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A New Tool for the Automatic detection of Muscular Voluntary Contractions in the Analysis of Electromyographic Signals

ANGELA PIMENTEL[1,*], RICARDO GOMES[1], BJØRN HARALD OLSTAD[2] AND HUGO GAMBOA[1,3]

[1]Department of Physics, LIBPhys-UNL, FCT-UNL, Lisbon, Portugal
[2]Department of Physical Performance, Norwegian School of Sport Sciences, Oslo, Norway

[3]PLUX – Wireless Biosignals, Lisbon, Portugal
* Corresponding author: a.pimentel@campus.fct.unl.pt

Abstract:
Electromyographic (EMG) signals play a key role in many clinical and biomedical applications. They can be used for identifying patients with muscular disabilities, assessing lower-back pain, kinesiology and motor control. There are three common applications of the EMG signal: (1) to determine the activation timing of the muscle; (2) to estimate the force produced by the muscle and (3) to analyze muscular fatigue through analysis of the frequency spectrum of the signal. We have developed an EMG tool that was incorporated in an existing web-based biosignal acquisition and processing framework. This tool can be used on a post-processing environment and provides not only frequency and time parameters, but also an automatic detection of starting and ending times for muscular voluntary contractions using a threshold-based algorithm with the inclusion of the Teager– Kaiser energy operator. The algorithm for the muscular voluntary contraction detection can also be reported after a real-time acquisition, in order to discard possible outliers and simultaneously compare activation times in different muscles. This tool covers all known applications and allows a careful and detailed analysis of the EMG signal for both clinicians and researchers. The detection algorithm works without user interference and is also user-independent. It manages to detect muscular activations in an interactive process. The user simply has to select the signal's time interval as input, and the outcomes are provided afterwards.

RESEARCH HIGHLIGHTS
- An interactive analysis tool for electromyographic (EMG) signals has been developed.
- The tool gives the user control over signal processing algorithms, enabling human–computer interaction and provides visual information from the signals and processing results.
- This tool differs from the existing ones due to the inclusion of an automatic detection algorithm for the muscular voluntary contraction—threshold-based method with the inclusion of the Teager–Keaser energy operator.
- It allows a careful and detailed analysis of EMG signals both for clinicians and researchers.

1.   INTRODUCTION

In our daily activities, motor neurons carry electrical signals from the peripheral and central nervous system causing muscles to contract (Bronzino, 2000). Electromyography (EMG) is the registration and interpretation of action potentials generated in the muscle during contractions and represents neuromuscular activities. Detection of EMG signals with powerful and advanced methodologies is becoming a very important requirement in biomedical engineering. The main implementation of EMG signal analysis is in clinical diagnosis and biomedical applications. The field of management and rehabilitation of motor disabilities is identified as one of the most important application areas. EMG signals are used diagnostically by gait laboratories and by trained clinicians in tasks of biofeedback or ergonomic assessment. EMG is also an important biosignal to analyze in biomechanics, motor control, neuromuscular physiology, movement disorders, postural control and physical therapy (Reaz et al., 2006). Many clinical applications, such as gait analysis and coordination studies, require accurate detection of when, and for how long, muscles are activated. Generally, visual inspection is considered to provide highly accurate event detection, because all details of the signal can be assessed by the clinical specialists. Besides the accuracy in the detection, the speed of the algorithm can be an important consideration for specific applications (Merlo et al., 2003). However, for long acquisitions of repetitive movements the visual inspection can be time consuming, becoming an impracticable method for the biosignal analysis. Therefore, the use of an accurate algorithm for activation detection will benefit the user. There are several methods for analyzing the EMG signal. The most commonly used methods are in the time and frequency domain. In the time-domain analysis of EMG, the histogram is a valuable feature since it can provide information about the frequency with which the EMG signal reaches various amplitudes (Zardoshti-Kermani et al., 1995). Also important are the mean, maximum value, standard deviation (STD), root mean square (RMS) and total area of the overall signal (Bilodeau et al., 1992; Tkach et al., 2010). However, one of the most important parameters to extract from this type of biosignal is the activations. When the subject uses his muscles to perform a determined activity, the EMG signal varies. The detection of muscular voluntary contractions is an important EMG processing feature in many applications such as in the field of biomechanics of the human body, in the field of medicine and clinical diagnosis, in the development of rehabilitation devices and so on (Vannozzi et al., 2010). There are several onset detection algorithms developed for EMG signals. One of the most widely used algorithms is the EMG amplitude thresholding, introduced by Hodges and Bui. This technique is characterized by simple and fast implementation (Zhou and Zhang, 2014). However, the simplicity of threshold methods has drawbacks when the amplitude of the signal varies or when it is affected by noise. Besides threshold methods, there are other methods to detect when a muscular activation occurred, such as the generalized likelihood ratio, described in Micera et al. (1998). This showed better results than the threshold methods at a low computational cost. Other approaches have emerged as an answer to the problems when detecting EMG activations from signals with high levels of noise, such as the wavelet transforms method presented in Vannozzi et al. (2010) or the Teager–Kaiser energy operator (TKEO) (Solnik et al., 2010). Frequency domain analysis of EMG can also provide valuable information concerning certain characteristics of muscular activity in the human body. It has been shown, for example, that the mean power frequency of the EMG power spectrum can be used to estimate the muscle fiber types (I or II) content of a given muscle (Bilodeau et al., 1992). According to Alty and Georgakis (2011), the most commonly used spectral variables in EMG fatigue analysis studies are the mean and median frequency. There are currently several EMG analysis frameworks available: Noraxon— Superior Evidence-Based Biomechanics (Noraxon, 2014), Motion Lab Systems Software—EMG Analysis (Motion-Labs, 2014), EMGWorks Software (Joe, 2014), MindWare—EMG Analysis tool (MindWare, 2014), B&L Engineering—EMG Analyzer Software (B&L Engineering, 2014). These are some examples of EMG processing tools that can be found in the literature which provides time and frequency analysis such as our tool. However, they do not allow the automatic detection of muscle activation. The user has to manually identify each activation in order to get the information of interest. EMG analysis is of the utmost importance in several applications where the

muscular activity assessment is needed. Since the majority of EMG analysis tools require manual EMG activation detection, the development of an automatic muscular onset detection tool for this type of biosignal processing would help the scientific community. Our main goal was to develop an EMG analysis tool with the inclusion of an automatic detection algorithm for muscular voluntary contractions. The developed tool also surpasses the currently available tools in what portability is concerned, since it can be executed in a web environment. This tool also provides time and frequency parameters from an EMG signal. The algorithm performance was assessed by visual inspection, where in this case in particular, all activations performed were correctly identified. However, further usability tests should be undertaken in order to validate our tool. Besides, as a mean to assess our algorithm's performance, we will test it with signals from different subjects (each subject might perform many different activities) in order to validate the algorithms robustness. In the following section, the EMG analysis tool is explained in more detail. This includes the acquisition system used to test the tool, the application platform where the EMG tool was inserted and a description of the algorithm implementation. The activation detection algorithm is used for two different approaches— Fig. 1: (1) in a rapid assessment environment where the activation starting time is displayed before finishing an EMG acquisition. This allows to discard possible outliers when dealing with many EMG acquisitions; (2) in a post-processing environment where the user may study more carefully each EMG signal with a variety of time and frequency parameters. Two applications using this tool are stated and the results are then assessed using visual inspection. Finally, we discuss some improvements that can be made and conclude the work.

2.   EMG ANALYSIS TOOL

We developed an interactive tool which runs in a web environment, and can therefore be easily accessed from anywhere with an Internet connection. The tool gives the user control over signal processing algorithms, enabling human– computer interaction and provides visual information from the signals and processing results. The EMG detection is processed very fast, and the user can have immediate feedback over several features of the signal, which will be described.

2.1.   Acquisition system

The EMG signals were acquired with a Bioplux (Plux, Lisbon, POR) system that allows the real-time and combined acquisition of eight EMG signals. This device collects and digitalizes signals from sensors transmitted via Bluetooth to the computer where signals are shown in real-time. The signals are sampled at 1 kHz, which is the maximum frequency allowed by our acquisition device, with a 12 bit resolution and recorded in a text or HDF5 format. This device also provides a channel for the connection of a reference electrode, an essential requirement to correctly monitor EMG signals (PLUX, 2014). The electrodes were placed in the arm and a simple task, such as open and close the hand was executed three times, in order to provide three distinct activations.

2.2.   Acquisition and visualization framework

In order to allow users to analyze EMG recordings immediately after the signal acquisition, we incorporated the developed EMG processing algorithm in an existing web-based biosignal acquisition and processing framework (Gomes et al., 2012). This enables the simultaneous acquisition and real time visualization of eight analog sensor channels. The signal acquisition and management tool, where the EMG processing tools were incorporated, was based on a client–server model.

In the server side, a python engine manages connections to the Bluetooth port, allowing the communication with the acquisition devices, saves data and responds to the clients requests. According to Gomes et al. (2012), the data management is done using a biosignal data structure based on the HDF5 file system (HDF-Group, 2014). This allows the storage of very large datasets with easy and fast access, since this is a hierarchical data format which facilitates data querying. There is

graphical user interface based on HTML5 and CSS. To enable interactivity, JavaScript functions were developed to create a communication channel between client and server. For this communication, we used the standardized websockets protocol. The client application offers several functionalities related to biosignal acquisition and processing. The user has the possibility to set up the acquisition variables, such as the selected device, the sampling frequency, the channels to acquire and the sensor types. During the acquisition, the user is able to see the acquisition data streaming in real-time, being able to manipulate the graphs.

After the acquisition is concluded, the user can save the acquired data in the specified data structure, or in a simple tab separated text file. In this step, not only the raw acquired data is saved, but also the data mining presented in Gomes et al. (2012). With the saved files, users are then able to visualize the acquired data in post-acquisition mode. The visualization is done by layers, and the user has access to higher detail data when visualizing small portions of the signal. This allows an easy navigation through the entire signal, through zooming and panning operations that are leveraged by the speed of our tool. When analyzing large acquisitions, the visualization tool displays the subsampled data resulted from the data mining process also described in our earlier work. The client-side graphical interface was created aiming at speed and efficiency. Thus, all the signal channels are displayed using the scalable vector graphics (SVG) technology, and not a standard, off-the-shelf drawing library for HTML5. This approach involves the manipulation of low-level programming of the drawing routines, instead of calling standard display methods already developed on top of HTML5 canvas. Since SVG is XML based, every SVG element can be attached with JavaScript handlers. Each SVG drawn shape is remembered as an object, which can be changed later, and re-rendered by the browser, while for canvas elements, there is no memory, which implies that with any change in the data, the browser needs to repeat the drawing process from the beginning. Since the signal acquisition and visualization application is executed in a web browser, the proposed tool is highly portable, and has potential to be accessed from anywhere with an Internet connection. Besides the wireless data transmission using Bluetooth technology and biosignal visualization in real-time, our base framework enables users to run the analysis of EMG records on the acquired data. In this EMG analysis tool, it is possible to simultaneously visualize the portion of the signal being analyzed and the processing results in an interactive process. The user is able to select only the part of the signal that must be analyzed, and receives the signal processing results for that interval. In this visualization tool, an ECG analysis has already been implemented (Chorão et al., 2012), providing the user a higher variety of signal processing analysis. Besides these two signal analysis functionalities, our biosignals framework also features a video synchronization feature, which can be very useful even in EMG studies. This feature allows users to synchronize a video from the recorded activity with the acquired biosignals, and playback the acquisition and the video simultaneously. Using this functionality, data analysis is leveraged since the biosignals can be associated with a record of the subjects activities, providing the researcher with a useful way to analyze these data.

2.3.   EMG activation detection

EMG analyses require detection of different muscular contractions. In our work, this is achieved using an EMG algorithm that detects both starting and ending times of the existing muscular contractions. The detection was an adaptation of the threshold-based method (Hodges and Bui, 1996) with the inclusion of the TKEO. As it was already reported, the addition of TKEO as a step in conditioning surface EMG signals increases the detection accuracy of EMG burst boundaries (Solnik et al., 2010). The algorithm for events detection has several phases. The first operation consists in filtering the acquired signal to extract outliers resulted from noise or artifacts introduced by the movement of the subject. For this purpose, a band pass filter was applied between 10 and 300 Hz. According to Merletti et al. (2009), to efficiently filter surface EMG signals without loss of information, a high-pass filter with a 10–20 Hz cutoff frequency and a low-pass filter with 400–450 Hz cutoff frequency should be used. However, these cutoff frequencies did not produce the expected results in our signals. Therefore, we had to adapt these frequencies, and finally got to the range 10–

300 Hz for our band pass filter. After filtering, the muscular detection activation signal (TKEO operator) at each time point j was calculated from the filtered emg signal with the following formula:

$$TKEO[j] = emg[j]2 - (emg[j + 1] \times emg[j - 1]). \quad (1)$$

A smooth filter was applied over the activation signal to smooth variations, thereby allowing more stability in the detection of the muscle activations instants. The activations operator (TKEO) was then compared with a threshold that was set to 8. The threshold value indicated by Solnik et al. (2010) should be: $T = \mu + h\sigma$, where μ and σ stands mean and STD of the EMG signal, respectively, and h is a preset variable defining the level of the threshold. The value 8 was chosen after several values had been tested and which resulted in lower detection efficiency, however, as future work we intend to allow the user to edit this value before processing the algorithm. The final output of the algorithm generates a unitary signal where the operator assumes values above the threshold and zero values in the remaining moments. With this final signal, the start and end instants of each muscular activation were calculated. All signal processing algorithms were written in Python and SciPy, a Python package for scientific computing. The application platform was created using JavaScript and HTML browser-supported languages.

2.4.   Rapid assessment

This section describes the algorithm on a rapid assessment environment. The user executes a real-time EMG acquisition and before saving the recording, the algorithm outputs are shown. This allows the user to compare different EMG signals at the same time, understand which muscles are activated first and discard possible outliers. An example is shown in Fig. 2 for three EMG sensors placed in different positions in the arm. The algorithm in this rapid assessment environment detects the first muscle voluntary contraction and displays the starting time of that activation with its maximum voluntary contraction.

Figure 2 shows the pop-up message used to finalize and save a signal acquisition with the algorithm outputs. The results are ordered according to starting time in seconds. The maximum voluntary contraction is also displayed in mV and each EMG signal can be labeled to facilitate its investigation. However, to have a better understanding of each EMG signal a post-processing analysis is suggested, where more time and frequency parameters are displayed. Figure 1 shows the architecture of our tool.

2.5. Post-processing

The EMG signal can be analyzed in all its extension. However, the user may choose to analyze only a particular time interval of the signal. The EMG analysis tool is composed of time and frequency parameters. The time parameters are displayed for the overall signal and individual activations detected. The outcomes can also be presented in percentage. If that is of the user interest a 'Convert to %' button is displayed before processing the signal. A new input section will be displayed so that the user can include the maximum activation in mV. Also, some visual representations are presented. All of this information is allied to the biosignals visualization tool to allow for a more detailed data inspection (Fig. 3).

The time parameters for the selected time interval is visible in Fig. 3. These parameters are: mean (Mean); maximum value found in the signal (Max); minimum value found in the signal (Min); STD; RMS; total area (Area). The activations analysis is also presented. This analysis uses the activation detection algorithm explained in Section 2.3. The number of activations found in the overall signal is shown (Nr Act.) which are in agreement with the number of executed activations. If the user want more information regarding the activations, he can select the activation of interest from the drop-down list (Get info from Act. Nr). This includes the starting time of the activation (Start) in seconds, the ending time of the activation (End) in seconds, the maximum value of the

contraction selected (Max), the mean (Mean), STD, the RMS and the total area (Area) of the contraction selected. For this signal in particular, starting and ending times of all activations are in agreement with visual inspection. The algorithm results for all activations are shown in Table 1 and the starting and ending times can be compared with the signal visualization displayed in Fig. 3. It is also important to note that all of the information is automatically saved in a file allowing the user to later access the information for statistical purposes. As it had been reported in Gomes et al. (2012), we used the HDF5 file format, since this is an easily accessible format and has little access times if we are aiming at dealing with long-term EMG acquisitions which might contain a large number of muscular activations to detect.

A different case study was performed in order to prove that this algorithm can be used in other situations. A female world-class swimmer and Olympic medalist was tested during breaststroke swimming at 60% of maximal effort. She swam 25 m and for a specified time window she performed 12 stroke cycles. The algorithm was tested in one muscle—the tibialis anterior. The tool proved once again its effectiveness, since the algorithm accurately detected the 12 movements and the starting and ending times were in agreement with visual inspection. Still, more usability tests need to be executed in order to strengthen our tool and our algorithm detection. The frequency parameters are shown in Fig. 4. It includes the mean, median and maximum power frequency in mV and the total power in mV 2. The visualization tools available are the histogram shown in Fig. 5 and the power spectral density (PSD) in Fig. 6. According to Zardoshti-Kermani et al. (1995) and Alty and Georgakis (2011), these are important features to study in EMG signals. This graphical information complement the user's analysis by allowing verification of the noise effects in the signal. The histogram's shape and statistical information can be used to assess the data distribution, and the PSD will allow determining the power spectral over the different frequencies.

3.   DISCUSSION

We have successfully developed an EMG analysis tool that can be used both by researchers and clinicians. The findings over the two different applications described are that the algorithm accurately detected all activations performed. Time and frequency parameters can be obtained from the processed signal as well as individual information of each activation detected. Still, more usability tests should be performed in order to strengthen our tool and our activation detection algorithm. Feedback from users regarding the functionalities in the developed tool will be important for future improvements. We also compared our results with the Noraxon software. The mean and maximum values of the time domain and the mean and median frequency values of the frequency domain were the only metrics that could be compared, and although we had to manually identify each activation with the Noraxon software, the results were in agreement with our tool.

Despite our good results, our tool also presents some limitations: the threshold cannot be modified and was set at 8; the signal is filtered with a band pass filter from 10 to 300 Hz and we can only process one signal at a time.

Like any algorithm, and given that a threshold-based method was used, the developed tool may fail to identify a voluntary contraction. Therefore, the inclusion of different algorithms for the muscular contraction detection should be addressed, in order to strengthen this tool by providing different approaches for EMG analysis. For this, adaptive threshold methods are a possible approach to avoid errors in the analysis. We believe that this tool can also be improved by allowing the user to set up his preferences in signal filtering, before processing EMG data and running the activations detection algorithm. We also intend, as a first approach, to provide the user with the possibility to edit the threshold weight factor before processing the signal, since the algorithm accuracy depends on this factor, and may vary according to the type of exercise that was performed. Later we intend to provide automatic threshold detection by using a calibration process where the user should provide a known EMG signal with manual annotations of the activation timings. With these manual annotations, the tool should test different threshold values and select the value that enables to

correctly determine the activation timings. A future development should also be the inclusion of accelerometry data as a mean to minimize the influence of movement artifacts from the EMG data (Luca et al., 2010). In the post-processing circumstances, a single signal must be processed at a time, and we intend to expand this processing to all signals simultaneously to allow the comparison of all the processing results at the same time. Last but not least, to facilitate the researcher's analysis, we intend to display the detected activations by drawing its starting and ending times in the visualization tool along with the signal. With these future improvements, we will overcome the current limitations of the presented tool, meaning our goal is to present a versatile tool for automatic activation detections allowing the user to previously set its preferences according to the type of protocol that is using with EMG signals.

4. CONCLUDING REMARKS

In this work, we developed an interactive analysis tool for EMG signals that differs from the existing ones in the literature due to the inclusion of an automated detection algorithm for muscular voluntary contractions. This tool runs in a web environment and enables human–computer interaction by providing the user access to visual information from the signals and processed results. Taking into account the described features, we conclude that it offers a flexible, detailed and accurate way of analyzing EMG signals. The analysis tool takes only a few seconds to perform the EMG activations detection. Its flexibility and possibility of a personalized and detailed analysis make it suitable for both clinicians and researchers. Its user-friendliness makes it pleasant to use and easy to learn, two very important characteristics in any software project according to Holzinger (2005). The zooming capabilities and synchronization with a biosignals visualization tool makes it highly interactive and provides a better and faster data discovery. For future work, we intend to add new important features for the EMG analysis, different types of activation detection algorithms (e.g. double-threshold detector Bonato et al., 1998 or adaptive threshold methods), simultaneously run the activations detection algorithm for all measured EMG signals and allow for individual preferences in the signal filtering steps before applying the activation detection operations. We also aim to perform more tests with the developed algorithms, not only for accuracy and speed performance, but also concerning the possibility of adding noise to the EMG signals and analyze the influence in the detected activations.

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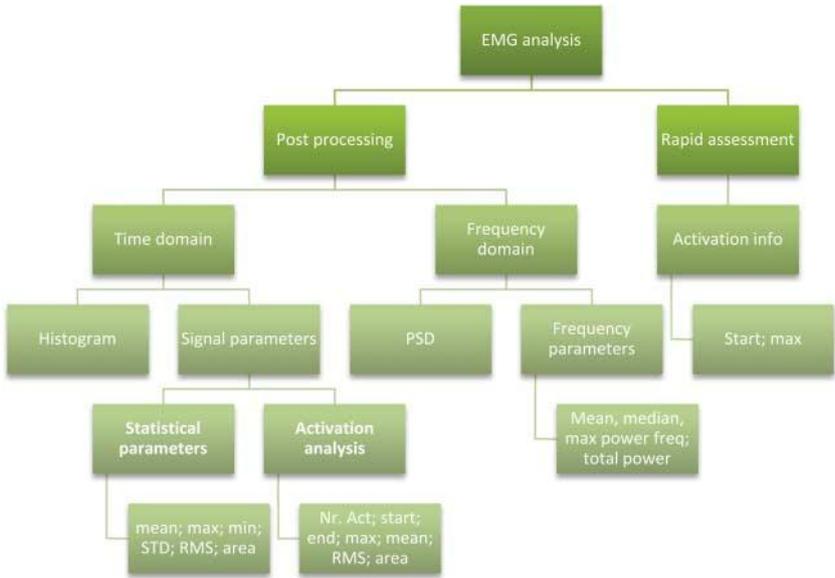
Figure 1. Architecture diagram for the EMG analysis tool.

Figure 2. Rapid assessment for EMG algorithm activation detection. The algorithm outputs are displayed before saving the acquired signals.

Figure 3. Time parameters of an EMG signal for the overall signal—statistical parameters; and for each activation found—activation analysis. The EMG tool was incorporated in parallel with the visualization biosignals environment.
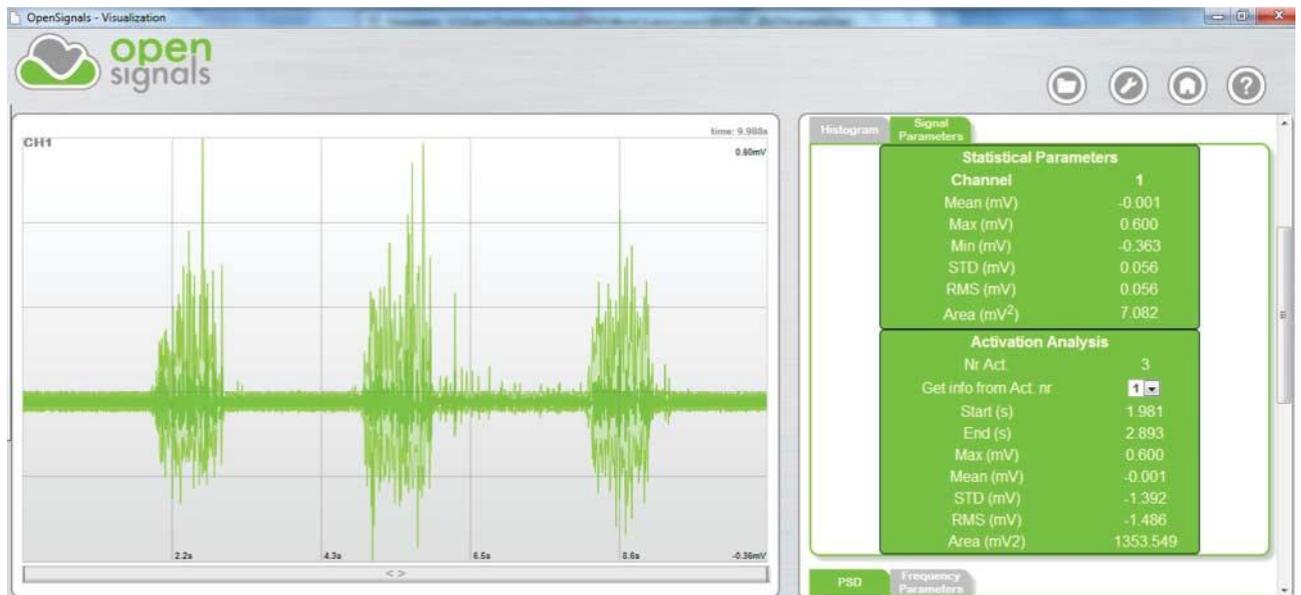

Table 1. Results for each activation detected.

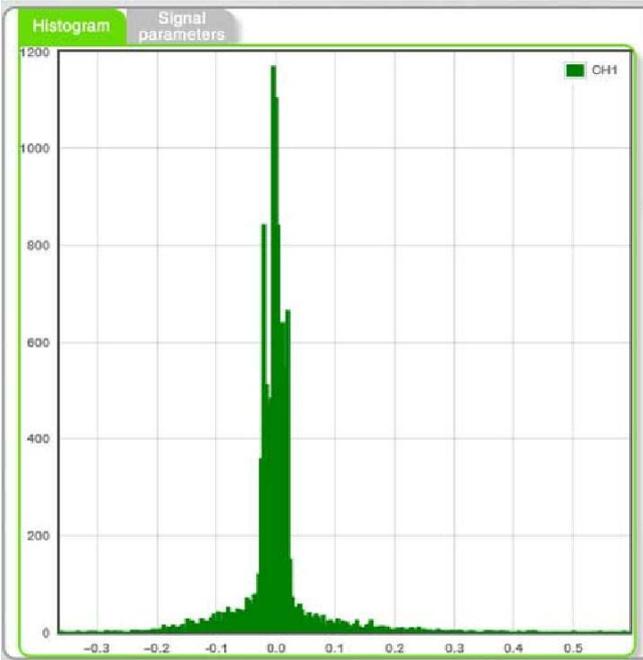| Act. Nr	1	2	3
Start (s)	1.981	4.940	8.206
End (s)	2.893	6.009	9.147
Max (mV)	0.600	0.587	0.437
Mean (mV)	0.001	0.001	0.001
STD (mV)	1.392	1.376	1.385
RMS (mV)	1.486	1.483	1.484
Area (mV^2)	1353.549	1587.130	1399.509

Figure 4. Frequency Parameters of the selected signal.

Figure 5. Histogram.

Figure 6. Power spectral density.