RESEARCH OF ELECTRO-OCULOGRAM (EOG) CONTROLLED MOUSE CURSOR

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ABSTRACT: In this article a Human Computer Interface (HCI) based on electro-oculogram (EOG) measurements will be presented. EOG domain is focusing on the human eye's movements. The signals are recorded using Ag/AgCl electrodes and fed into an analog-to-digital converter (ADC) and are processed by a computer or laptop. In our application the EOG signal processing program is running on a PC. Only 3 recording channels and electrodes were used in our setup.
After processing and filtering, the program was able to give different commands based on the recorded EOG signals. The program used Artificial Neural Network (ANN) toolbox of MATLAB®. The proposed HCI can be used by healthy or by disabled people. Disabled people can use this HCI to control the computer / laptop or any electronic device connected to it.
This HCI is meant to offer a new way of computer control - different than the other existing standard control possibilities (like keyboard and/or mouse) and it can be especially useful in the case of diseased people - by giving them a new or even the only way to communicate with the external world.
KEYWORDS: Artificial Neural Network, Bio-Signal Acquisition, Electro-oculogram, Electromyogram, Human-Computer Interface, Mouse Control.

1. INTRODUCTION

This article presents a Human Computer Interface (HCI) based on the electro-oculogram (EOG) bio-signals and its realization process, which - in the end - should be able to control the computer's mouse cursor on the screen of a target device (computer or laptop).

Electromyographyc (EMG) domain is the science based on the (de)activation (onset and/or cessation) of the human skeletal muscles activation (tensing or releasing the muscle). It is used in several different applications, beginning from sport or recreation, up to electronic device control. EMG has multiple subdomains, like Electro-oculography (EOG) is. EOG focuses primarily on the human eye's movements. The EOG signals are generated by the movement of the eye, mainly in the 4 main directions (left, right, up, down). These signals are recorded from the skin around the eye of the user. Usually EOG bio-signals are recorded using Ag/AgCl electrodes, but not limited to this type of electrodes. Other examples are gold-plated electrodes, modified headbands, needle electrodes or reusable electrodes. In our HCI application we used disposable Ag/AgCl electrodes to record the EOG bio-signals.

The Ag/AgCl electrodes are connected on the user's skin - near the eyes - as close as possible. The recorded EOG bio-signals are fed into an ADC. After the ADC converts the analog signals and the computer/laptop records them, the filtering step comes. It has to filter out the 50Hz power grid created noise and other noises as much as possible. Based on the form of the digitized and filtered signals (which are steps in the processing procedure), the commands can be issued, according to the specific form of signals for each action. These commands can be used in different applications, like gaming control in a low action rate manner, Internet browsing, mail writing, move cursor on the screen, music listening, recognize reading activity, robot control, type with a virtual keyboard, wheelchairs control, word file editing, etc.

This type of EMG/EOG system is a new possibility to control the electronic target devices (laptop or computer) or even a new way of communication for healthy users or by disabled people. It can be considered as an alternative option to a keyboard or a mouse in controlling the electronic devices.

The other articles from this field are very scattered in terms of sub-domains of use and also the possibilities of use of the EMG and/or EOG bio-signals.

Before we can speak about the EOG/EMG signal's uses or types of applications, we need to define them. According to [1], EOG is the technique of recording the bio-potential signals generated by the movement of the eyes. Also, the observed / recorded bio-signals are in the terms of lower voltage, usually between 10-100µV. Another definition, the definition of blinking, can be found in [2], where the involuntary action of opening and/or closing the eye is called “blinking”.

In articles [3] to [12] the different uses of EOG/EMG signals are presented, where in [3] a biometric system for human recognition is presented, using EMG and EOG signals to discriminate individuals; [4] presents a new statistical way to discriminate the noise regions from the EMG bio-signals; in [5] amplitude analysis of the EMG signal is presented, and the signal’s linear envelope is calculated; in [6] and [7] the drift-diffusion, Bayesian models and improved empirical mode decomposition in EMG signal processing are presented; in article [8] the identification process of eye movements from non-frontal face images is discussed and presented. Article [9] reviewed the existing wearable commercial assistive technologies and in [10] blink analysis was performed using also a commercial eye gaze tracker; [11] and [12] presents EMG noise level approximation in the recorded electrocardiogram signals using stationary wavelet transforms and an onset detection method to filter the weak and/or noisy EMG signals.

The EMG bio-signals can be used in different applications, as can be seen above, but it can be also a problem in other domains, like it is in the EEG domain. Articles [13]-[18] present methods to remove EOG and/or EMG signals from the recorded signals. In articles [13], [14], [17] and [18] methods of removing the EMG/EOG generated artifacts from EEG measurements are presented, by using e.g. wavelet neural networks, in order to obtain a higher quality EEG signals; [15] and [16] are reviews about the EOG/EMG signal artifact removal approaches in the EEG recordings.

The domain using EOG bio-signal is presented in articles [19]-[33]. In article [19] and [20] eye movement’s processing in narcolepsyc people’s case and drowsiness detection method based on eye blinking features is presented; according to [21], the characteristics of EOG signals can provide important information in case of several neurological disorders. EOG signals are generated by horizontal and vertical (or diagonal) eye movements and also blinks and were recorded with two surface electrodes with respect to a reference electrode on the forehead in [22]; [23] analyzed how eye tracking methods and eye movement metrics can be used in the process of user interfaces assessment; in [24] combination of eye tracking and functional EMG (fEMG) during discrete choice experiments was presented; [25] presented EOG detection algorithms and an EOG-based HCI. In article [26] two paradigms of HCI were presented: EOG-based and video-oculography-based systems; in [27] the authors proposed an eye-movement tracking system and in [28] they solved problems when EOG-based HCIs were used for long periods of time and the users become tired. [29] and [30] presented a low cost EOG-based HCI mouse controlling system.

Articles [31] and [32] presents two EOG-based HCIs using eight separate directional eye movements and in [33] a prototype of a wearable EOG-HCI was presented to be used by persons with severe motor disabilities - it was also capable to differentiate eight directions with an average accuracy of 82.9% and weighting only 15g.

1.1 Electro-oculography

In this subchapter the concepts, the basic rules of working of this system and the workflow will be presented. Our novel eye movement based human-computer interface (HCI) aims to offer people, with higher emphasis to the disabled persons, a new way of communication with the surrounding electronic devices and through them communication with the whole external world.

Eye movements can be used and considered as a new way or method, based on eye movement direction and also blink detection, in order to control the target electronic device(s). The left click button control of the mouse and controlling the mouse’s cursor on the screen can be considered as an example in this case. This conceptual system is based on recording and on the detection of muscle activities (onset and/or cessation of muscle strain) and its afferent amplitude variation is also very important.

The definition of electro-oculographic (EOG) activity is, according to [1]: “EOG is the technique of recording the bio-potential generated by the movement of the eyes.” The EOG signals are generated willingly by the user. The only important need in case of a disabled user is to be able to control his/her eyes direction (to have control of their eyes movement) - it is recorded, sampled by the analog to digital converter (ADC), filtered, processed by the program and as a final step, translated into intents or commands.

The movement patterns are recognized by the written program in Matlab and are used to control the electronic appliances that are connected to it. This is the ground concept of functioning of the EOG-based HCI system.

Blinking is defined in [2], as “an involuntary action of opening and closing the eye”. This factor is important, because it can be also generated willingly by people and it can be used as a command; so it can be interpreted as a willingly given command or an "automated" movement of the human eye's lid.

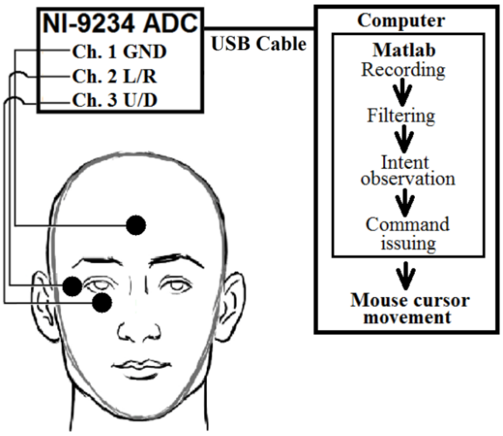

Figure 1. Synthetic concept of the proposed EOG-based HCI system and its main subparts

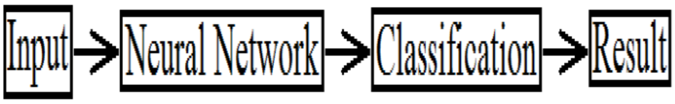

Figure 2. The extended Intent observation subpart (the flow diagram of signal classification)

Recording of the EOG bio-signals is done by positioning the surface electrodes (Ag/AgCl electrodes in our case) around the eyes, as shown in Figure 1 and the extended Intent observation subpart (the flow diagram of signal classification) is shown in Figure 2.

Thresholding techniques can be used in the EOG field: it is relatively simple and it implies a predefined voltage level - that is fixed before. When the eye's muscle is activated, the recorded signal's amplitude simply crosses the threshold's value and that tell to the system that there is an issued command, and it reacts accordingly. The intents of the user are translated into eye movements and the movements are translated into different threshold levels. Our developed system is an eye movement classification system, based on the user's eye movements and is measuring the EOG signals in real-time to detect where a person is looking at any given moment.

This EOG setup/application is closely related to electromyography (EMG) or surface electromyography (sEMG) field, because both domains use the recording and evaluation of the electrical activity created by the muscles. EMG/sEMG is the electric potential recorded on the skin, which is the result of generation, propagation and extinction of current sources. These current sources induce muscle fiber contraction, that we call "movement" or "muscle movement".

EOG-based systems have usually high accuracy and are also reliable. If EOG signal's amplitude is compared to EEG, the EOG input signals have several orders higher amplitude; the signal-to-noise ratio (SNR) is also good enough to be interpreted correctly, using maybe a small amplification factor bio-signal amplifier.

2. EXPERIMENTAL SETUP

In this section the EOG-based HCI system's preparation, used devices list and EOG recording positions will be described and also presented through pictures. This article is the continuation of articles [34] and [35] and the presented experiment was realized by the authors, using the equipment described below.

Before describing the system, the problems that can appear during recording must be presented; these problems may seriously affect the results of the recordings. The list contains:

- Crosstalk between electrodes;
- Electrode measuring adjacent muscle's activity too;
- External noise - most of it generated/induced by the 50Hz power grid;
- Increased fatigue over long period of use;
- Posture adjusting of the user - in case of healthy users;
- Sensors may create discomfort to the user;
- The movement of the eye may be performed in different ways.

The eye's muscle's movement can be relatively easy to see on the recorded signal's graph, while the eye was in onset (moved) or cessation (relaxing).

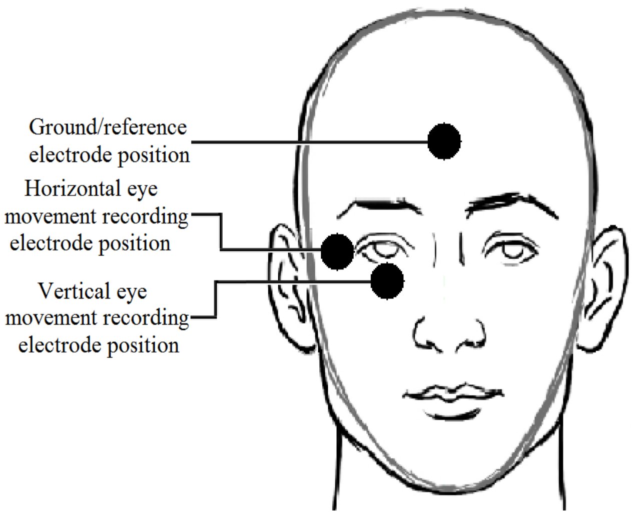

Figure 3. Recording electrode positions on the user's face

Figure 4. Ag/AgCl electrode used for recording (left - front, right - back)

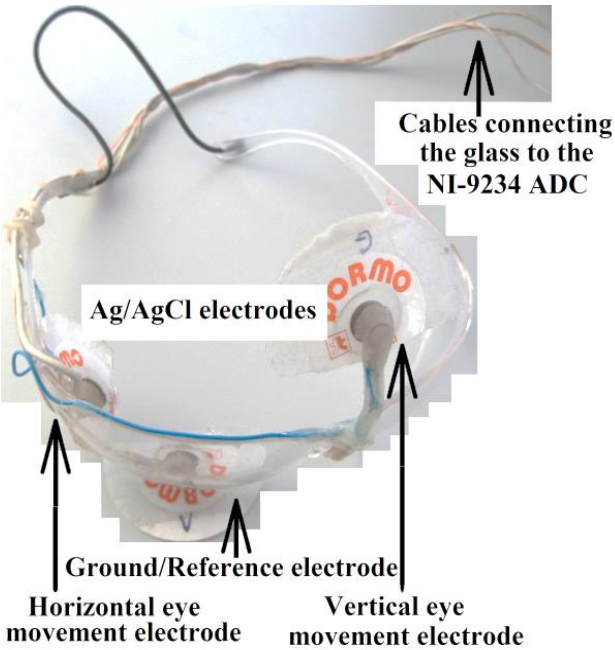

Figure 5. The modified glass used in the EOG bio-signal's recording process

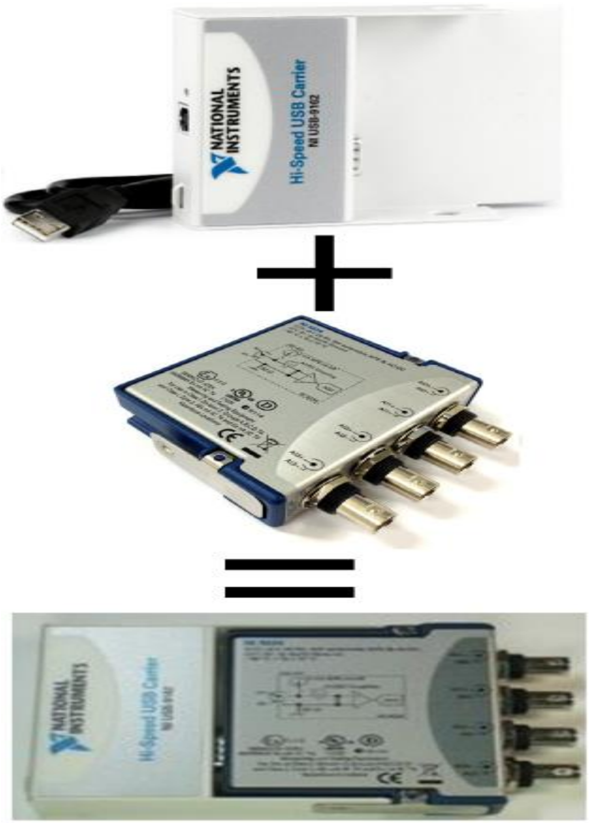

Figure 6. The Texas Instruments NI-9234 ADC and the NI-9162 Hi-Speed USB Carrier

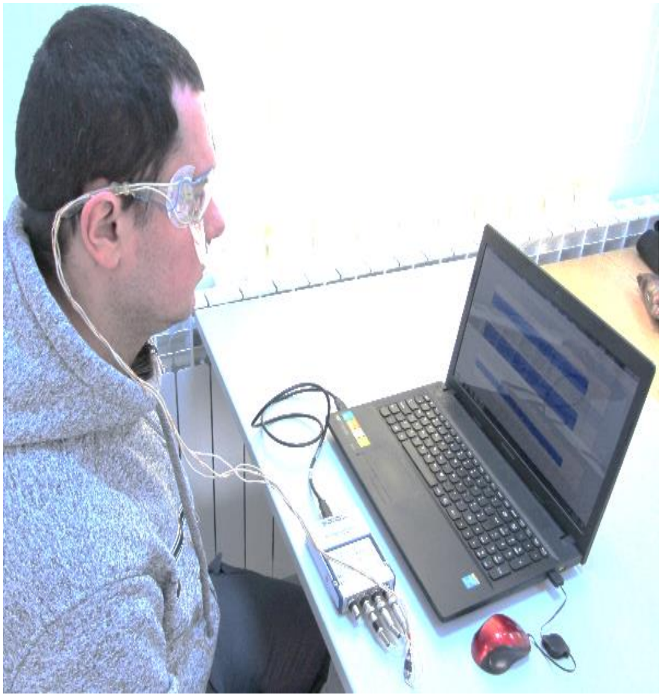

Figure 7. Moment while recording the EOG bio-signals

In Figure 3 the EOG recording positions, in Figure 4 the used Ag/AgCl electrodes, in Figure 5 the used modified glass is presented. On the glass were glued the changeable electrodes and it also was used as a carrier for them. Figure 6 presents the ADC sub-part of the proposed HCI system and in Figure 7 an actual moment in recording can be seen.

The ADC used for data acquisition in our HCI is the Texas Instruments NI-9234 ADC, and it has the following main parameters:

- 4 input channels;
- 51,2kS/s per channel;
- 24-bit/channel (24 bit resolution);
- ±5V input;
- 102dB dynamic range.

The ADC's sampling rate was set to 51,2kS/s during recording and each time 10 seconds of recording were recorded and processed.

After passing through the ADC, the digitized input analog EOG signal was recorded, filtered, processed with a table of truth and converted in mouse cursor commands using MATLAB (version R2016b), using from it the integrated ANN toolbox also together with our original script files.

3. EXPERIMENTAL RESULTS

3.1 Signal conditioning

The signals acquisitioned with the above described system were processed by filtering and normalizing using software developed in MATLAB language for this purpose.

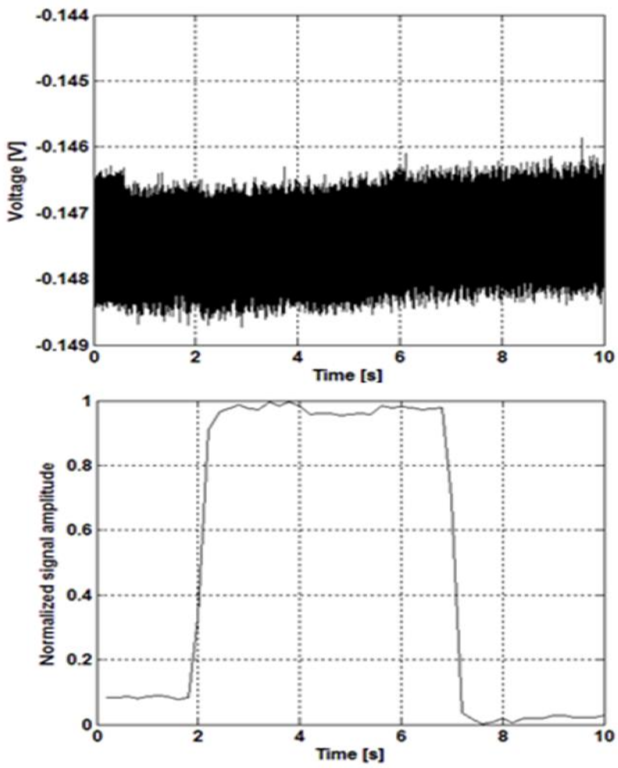

Figure 8. Acquired raw signal (above) and processed (filtered and normalized) signal (below)

In Figure 8 - above - the original (raw) recorded EOG signal is shown (10 seconds long, 1 channel) and it can be easily seen that the quantity of noise is considerable. After filtering it and normalizing it, we obtained the filtered signal, like an example is shown in Figure 8 - below. The signal was down-sampled to only 50 points to fit better the following processing by the neural network (NN), namely to reduce the number of input neurons required for this application and thus reducing the size of the NN.

We recorded 50 signals during the experiments for each sensor (H - horizontal, V - vertical, G - ground) and for each direction of movement of the user's eye (R - right, L - left, D - down, U - up), and also the blinking with the eye, which resulted in a database of signals of 600 samples for the main four directions (grouped 3 in each case for each direction) and other 150 samples for the blinking. Each sample type (up/down/left/right/blink) has 50 measurements.

Analyzing the diagrams of the filtered signals, we coded their signal shapes into four categories. In the case of the signals for right, left, down eye movements and blink, we coded their shape with a rising edge first as "1" and the shape with a falling edge with "0". In the case of the up movement, we coded the falling edge first as "1" and the rising edge first as "0". This was important to be done, because the up movement's signal shape is way different from the other three types of movements.

In Figure 8 is shown one example for each type of eye movement (R - right, L - left, D - down, U - up) each of which contains the diagram of the three signals acquired from the three sensors (H - horizontal, V - vertical, G - ground).

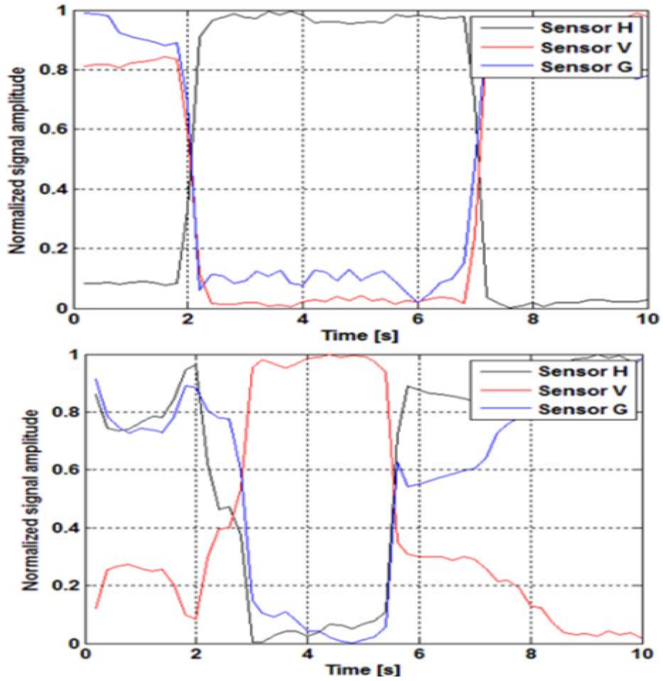

Figure 9. Example of the form of two different EOG filtered signals (Left and Right eye movement) [34]

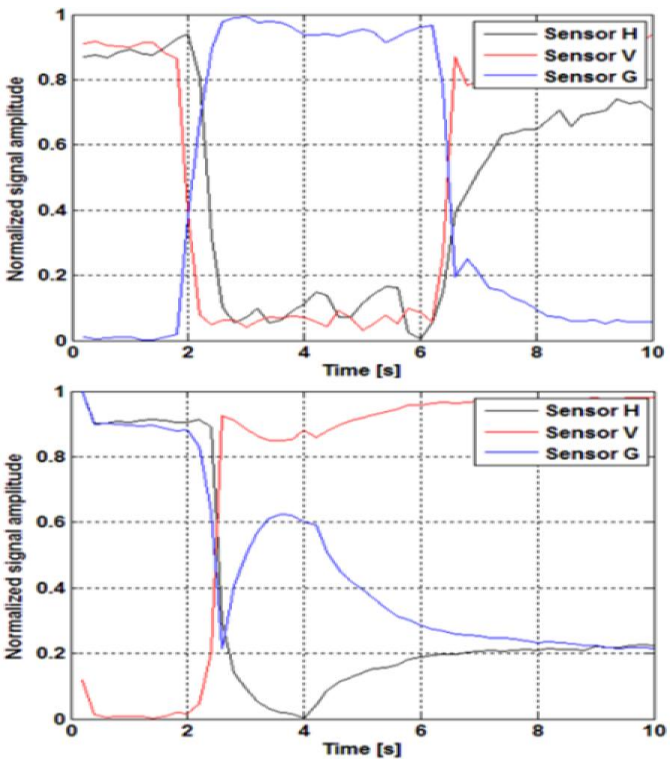

Figure 10. Other examples of different EOG filtered signals (Up and Down eye movement) [34]

Figure 9 and Figure 10 presents the complex signals (all the 3 channels) in one graph. It can be observed that these complex signals can be set apart in separate signal forms, like in Figure 11 and Figure 12.

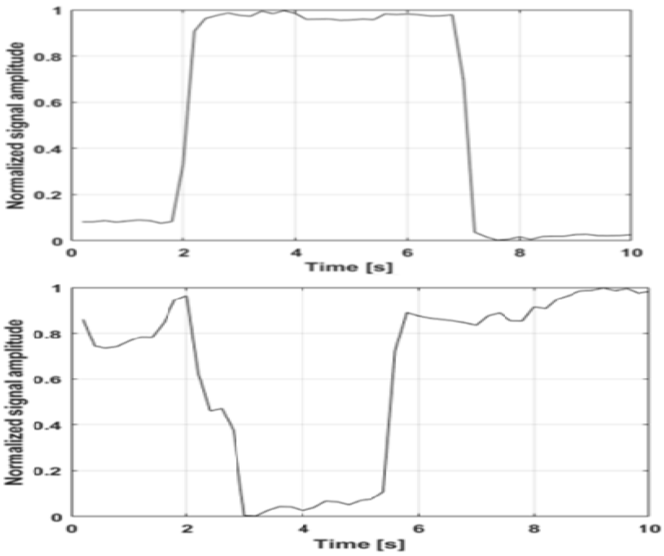

Figure 11. Signal type T1 and T2

The different forms of signals recorded on the three different input channels can show what movement is done by the user, as can be seen in Table 1 below.

As it can be seen, the form can be coded and used later as an easier way to separate the input EOG signals, and also the ANN can differentiate between these signals.

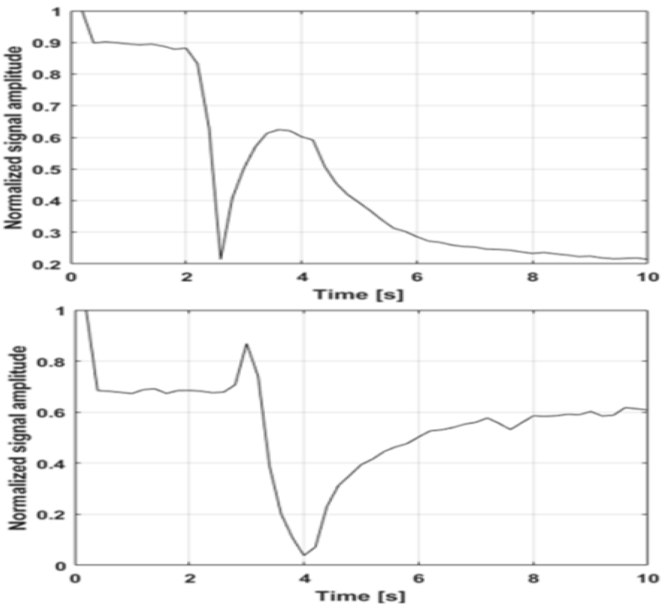

Figure 12. Signal type T3 and T4

Table 1. Table 1: Sensor signals corresponding to eye movements - T1, T2, T3, T4 types of signal shapes

		Sensor Number		
		0	**1**	**2**
Eye movement's direction	**Right**	T_1	T_2	T_2
	Left	T_2	T_1	T_2
	Down	T_2	T_2	T_1
	Up	T_4	T_4	T_3
	Blink	T_2	T_1	T_1

To recognize and classify the input bio-signals and also identify the type of movement of the eye performed by the user, the signals from the three sensors were analyzed according to their signal shapes and we divided them into 4 categories, e.g. if sensor 0 records a signal of type T1 and sensors 1 and 2 will records signals of type T2, we know that the eye movement was in the direction "R" (right). The recorded signals were down sampled to be efficient (to reduce processing time and memory space needed by the program).

For the recognition and the classification process we used an artificial neural network (ANN) and analyzed the obtained results. ANNs can be used efficiently in pattern recognition purposes for more than 4 decades usually with high success (recognition) rate. A new approach emerged in the last decade, called "Deep Learning". These methods proved themselves to be very useful in a large number of types of applications. In the last releases of Matlab's NN Toolbox a Deep Learning module also included; it is based on aotuencoders. We used this NN module in our analysis [36].

Autoencoders can perform unsupervised learning to extract features from the input data. We trained in our NN two autoencoders and a softmax layer. It has the input samples consisting of 50 samples of each eye movement type, thus representing all the four types of signals (T1, T2, T3 and T4). We left aside 10% from the recorded samples which were used to test the network's recognition rate after the training.

After an unsupervised learning session both autoencoders and also the softmax layer were stacked (connected) together to form the final NN. The first autoencoder had 30 neurons, the second had 10 neurons and the softmax layer had 4 neurons to match the outputs. The output of the NN consist of a column vector made by 4 elements in double precision format, containing values between 0 and 1 and representing the four types of classified shapes. The developed neural network is shown in Figure 13.

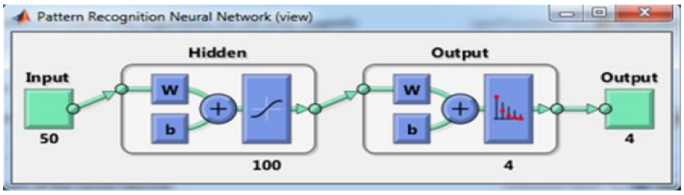

Figure 13. Matlab's ANN and it's design of hidden layers used for the input EOG signal classification

We trained the NN and we obtained a total performance of 94,5%. This result is shown in the confusion matrix in Figure 17. The numbers appearing in the green squares show the correctly classified samples and those in red squares show the incorrectly classified samples.

Figures 14 - 17 present the training confusion matrix, the validation confusion matrix, the test confusion matrix and most importantly the overall confusion matrix.

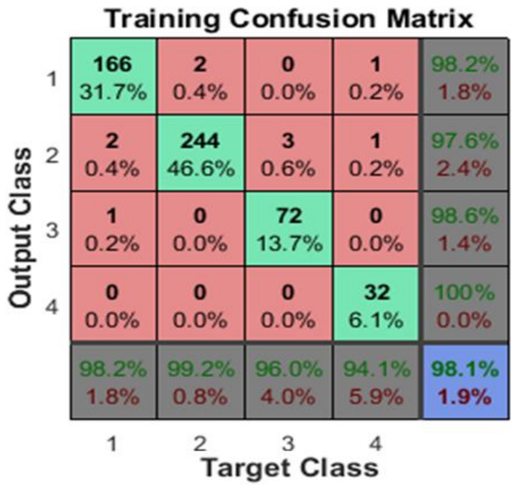

Figure 14. The training confusion matrix

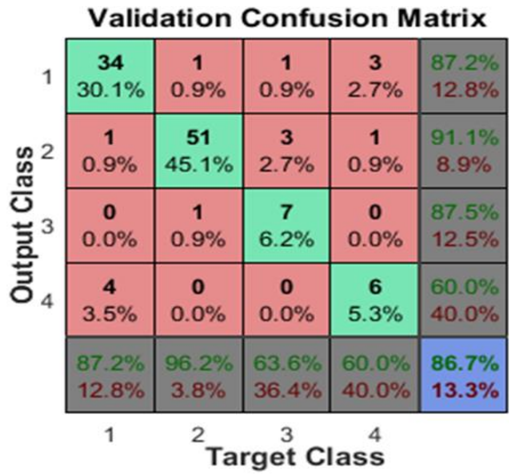

Figure 15. The validation confusion matrix

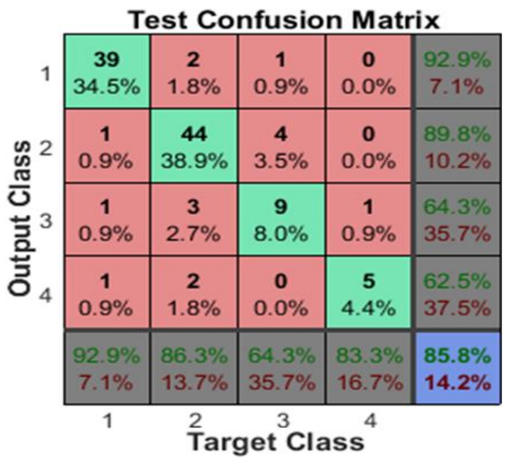

Figure 16. The test confusion matrix

Figures 18 and 19 present the error histogram and the best validation performance's epoch.

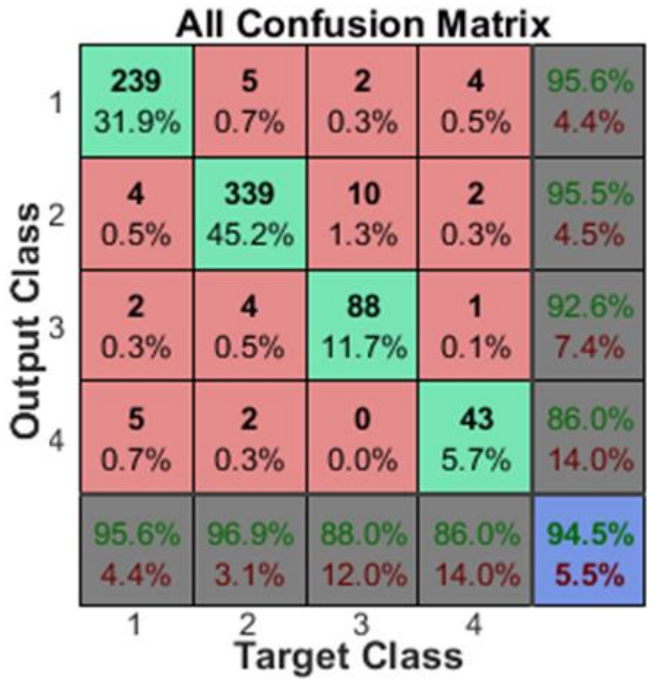

Figure 17. The overall confusion matrix

4. CONCLUSIONS

The experimental system worked satisfactory well and could recognize the eye movements, with an overall performance of 94,5%. Care must be taken for a firm contact of the electrodes to the skin in the proper recording places. The classification using the NN worked very well and classified correctly the vast majority of the input signals. (We can say that those input signals which were incorrectly classified by the NN could not be classified correctly even by a human analyst.)

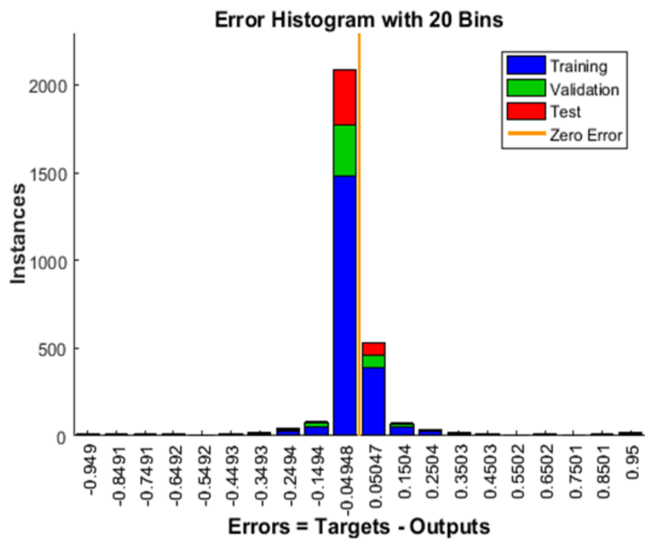

Figure 18. Error histogram

The described HCI system is also a good laboratory application for students to learn about bio-signal acquisition techniques, bio-signal processing and also bio-signal analysis using ANNs.

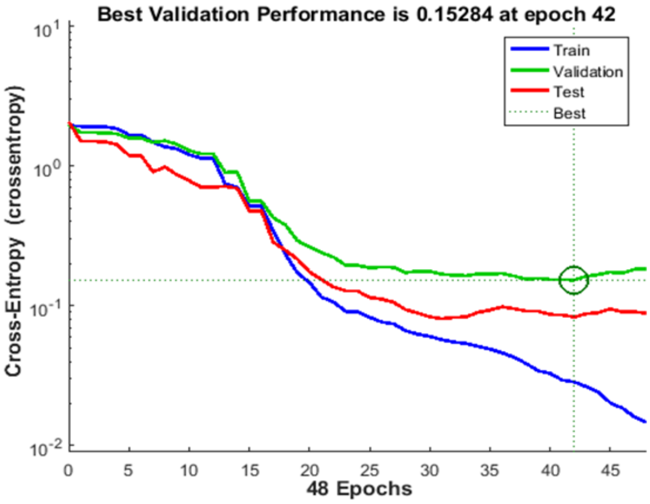

Figure 19. Best validation Performance

This EOG-signal based HCI system proves its ability to act as a future mouse cursor control system and be used by any semi-paralyzed user. In this way the user will be able to control an electronic device or a computer through controlling the computer's mouse cursor. For example, by using virtual keyboards, the user can have total control of the target computer and/or any other electronic smart appliance controlled by the PC itself. It is a relatively simple and yet still very reliable way to create an HCI without encountering the technical problems that challenge or even totally jeopardize an equivalent EEG-based HCI system and also its reliability.

5. ACKNOWLEDGEMENTS

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