COMPARISON OF NEURAL NETWORK CORRECT CLASSIFICATION RATE USED IN A WIRELESS ROBOT CONTROL SYSTEM

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In this paper the comparison of correct classification rate (CCR) of two neural networks (NNs) will be presented. A wearable human-computer interface (HCI) robot control scenario with visual feedback loop was set up, employing electro-oculographyc (EOG) bio-signals to command the robot wirelessly. It can be used by people with neuro-degenerative diseases or high-level spinal cord injuries - used as an alternative way to move or communicate and it can be used in assistive robotics. It has a CCR of 94%, control speed (CS) of 3 commands/minute, relative control speed (RCS) of 2,82 commands/minute and precision (P) of 0,94.

Keywords: Neural Network, Human Computer Interface (HCI), robot control, electrooculography (EOG), visual feedback, synchronous robot control, classification comparison

1. Introduction

In recent years the field of human-computer interfaces (HCIs) registered an explosive-like growth. These HCI systems can be used to extend the existing communication means with computers, users not being limited to keyboards, mouse and joysticks as inputs. The command signals used in these HCI systems can employ electromyographyc (EMG), electrooculographyc (EOG), electroencephalographyc (EEG) or any other, user-controlled signals.

Electromyography (EMG) bio-signal based HCIs are recording their command signals from muscle activation. A muscle's activity (onset or cessation) is recorded and can be translated into a "yes-no" or in a more complicated set of commands. Electrooculography (EOG) domain is measuring the eye's angular movement [1]. Electroencephalography (EEG) records the signals created by the brain's activity from the scalp. The brain signals can be willingly and consciously modified, so the recording system can observe the small EEG signal modifications and act accordingly.

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In this article the EOG signals will be employed and the proposed physical setup is using Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) classification Neural Networks (NNs). LDA's and SVM's Correct Classification Rate (CCR), Control Speed (CS), Relative Control Speed (RCS) and Precision (P) will be presented and compared, that will be used in the future in a wireless robot control scenario.

NNs are complex systems inspired by the nature and the biology. They are an elaborate framework for different machine learning algorithms to learn (by taking examples) and later to process or classify complex new data inputs. NNs automatically generate identifying and specific characteristics from the provided learning material. The used NNs in this article are integrated in Matlab® 2017a.

LDA is used mainly in statistics, pattern recognition and machine learning. It can find a linear combination of features that characterizes or separates different classes of inputs. LDA explicitly tries to find the difference between the different classes of data and it can be used when the groups are known a-priori. LDA reduces the data's dimensions before later classification. It explicitly tries to find linear combinations of variables which describes and separates the best the data and it tries to model the discrepancy between the different classes of data. It is very sensitive to the size of the smallest data group used to teach it - all the time this group must be larger than the number of predictor variables used by LDA.

SVMs are supervised learning models and they are analyzing the data used for classification. Each input dataset used for training must be marked as belonging to a category and the SVM's training algorithm finds a model to assign all new inputs to an existing category. SVMs can solve various real-world problems. A drawback of SVM is that it needs full labeling of the training data. SVMs are part of generalized linear classifiers and can be seen as an extension of the original idea of the perceptron. They can simultaneously minimize the classification errors and also maximize the distance between two or more groups of labeled data - SVMs are also known for this as maximum margin classifiers.

EOG signals can be considered as command signals, but also as artifacts that can modify other types of input signals and act as noise, like in the case of EEG. Articles [2-7] present different methods in Brain-Computer Interface (BCI) use cases to reduce the effects of EOG-generated noise in the recorded EEG signals. In other articles the EOG signals are used as command and/or control signals for the developed HCIs, like in [8-10]. In case of reference [8], two channels EOG based HCI was set up, with success rate being around 91%. In [9] the authors investigated EOG-based eye-writing or a real-time robot control system integrating an EOG measuring device in the HCI was developed in [10].

Hybrid EOG-EEG control paradigms also do exist, like in [11] and [12]. A hybrid simultaneous acquisition of EOG, jaw EMG, EEG, and head movement with consumer-grade wearable devices or a multi-modal EEG-EOG system with visual feedback was described in [11] and [12]. Other applications of EOG use involves insomnia observation [13], automated wake/sleep classification [14], simultaneous fMRI and recordings of polysomnography (including EOG signals) during sleep [15], comparison between EOG and infrared video-oculography (VOG) by eye movement velocity measurement [16]; also, comparative studies were done regarding finding new methods for EOG classification in order to use it as control signal [17] or soft electrode skin design, sensing and stimulation used in various HMIs, including EOG was presented in [18].

An EMG-EOG-EEG field review is presented in [19]. Children with ADHD underwent to a blink-rate, blink-modulation and blink-timing test in [20]. A robust eyeblink detection algorithm is presented in [21] and in [22] the authors compared eye tracking, EOG and an auditory BCI for binary communication.

This paper is organized as follows: Chapter 2 describes the EOG measuring process, Chapter 3 explains the EOG commands; in Chapter 4 and 5 is presented the system's layout and the CCR of the employed NN's; the statistical results can be seen in Chapter 6 and Chapter 7 contains the final conclusions.

2. EOG measurement

Our EOG application is based on EMG - it records and evaluates the electrical activity created by the muscles near the eyes. Intentional eye movements are a possibility in controlling the target electronic device(s). The only mandatory need for the (disabled) user is to be able to control his/her right eye in left and right direction in our application. The eye movement patterns are identified by the program written in Matlab® and are used to control the NI Starter Kit 2.0 robot that is connected to it. This is the working concept of our proposed EOG-based HCI. However, a greater accent is put on the testing and comparison of classification accuracies and presenting the CCRs of the NNs then on the physical system itself.

This article is the continuation of other papers presented earlier ([23], [24] and [25]). Reference [23] was focused on the signal processing/filtering part, [24] on the physical setup, and [25] presented only one NN's preliminary capabilities in EOG classification and showed that this concept is suitable to build on it a real EOG-based wheelchair control system.

This article is presenting the results regarding commanding and controlling the system described before. It uses two different NNs than in [25] and also compares the Correct Classification Rate (CCR) of the two used NNs, namely LDA and SVM in the online control scenario application. In [23], [24] and [25] there were four eye-movement directions and blink recorded - in this article this number was reduced only to two: left-right eye-movement command issuing system only and other NNs were used, as compared to [25].

This paper's novelty and the author's contribution relies in setting up the whole system, making hundreds of measurements to teach with them the used NNs and presenting the setup's evaluation of real-life usability metrics (CCR, CS, RCS, P), and describing the real-life testing of the system with real (online) EOG signals (even if the robot final effector was not connected all time - it does not change the usability metrics and real-life online functionality of the system).

This article has the potential to have an impact in the research field by showing a real-life comparison of LDA's and SVM's CCR and other metrics, and also in creating a real system to assist people in their wheelchair to be able to move around in their homes or even outside of it.

The EOG bio-signals were recorded with two active electrodes, as shown in Fig. 1. Figs. 2 and 3 present one eye movement to left or right, it's raw signal form and the same filtered signal, each recording sessions being 10 seconds long. During measurements it was observed that the two channels record mostly identically formed EOG signals, so only one channel was used in the final testing setup, to reduce the computational needs and required time.

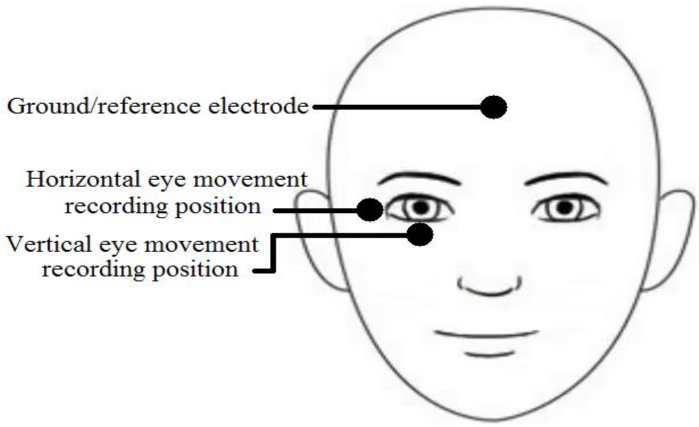

Fig. 1. Points of recording of the EOG signals

After recording the EOG bio-signals, those were filtered and reduced in size and we trained with these signals the two Artificial Neural Networks (ANNs): LDA and SVM. The results of signal filtering can be seen in Figs. 2 and 3, and in Fig. 4 is presented the EOG signal's filtering process.

It is worth to mention that our EOG bio-signal recording application is based on EMG or surface EMG (sEMG) domain, because both fields record and later evaluate the same electrical activity created by the muscles near the eyes.

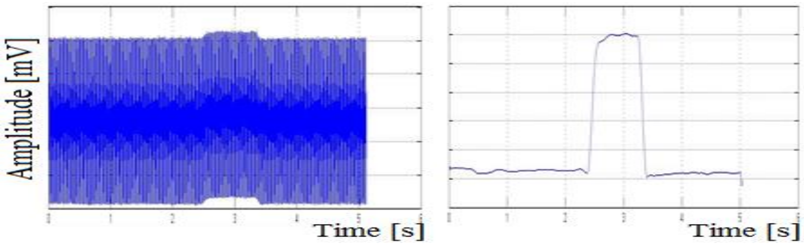

Fig. 2. One eye movement to right, raw signal and the same processed signal, 10 seconds long recording session, signal form found on both channels

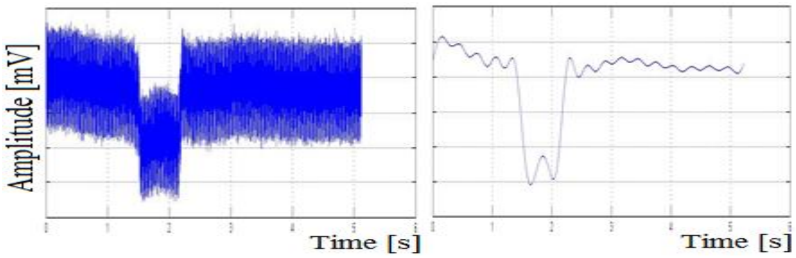

Fig. 3. One eye movement to left, raw signal and the same processed signal, 10 seconds long recording session, signal form found on both channels

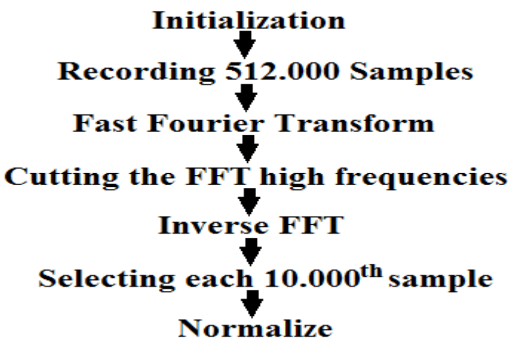

Fig. 4. EOG signal recording and pre-processing steps

3. EOG command description

After recording and pre-processing the EOG bio-signals, we created a database with 800 sessions. This meant 100 eye movement-emitted control commands per each direction or command type. In the preparing session both vertical and horizontal electrodes were used. The command types and also the 100 eye movement-emitted control commands were as follows (each action was represented by a 10 seconds long recording session): one eye movement to the right, one eye movement to the left, eye movement up, two movements down (which is equivalent to two movements to right), two blinks (it is equivalent to two movements to left), right-and-left eye movement, left-and-right eye movement, right movement three times and finally left movement three times. Looking up was not conclusive, probably because of electrode contact failure, so this movement type was discarded.

After inspection of the diagrams, it was chosen to use only five signals from the above presented list. It was also decided to use only the left-right eye movements, because signal-form redundancies, as mentioned above. The LDA and SVM in our application is analyzing only the pre-processed EOG bio-signal's form, not it's amplitude, nor uses pre-set threshold levels, so if the user cannot move his or her eyes angularly too much, the system can still be controlled. We trained with these signals both of the ANNs, as can be seen in Fig. 5.

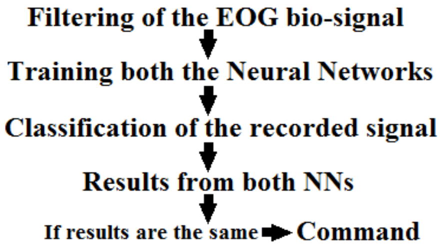

Fig. 5. Training steps of both LDA and SVM NN's and the HCI system's logic/working principle of command issuing, adapted from [24]

4. System layout

The concept of the system was twofold: firstly, setting up a HCI for people with movement problems, and, secondly, to compare the classification results between the two trained NNs (LDA and SVM). Though, a bigger emphasize is put in this article on the CCR and other parameters of both LDA and SVM NNs than on the physical HCI setup. The EOG signal-based HCI has a closed-loop design. The user's EOG were recorded from the vertical position of his or her eye (one active electrode under the eye, one ground/reference electrode in the forehead). This one channel concept was realized in order to reduce the computational needs of pre-processing and also the processing time required for each EOG signal.

The bio-signal is converted by the used NI-9234 Analog-to-Digital Converter (ADC) and transferred to the main PC. On this main PC are 3 programs running in parallel: LabVIEW Robotics 12 program is the first, which is responsible to create a web-server interface on the robot and to maintain the communication channel; the second program is Matlab, which is responsible of receiving the converted EOG bio-signals from the ADC, to pre-process it and to employ the LDA and SVM networks to classify the input signals. If both NNs gave the same classification result for the input signal, then Matlab calls the third program, which is the default web-browser of the PC, in our case Mozzilla.

Matlab calls the command's afferent local intranet link, and the robot executes the issued command. On the robot is an action camera, used to see where the robot is positioned, providing a real-time visual feedback about the robot's whereabouts through Wi-Fi on the screen of the second computer.

The final setup is a synchronous and online HCI, with visual feedback to the user and offering an audio cue signal at the session's beginning each time when the bio-signals are being recorded. Fig. 6 presents the HCI system's conceptual schematic, including the employed ADC, Computer 1 running LabVIEW, Matlab and Mozzilla, the robot and the visual feedback part (represented by Computer 2), while Fig. 7 shows an actual moment while recording EOG bio-signals to train the NNs. The whole physical setup was tested too in the testing and evaluation environment, not only Matlab's NNs. It was tested in a "reduced state"- the robot was not moving too many times or for a prolonged period of time. This physical testing phase was not the main goal of this article. It moved only for a few times/commands in all directions, to prove the viability of the whole setup and of the concept. The robot was roaming in the laboratory, with some furniture in the laboratory. Each time the robot was moving forward or backward, it was set to move for 2 seconds – it is equivalent to approximately 1 meters of movement. Turning left or right or wait/stop periods were also tried. It was an easy-to-use system, if the commands were correctly learned and issued by the user.

The future work will be to test the robot's real-life behavior and the system and also to measure the maximum distance to what it can be controlled.

5. Learning and classification results

During the NN's teaching process and EOG signal's classification test, the robot was not connected to the system, only for proof-of-concept purposes. It is functional but is not necessary for our proposed work to compare CCR of LDA and SVM. After the offline teaching/learning process, at the test step of the trained NNs, the LDA had a CCR of 74,5% and SVM had a CCR of 89% on the same test dataset EOG signals. The setup can be employed in a real situation in two ways: firstly, when both LDA and SVM has to give the same classification result for the same input signal (overall it has higher safety, but it is slower), or, secondly, when only the SVM is used to classify the EOG signals (it is faster, but a little more less safe overall). The same database with the same 800 examples for learning and testing was used in both NNs. The LDA in the real online testing process had a CCR of 69,8%, while the SVM had a success rate of 94%.

Three types of symbols were used to note the results of the EOG signal's classification. These notations are: "|", when both LDA and SVM classified the input EOG signal correctly; "•", when only SVM succeeded; and "x" when both LDA and SVM failed to classify correctly. From the 500 commands 100 were "forward" commands, 100 were "backward", 100 were "left", 100 were "right" and 100 were "stop/wait" commands. The results of classification are in Table 1.

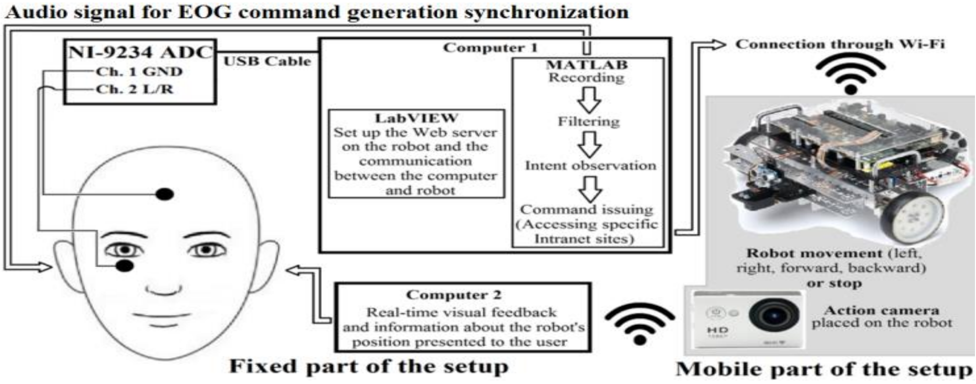

Fig. 6. The proposed system layout, modified from [24]

From the total of 500 real online measurements, that were made to try the setup, 349 times the classification's result was "|", 121 times the result was "•" and there were 30 times when the result was "x". This means that the grand total Correct Classification Result (CCR) for LDA was 69,8%, while for the SVM this value increased to 94% of correct EOG signal classification. The 500 measurements were not made in a single day, but in 5 days. In each day 100 movements were measured, in a semi-random order of commands.

In Table 1 must be observed that SVM's CCR is the sum of percentages of columns with the symbols "|" and "•"; LDA's CCR is only the first column (only the column noted with "|").

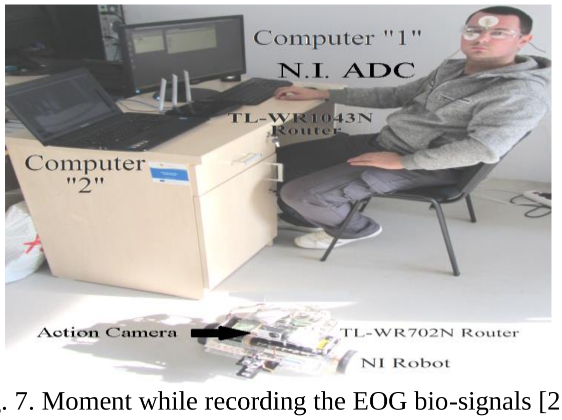

Fig. 7. Moment while recording the EOG bio-signals [25]

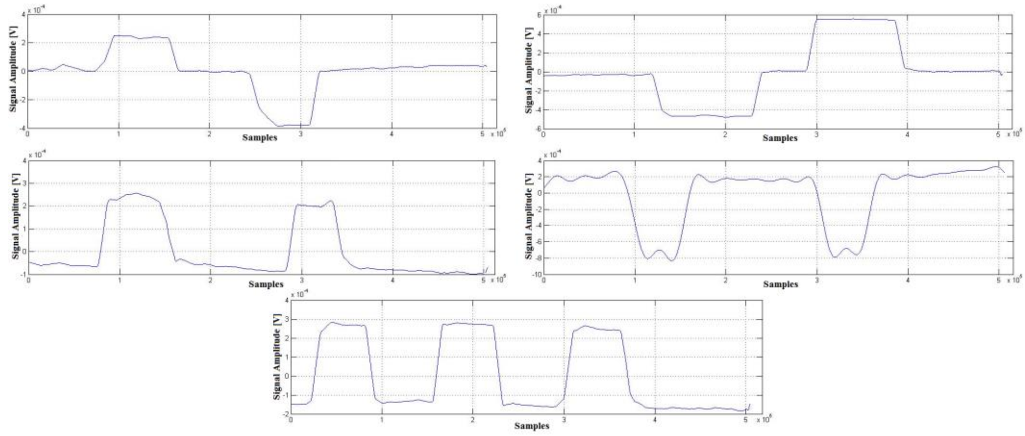

Fig. 8. Effective filtered command signals of the system: once to right and once to left eye movement for forward movement (left above), once to left and once to right for backward movement (right above), twice to right for right turn (middle left), twice movement to left for left turn (middle right), three times to right to stop/pause (down)

Table 1

Different directions and the afferent CCR of LDA and SVM

	From which ǀ	From which •	From which x	SVM success rate	LDA success rate
Total Forward = 100	100 (100%)	0 (0%)	0 (0%)	100%	100%
Total Back = 100	86 (86%)	13 (%)	1 (1%)	99%	86%
Total Right = 100	73 (73%)	23 (%)	4 (4%)	96%	73%
Total Left = 100	53 (53%)	38 (%)	9 (9%)	91%	53%
Total Stop = 100	37 (37%)	45 (45%)	18 (18%)	82%	37%

It is also important to mention that in time the results were better and better (from day to day), due to the learning process of commands to be issued to the system by the user. In a real scenario, after some days of accommodation, it is possible that the real-world values in case of a real user could reach higher values.

6. Statistical results

As can be seen, the CCR for LDA was 69,8%, while for the SVM this value increased to 94% in the case of all the 500 online EOG measurements. These values can be translated also into other values to evaluate this setup, by taking into account other parameters: time, Control Speed (commands/min), Relative Control Speed ((commands/min)*CCR) and Performance (Precision) can be also calculated and evaluated this system's performances.

Control Speed (CS or Information Transfer Rate (ITR)) is defined simply as commands/minute. This is calculated as the number of commands that can be issued in a minute. In our case the EOG signal's recording time length is set to 10 seconds; this time is added together to the signal's processing time, command issuing to the robot and movement execution.

The total time per command summed up is approximately 20 seconds per cycle, until the program can start the EOG recording process again, so the Control Speed (CS or ITR) is approximately 3 commands/minute. This value does not have anything to do with the type of NNs used in EOG signal classification.

Relative Control Speed (RCS) is a derivative of Control Speed/ITR, and it takes into account also the CCR of the system. In this case, the possibility that the NN classifies correctly the input EOG signal is taken into account. This is why, now the values for LDA and SVM NNs will change. The formula for RCS is:

$$RCS = CS*CCR \text{ [commands/minute]} \quad (1)$$

In case of LDA, the 3 commands/minute values have to be multiplied with the probability of 69,8%. The result in this case is RCS = 2,094 commands/minute and in case of SVM, this value will be 2,82 command/minute average Control Speed in the long-term use.

Performance (Precision) is also different for LDA and SVM and it is:

$$P = N_{Correct} / (N_{Correct} + N_{Incorrect}) \quad (2)$$

Because our system can only have two results (correct selection or wrong selection), the sum of NCorrect and NIncorrect equals to all the 500 measurements. In this case, LDA's and SVM's P will be calculated as:

$$P_{LDA} = 349 / 500 = 0{,}698 \text{ (LDA)} \quad (3)$$
$$P_{SVM} = 470 / 500 = 0{,}94 \text{ (SVM)} \quad (4)$$

P_{LDA} of 0,698 is acceptable but is less than P_{SVM} of 0,94. This P_{SVM} value is a good result and it is comparable to other setup's results.

7. Conclusions

An innovative and non-invasive HCI robot control setup was presented in this article, using EOG bio-signals, and also comparing CCR of LDA and SVM NNs in a real wireless robot control scenario integrating also visual feedback to the user. The setup is conceived to have five navigation commands (moving forward, backward, turn left, turn right and no movement/wait state).

The experimental results show that this system has a Performance of LDA's NN (P_{LDA}) of 0,698 (69,8%), and Performance of SVM (P_{SVM}) of 0,94 (94%). The P_{SVM} value is a relatively good result and it is comparable to other described and used setup's results in this field.

This experimental application can be used in healthcare, assistive robotics or even in the rehabilitation fields and also presented the limitations of LDA and SVM NNs in terms of CCR, CS, RCS and Precision. The high CCR and Performance/Precision values of SVM NN are a very promising sign that show that this setup can be used in the afore mentioned fields with good results, high reliability and high precision.

This article has the potential to have an impact in the research field by showing a real-life comparison of LDA's and SVM's CCR and other metrics, and also in creating a real system to assist people in their wheelchair to be able to move around in their homes or even outside of it.

The future work will be to test the robot's real-life behavior and also to measure the maximum distance to what it can be controlled. It also needs to be mentioned that the user has to adapt to the system too, so in time the Precision and other values can increase significantly, both in the case of the Precision of LDA and Precision of SVM.

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