RESEARCH ON RECORDING AND FILTERING ELECTROMYOGRAM (EMG) SIGNALS

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ABSTRACT: In this article will be presented a novel way to record and filter the Electromyogram (EMG) signal. EMG signals are generated when the muscles activates. In our case the user's eye muscle movements in any direction will be recorded and filtered, so we will be able to observe when the user looks with his/her eyes up, down, left or right. In this article we use the non-invasive EMG signal recording system (which uses Ag/AgCl electrodes for recording) to differentiate the user's eye positions.
The EMG signals are recorded from near eyes positions, using only 3 differential channels out of 4 differential channels offered by a 24-bit Analog Digital Converter (ADC), model NI-9234 and it's afferent NI-USB 9162 High Speed USB Carrier, both made by National Instruments (NI). The signal recording and filtering program is made in Matlab R2012b (mathworks.com).
The experimental research presented in this article is made during the studies to realise the author's doctoral thesis.
KEY WORDS: Electromyography, Electrooculography, EMG, EOG, eye muscle movements, mouse cursor control.

1. INTRODUCTION

The electromyographic (EMG) signal is generated by contraction of muscles. According to [1], in the 20th century the EMG became widely used in medicine and kinesiology. Detecting the muscle activities onset and cessation and its overall signal amplitude is of great importance in this domain.

As historical review, the use of the EMG for control purposes of limb prostheses was first demonstrated by Reiter in 1948 [9].

The threshold is a fixed voltage, expected to be exceeded upon muscle activation [1]. A simple thresholding method is related to the maximum value of the EMG signal's envelope [1].

The detection of relative minima, maxima, inflexion points etc. provides an alternative way to thresholding, so the problems which can emerge with proper threshold adjustment can be eliminated [1].

In some articles (articles [1]-[9]) are presented some information from the EMG domain: for example in [2] a high density surface EMG (HDsEMG) was used. The detection of muscle activity using EMG can be used in many applications, like posture and gait analysis, motor control, and myoelectric control of prosthetic devices, as found in [3].

In Figure 1 is presented the EMG recording and filtering diagram.

In article [10] eye movements in acute sensory stroke patients was evaluated. In [11] the EOG signals were used as indicative of Parkinson's disease (PD). Their study suggests the existence of early PD biomarkers. In [12], non-invasive EOG recordings were used to detect a person's alertness/drowsiness level.

Surface electromyogram (EMG/sEMG) is the potential recorded over the skin resulting from the generation, propagation and extinction of current sources that induce muscle fibre contraction [2].

Real-time eye movement classification "is a technique based on eye movements, which are measured to determine where a person is looking at any given time and the sequence in which their eyes shift from one location to another" [14].

In [3] the time-frequency representation, in [4] a wavelet based method for artefact removal from EMG signals is presented; in [5] and [6] the authors compared the power spectral changes and spectrum in muscle fatiguing contractions and in [7] feature changes with muscle fatigue are presented. In [8], β and γ bands are compared to cognitive and emotional states. In [9] is presented the implantable MyoPlant EMG system, which is measuring and using the intramuscular EMG (imEMG) signals.

1.1 Electrooculography (EOG)

Electrooculography (EOG) is a related domain with our MEG (sMEG) application, because in our application both are recording, filtering and using the eye's movement to control electronic devices.

The definition of EOG can be found in [13]: "EOG interfaces detect eye movements by measuring the

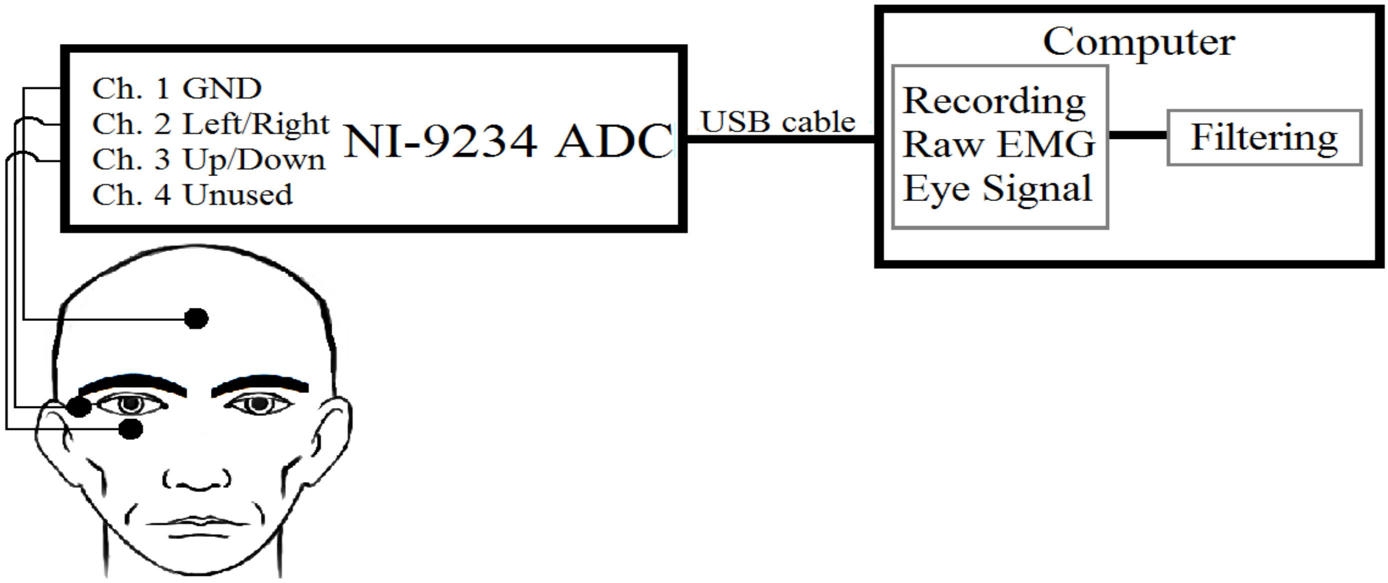

Figure 1. EMG recording and filtering diagram

difference of potential between the cornea and the retina".

In [13] an EOG robotic limb interface is presented, which is able to perform pick and place tasks. In [14] an online classification algorithm for eye-movement-based communication systems using two temporal EEG sensors is presented. In [15] EMG, EOG and other biosignals are used as biometrics for human recognition.

In [16] the authors reviewed the low-power technologies in wearable telecare and telehealth systems, including EOG and EMG based systems. In [17] is presented a manipulator based on EOG control signals.

2. METHODS

In this section will be described the procedure how we prepared the system and the user's skin, what electronic devices we used and what positions of recording we used and why we used them.

The experimental research presented here was made on the author, by using the equipment that will be described below and realised in the SmartMAT laboratory (Nanomaterials Research Laboratory) of the University of Oradea.

First of all, the recording/filtering problems must be presented, which can seriously affect the result of the recording. This list's elements were found in articles [1], [4], [9] and [14] respectively (the found problems are sorted in alphabetic order):

- (Induced) electrode artefacts;
- Crosstalk;
- EMG can also record electrical activities of adjacent muscles;
- External noise;
- Increasing fatigue;
- Movement optimization(s) during recording;
- Posture adjusting;
- Sensors can be obtrusive;
- Sensors can cause discomfort of the user;
- The human body can't perform precisely periodic movements;
- The repetitive movement is performed in slightly different ways;
- Tissue filtering.

Muscles around the eye were chosen because the contraction and relaxation of these muscles and their muscle activity are clearly visible and so the EMG signal is easier to record, filter and further to process [1].

The NI 9234 ADC has the following parameters [18]: 51.2 kS/s per channel maximum sampling rate; ±5 V input; 24-bit resolution; 102 dB dynamic range; anti-aliasing filters; Software-selectable AC/DC coupling; AC-coupled (0.5 Hz); Software-selectable IEPE signal conditioning (0 or 2 mA); Smart TEDS sensor compatibility; -40 °C to 70 °C operating range, 5 g vibration, 50 g shock.

The sampling rate of the recording was 51.200 Hz and we processed 10s of the steady part of the recording.

Signal recording and filtering was performed using MATLAB (version R2012b; The MathWorks, Inc.), using our original script files.

Surface Ag/AgCl disc electrodes were used, as presented in Figure 3. The designated places (the skin of the user) for the disc electrodes were cleaned with sanitary/rubbing alcohol before applying the electrodes. The cleaning procedure was used in order to provide a good skin-electrode contact.

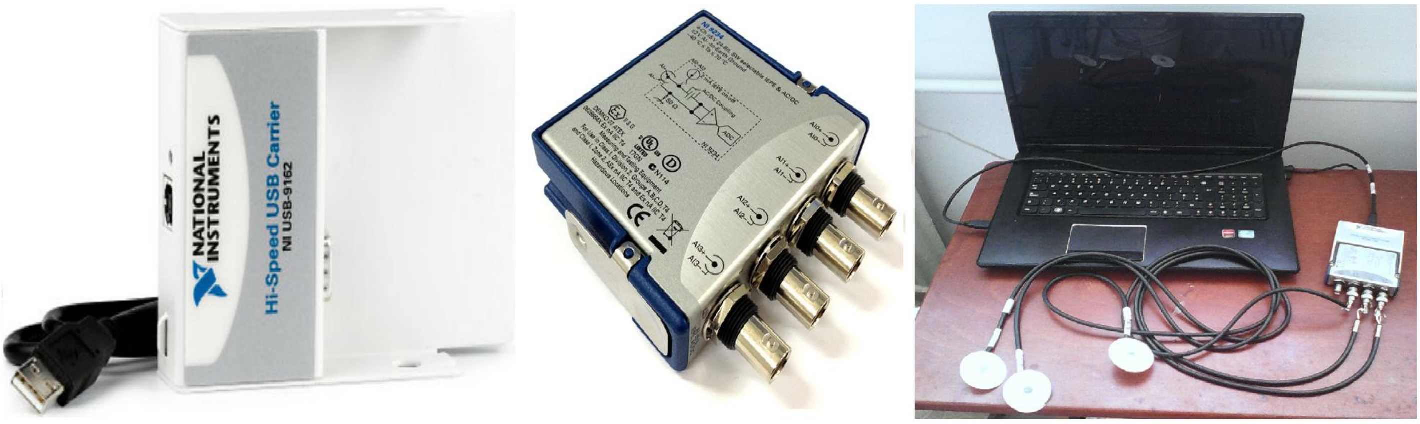

Figure 2. The NI-USB 9162 High Speed USB Carrier (left); The NI-9234 ADC (middle); The whole recording system (right)

Figure 3. Example of Ag/AgCl electrode used in recording

In Figure 2 is presented the NI-USB 9162 High Speed USB Carrier from [18], the NI-9234 Analog-Digital Converter (ADC) from [19] and the whole recording system respectively, including the Ag/AgCl electrodes, electrode cables, the ADC, USB cable and the laptop.

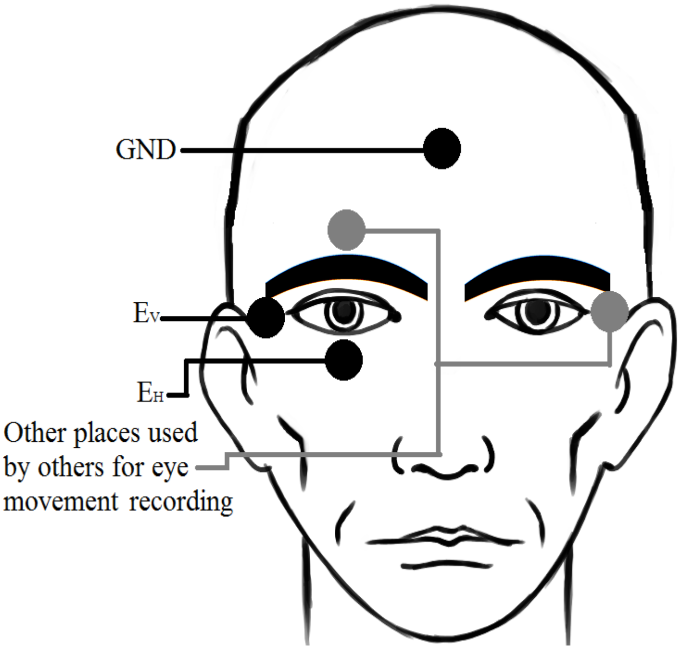

Figure 4. EMG signal recording positions

The used laptop, on which the program will run, is a Lenovo G770. Its processor is a 64-bit dual core Intel I5-2450M, with 8 GB RAM installed memory, 500 GB HDD and its afferent 17 inch monitor. The operating system is Windows 10, on 64 bits. The MATLAB program's version is R2012b.

In Figure 4 are presented the EMG signal recording positions, where E_V and E_H are the electrodes for vertical and horizontal eye movement recording.

In the following lines will be presented the algorithm written in MATLAB and which was applied to all EMG channels: first of all, the sampling rate was set to 51200 samples per second and the duration of the recording was set to 10 seconds.

In order to acquire the data from the sensors we use the session based acquisition mode "startForeground" to start an operation that blocks any MATLAB command until the operation completes. The sequence which allows the data acquisition is the steps specified bellow:

a) Create a session specifying the device (National Instruments) and define three analog input channels;
b) Configure the range of the channels in the session as +/- 5 Volts;
c) Set the rate to 51200 samples/sec and the duration to 10 seconds of the acquisition;
d) Acquire data in the foreground using the "startForeground" command.

After acquiring the data the signals are processed according to the following steps.

1. Subtract the mean value of the signal from the signal in order to eliminate the bias of the measurement;
2. Compute the values of the Fast Fourier Transform (FFT) of the signal using the following relation:

$$X(k) = \sum_{j=1}^{N} x(j)\omega_N^{(j-1)(k-1)} \qquad (1)$$

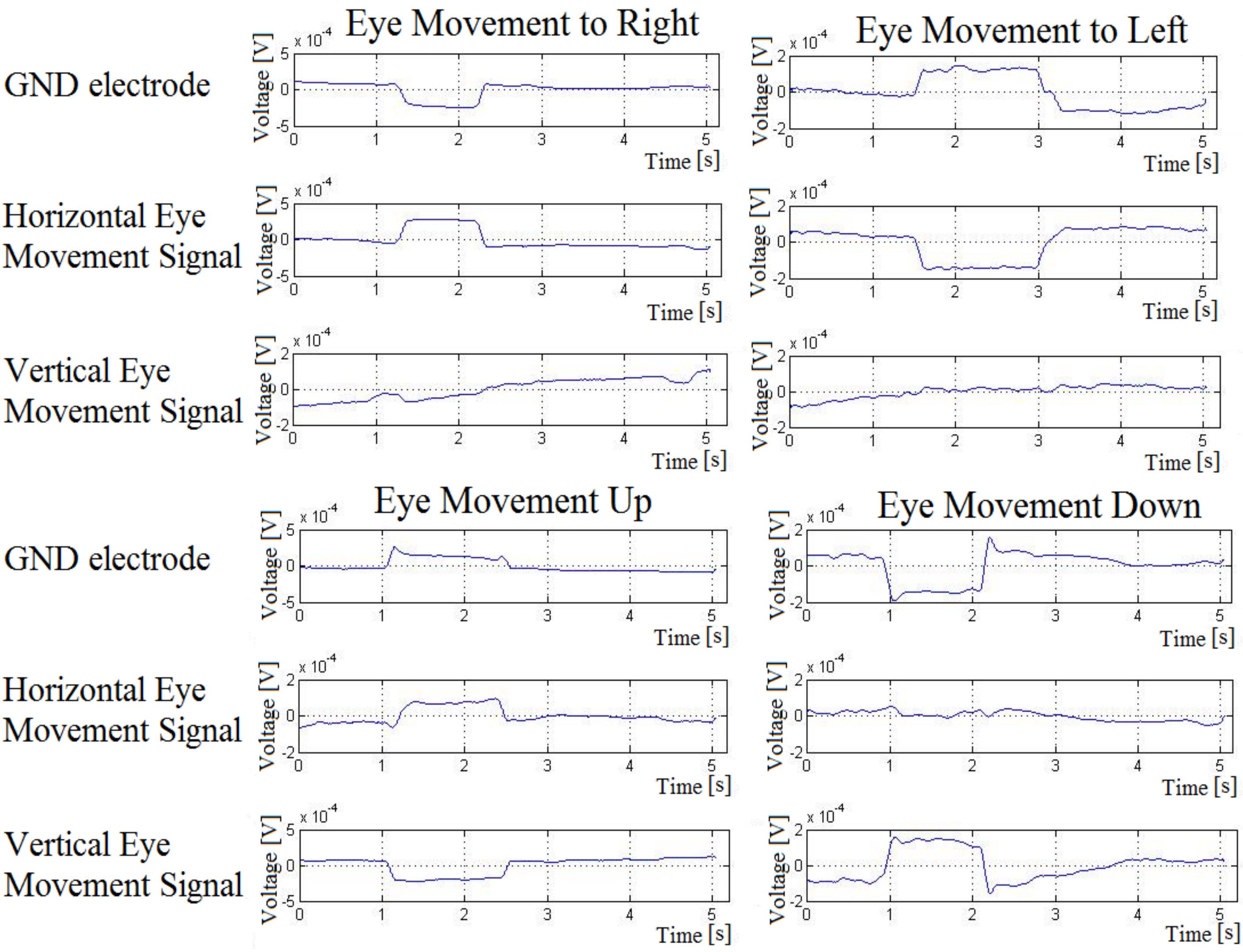

Figure 5. Recorded EMG signals on all the 3 recording channels for the 4 basic (left/right/up/down) eye directions

Where:

$$\omega_N = e^{(-2\pi i)/N} \tag{2}$$

is an N_{th} root of unity.

3. Cut out the high frequency components (higher than 30 Hz) form the FFT values;
4. Compute the inverse FFT to obtain filtered time domain signal using the following relation:

$$x(j) = (1/N)\sum_{k=1}^{N} X(k)\,\omega_N^{-(j-1)(k-1)} \tag{3}$$

5. Compute the convolution of the FFT filtered signal with a moving average signal on 10000 values (10000 values represent about 0.2 seconds);
6. Cut out the margins (10000 values at the beginning and the end) of the twice filtered signal.

3. RESULTS

As can be seen in Figure 5 and Figure 6, the recorded raw signals and the filtered EMG signals show clearly detectable peaks at every eye movement (onset and cessation), so we could obtain a simple on/off signal which is using all the 3 recording channels; so we were being able to record and describe the activity of the eye muscle. Doing so, we were able to see the eye movement's onset and/or cessation.

The system is able to record and filter the raw surface EMG signals and can inform us from every eye movement's direction (up, down, left, and right).

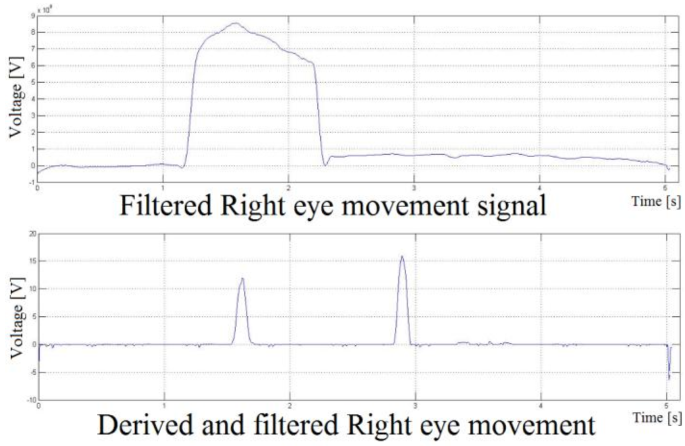

Figure 6. One example of filtered and derived EMG signals representing the eye's movement directions

4. CONCLUSIONS

An innovative and simple algorithm is proposed for filtering the raw recorded EMG signals by the described non-invasive EMG signal recording system.

The described experimental research lead us to the following conclusions: we were able to observe when the user looked with his/her eyes up, down, left or right; this possibility to differentiate the eyes position can open potential future applications for prosthesis control and biofeedback.

This technique could someday allow severely disabled people to control mouse cursor or any other electronic devices only with the movements of their eyes, which can help them in activities of daily life.

Research in this area will continue and will be presented in other future works.

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