad (3)$$

$$\text{WL} = \sum_{n=1}^{N-1} |x_{n+1} - x_n| \quad (4)$$

$$\text{SSI} = \sum_{n=1}^{N-1} |x_n|^2 \quad (5)$$

$$\text{IEMG} = \sum_{n=1}^{N-1} |x_n| \quad (6)$$

where N is the number of sMEG signals, x_n – the sEMG value at n^{th} point, and \bar{x} – the average value of the sEMG signals.

Proposed algorithm

In this section, we describe our proposed onset time detection algorithm. The proposed algorithm is distinguished into two processes: the smoothing process and the threshold calculation process. Both processes use those six statistic equations as described above to calculate the sEMG signals. We also describe how to implement the onset time detection algorithm on a real hardware by using the LabVIEW on the NI myRIO FPGA.

Onset time detection algorithm

To detect the onset time, the first intersection point between the smoothing and the threshold values of each sEMG movement is used in the processing. Six statistic equations in the previous section are used to create new 12 smoothing-threshold equations for testing the data. We use STD-STD, STD-RMS, STD-MAV, RMS-STD, RMS-RMS, RMS-MAV, MAV-STD, MAV-RMS, MAV-MAV, WL-WL, SSI-SSI and IEMG-IEMG to represent the notation of the corresponding smoothing-threshold equation. The first expression represents the smoothing process while the second expression represents the threshold calculation process.

In fact, six static equations can give 36 smoothing-threshold equations, but we use only 12 smoothing-threshold equations as mentioned above. This is because we cannot combine all six statistic equations as the smoothing and the threshold equation, since their calculated values are in the wide range. For example, the WL-STD cannot be used this way because the values from both equations are not in the same range. Using the WL as the smoothing process gets the value in range of 10^5 while using the STD as the threshold calculation process gets the range less than 10. Thus, both values cannot be combined as the smoothing-

threshold equation to give the good result. Therefore, we separate smoothing and threshold equations into four groups. The STD, the RMS and the MAV can be set in the same group, while the WL, the SSI and the IEMG are in three different groups. Consequently, there are 12 smoothing-threshold equations to be compared.

The method starts when the first motionless muscle signals were served into the system. Five hundred points of non-movement muscle are used to calculate the threshold value. This threshold value is used as the reference throughout the data set. Then, the window size is set to any arbitrary number of the data sample. The window is slid point by point since the first sEMG sample comes into the process until the end point of the data. When the first intersection between the threshold line and the smoothed sEMG signal at each window size is detected, the position is recorded as the onset time position. Finally, for detecting the next onset time position from the next hand movement signals, we move the window size out of the sEMG data range for 1,500 points. The list below shows the algorithm in the case of using the SSI-SSI as the smoothing-threshold equation at the 50-point window size.

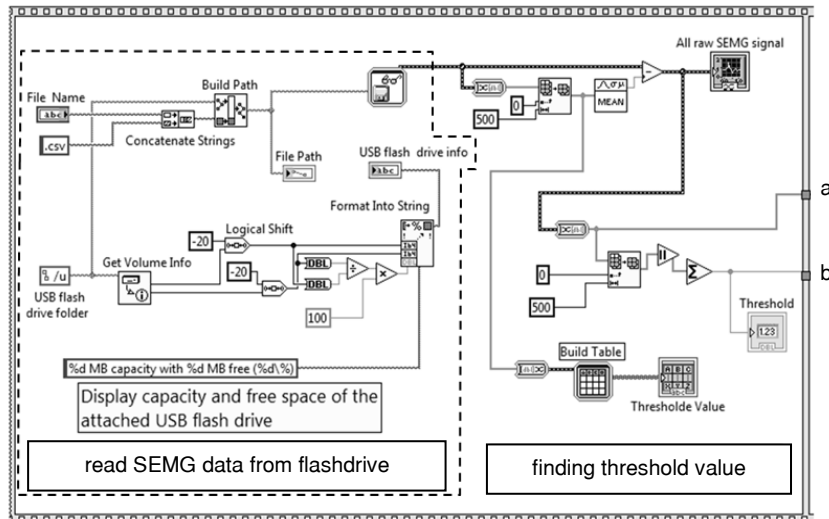
VARIABLES: *window_size, starting_point, ending_point, Smoothing, Threshold*

BEGIN

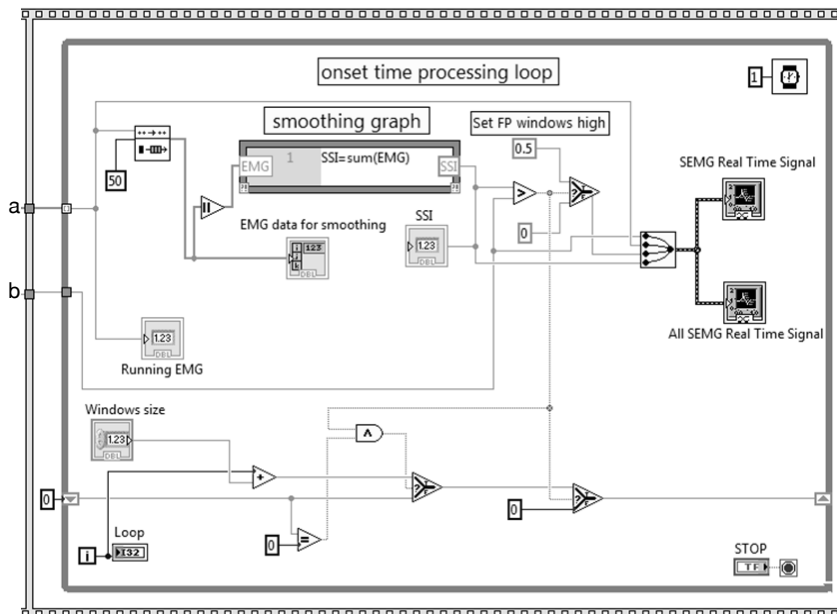
```
(1) // Initial value
(2) Window_size = 50;
(3) Starting_point = 1;
(4) Ending_point = number of sEMG data;
(5) // Main process
(6) Calculate Threshold from the SSI at 1-500 points of the first motionless
(7) FOR i = Starting_point to Ending_point
(8)   FOR n = Starting_point to Window_size
(9)     Calculate Smoothing from the SSI at this Window_size;
(10)  END
(11) IF Smoothing > Threshold THEN
(12)   Record the onset time position;
(13) // Move the considered point n and Window_size 1500 Point
(14)   n = n + 1500;
(15)   Window_size = Window_size + 1500;
(16) END IF
(17) ELSE IF
(18) // Move the considered point n and Window_size to the next Point
(19)   n = n + 1;
(20)   Window_size = Window_size + 1;
(21) END
END
```

Real-time onset time detection implementation

The real-time implementation is developed for testing the onset time detection algorithm. To evaluate the proposed onset time detection algorithm, ten sEMG data sets, as described in the previous section, were used to represent the real sEMG data from a patient. The sEMG files are stored in a flash drive which is connected to the embedded hardware NI myRIO. We used the LabVIEW program for writing the code to extract the sEMG data and to perform the onset time detection according to the proposed algorithm. Figure 3(a) shows the LabVIEW block diagram that reads the sEMG data sample by sample emulating the data sampling as in the real measurement. Then, the threshold value is calculated, and the result is sent to the smoothing calculation part in fig. 3(b). Finally, the onset time is determined. All parts are processed on NI myRIO in real-time.



(a)



(b)

Figure 3. The LabVIEW block diagrams (a) for reading the sEMG from the flash drive and calculating the threshold and (b) for smoothing the sEMG and finding the onset time

Results and discussions

In this section, the procedures consist of two main tasks. The first task is the algorithm analysis on the MATLAB program to find the best smoothing-threshold equation to be

used in the onset time detection algorithm. For the second task, the best smoothing-threshold equation is evaluated with the embedded hardware NI myRIO and the LabVIEW program.

Algorithm analysis

In order to investigate and to evaluate the performance of the onset time detection algorithm using the smoothing-threshold technique, we measure the displacement error between a manual detection and an automatic detection using the proposed algorithm. For the manual detection, the first peak sEMG data position is inspected by enlarging the signal graph to remark and record the onset time position. For the automatic onset time detection, 12 smoothing-threshold equations in the proposed onset time detection algorithm are performed. The displacement error is determined from the difference between the manual and the automatic detection positions of each technique from each hand movement.

From the experiment, the results show that using the WL-WL, the SSI-SSI, and the IEMG-IEMG gives the good results to detect the onset time positions, as shown in fig. 4. We found that, among these smoothing-threshold equations, the SSI-SSI provides the best performance. The example of finding the onset time position of the sEMG signal is also shown in fig. 5. In this figure, the onset time positions are determined when the different noises are presented. The result indicates that the efficiency of detecting the onset time position from the sEMG data with high noise is quite strong. For fig. 6, it shows the zoomed sEMG data with the onset time detection result. In addition, the displacement errors, while varying the window sizes 50, 100, 200, 300, and 500 points, are investigated, as shown in figs. 7 and 8. The results from this case show that using the SSI-SSI smoothing-threshold equation at the window size of 50 points gives the smallest error for finding the onset time detection. However, the window size smaller than 50 points has not been tried. From the result we can see the trend that if the bigger window size is used for the onset time detection, the onset time is found before the actual sEMG signal is activated. On the other hand, the sEMG signal is not smooth enough if the smaller window size is used instead.

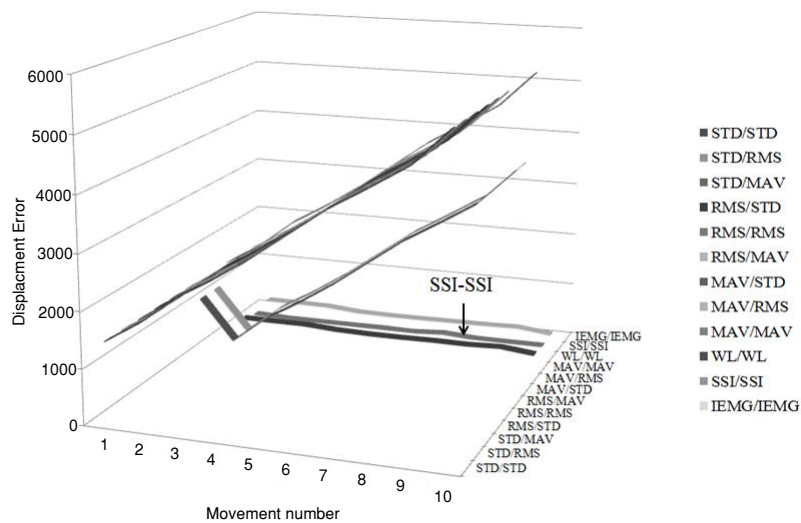


Figure 4. Displacement error from each number of movements in wrist extension motion

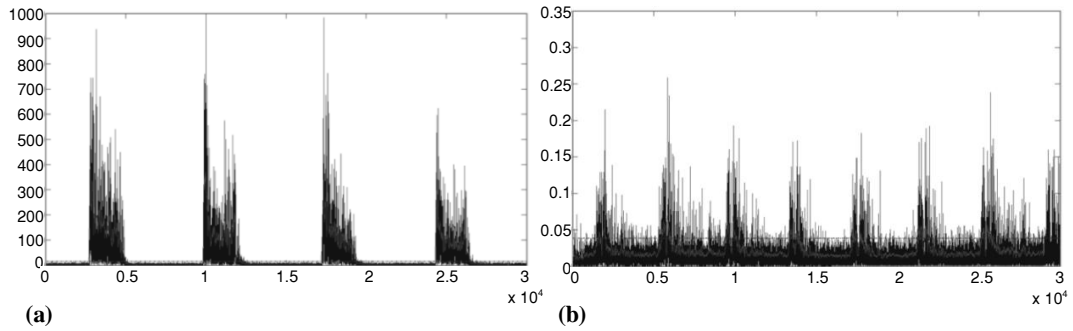


Figure 5. The example of finding the onset time position of the sEMG signal (a) at low noise and (b) at high noise

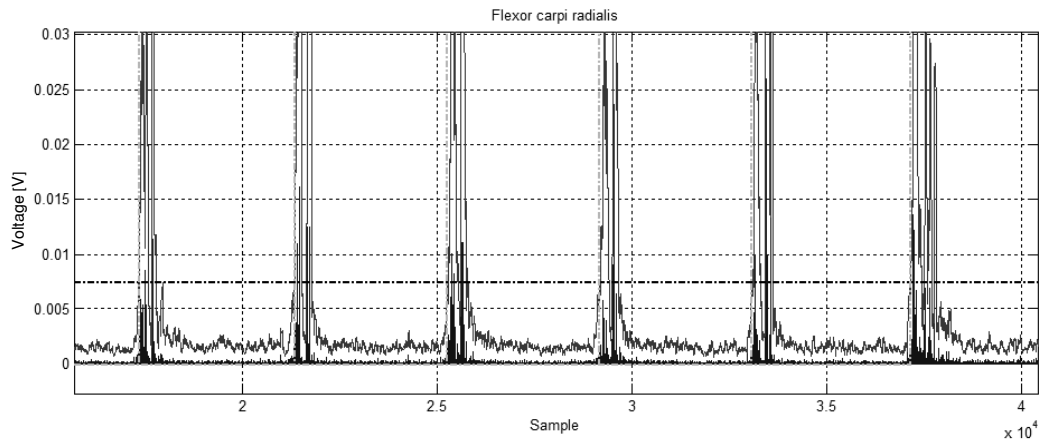


Figure 6. The zoomed sEMG data with the onset time detection result

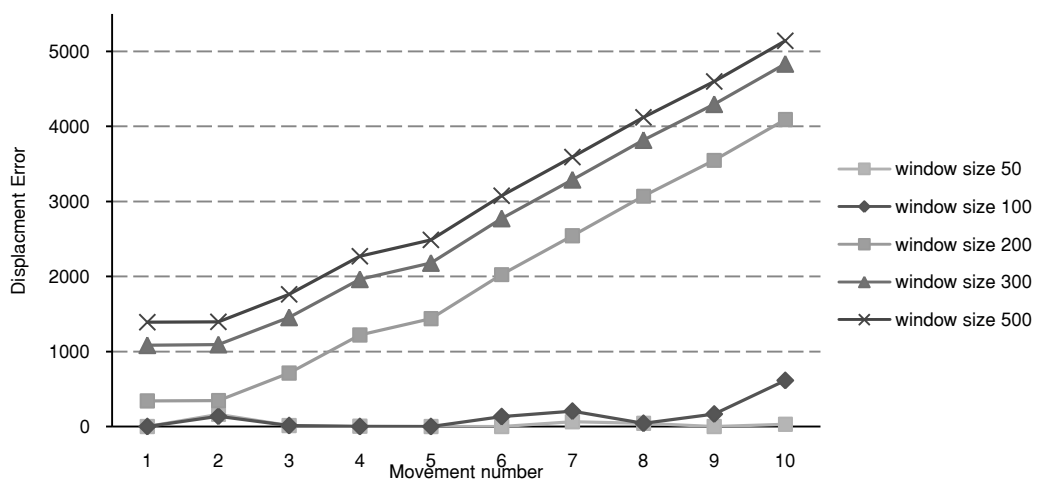


Figure 7. Displacement error using the SSI-SSI for the 50-point window sizes of the extensor muscle and wrist flexion movement

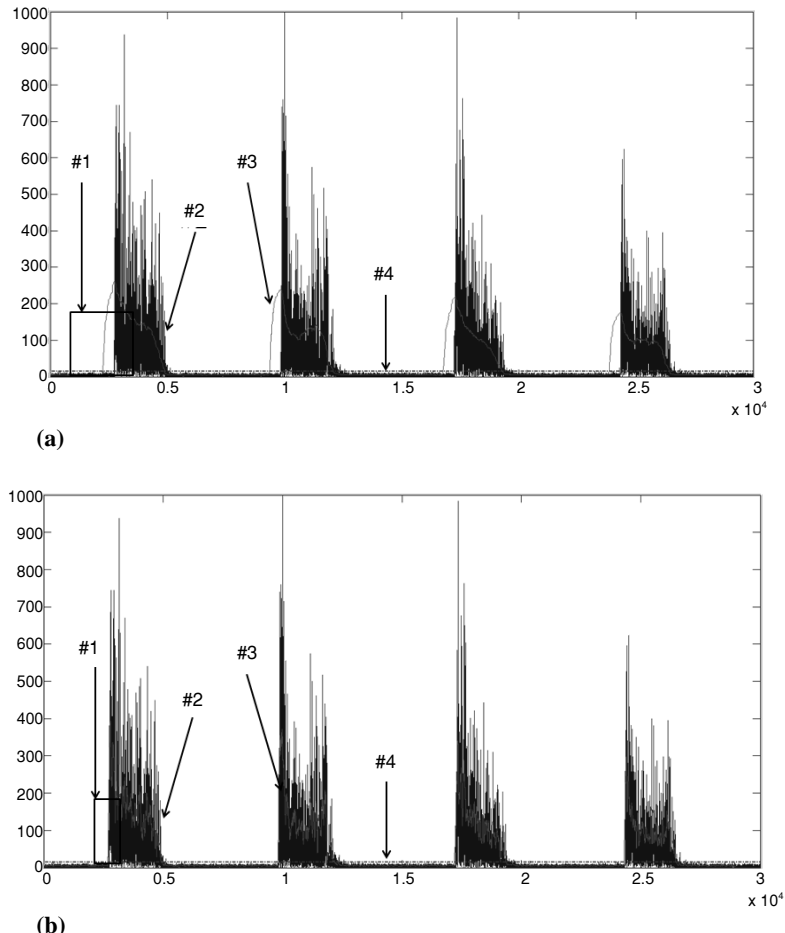


Figure 8. The onset time detection result (a) using the large window size and (b) using the small window size, the numbers #1, #2, #3 and #4 represent the window size, the sEMG signal, the smoothing sEMG signal, and the threshold line.

Test results

Before the algorithm is to be implemented on the real hardware for usage with a person in the real-time situation, the proposed algorithm was tested using the NI myRIO. The results are displayed on the LabVIEW program and the LED cube (for option), as shown in fig. 9. The recorded sEMG data is stored in the flash drive and released sample by sample to emulate the real-time sEMG signals from a real person. The algorithm is used to catch the onset time from the sEMG signals using the portable reconfigurable I/O device for studying from National Instruments known as the NI myRIO. It is the embedded hardware device that includes processor, communication and sensor parts. The main processing is the field programmable gate array (FPGA) Xilinx Zynq-7010 with two-core processors at the speed 667 MHz. The sEMG measurement system includes four main parts: the recorded sEMG (#1), the processing part (#2), the personal computer (#3), and the LED cube (#4), as shown in fig. 9. The real system as corresponding to fig. 9 is also presented in fig.10. For the processing part,

it consists of the onset time detection, the feature extraction, and the feature classification. As mentioned before in this work, we only focus on the onset time detection part for interpreting the sEMG signals. The implementation result indicates that using the proposed smoothing-threshold algorithm can properly detect the onset time of the sEMG signals in real-time, as shown in fig. 11(a) and (b).

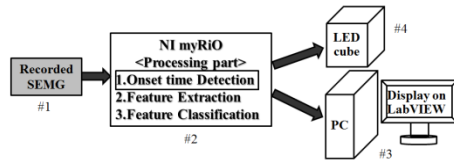


Figure 9. The diagram of the sEMG measurement system

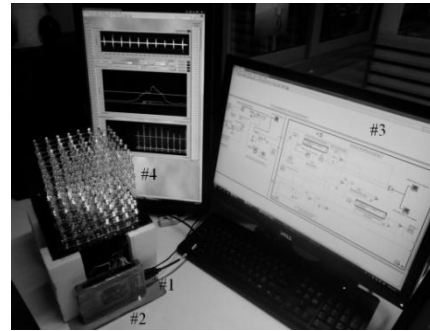
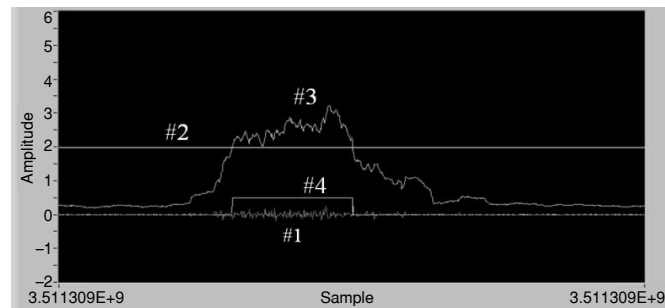
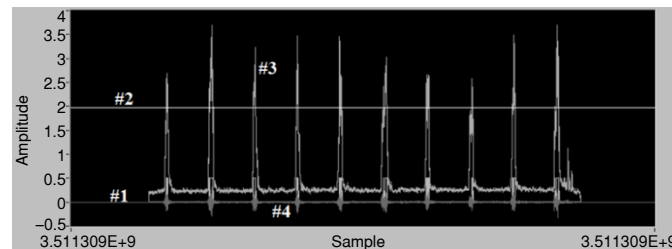


Figure 10. The experimental set-up of the onset time detection system using the NI myRIO; the onset time detection is displayed on the LabVIEW program and the LED cube



(a)



(b)

Figure 11. The onset time detection result (a) on a single movement in the real-time detection simulation and (b) on a continuous movement in the real-time detection simulation. The numbers #1, #2, #3 and #4 represent the raw sEMG signal, the threshold value, the smoothing graph, and the sEMG detection starting at the onset time detection

Conclusion

In this paper, we have proposed the new algorithm for the onset time detection of the sEMG signals using the relation between the smoothing data and the threshold. The performance evaluation by using the displacement error demonstrates that using the SSI-SSI for the smoothing and the threshold processes with the 50-point windows size gives the best result. Furthermore, the proposed algorithm has been continued to prove with the real-time sEMG simulation using the identical data. The NI myRIO was selected as the hardware to test the system preliminarily. The results show that using the SSI-SSI as the smoothing-threshold equation can appropriately detect the onset time in real-time. However, the whole process is attempted by only the given data sets. If we change the input sEMG signals, the result may change. The SSI-SSI may not give the best performance.

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