A New Approach for Electrooculogram Recognition Algorithms

Andrei Borges La Rosa, Virgínia Bordignon, Carla Diniz Lopes Becker and Sergio Jose Melo de Almeida

***Abstract*— In this work we analyze electrooculogram (EOG) signals' properties, and propose two recognition algorithms for translating signal patterns into actual eye movements. The objective is to provide a reliable and low cost classification method for Human Machine Interface (HMI) applications. An EOG signal database is generated through an acquisition system. This database is later used to validate the proposed pattern recognition methods, in which the discrete wavelet transform (DWT) was applied to represent the signal with less coefficients. Finally, the results are presented and compared with other extraction methods to distinguish patient's intents through EOG.**

***Keywords*— Eletrooculogram, Human machine interface, Pattern recognition, Discrete Wavelet Transform.**

I. Introduction

More than one billion people in the world have some type of disability, where 200 million people have considerable functional difficulties. Statistics show that people with deficiency have minor rates of schooling, lower economic participation and higher poverty rates [1]. A major motivation for developing Human Computer Machine Interfaces (HCMI) is to help people with different kind of motor disabilities in their daily tasks [2], [3]. There are many disorders that can disrupt the neuromuscular channels through which the brain communicates with the body, causing severe motor damage and dysfunctions. Among them, should be mentioned the Muscular Dystrophy, the Cerebral Palsy and the Amyotrophic Lateral Sclerosis (ALS). In this case, the disease can evolve into what is called the Locked-in Syndrome, in which the patient is aware and awake but cannot make any voluntary movement, except for the eyes [2]. The measurement of the eye movements and its precision are therefore of highest interest in order to establish a robust communication channel with disabled people [4], translating the patient's intents and thoughts directly into external actions.

The electrooculogram (EOG) is a non-invasive technique (without surgical intervention), which uses surface electrodes for measuring electrical variation of the ocular dipole. The signals captured have very low amplitude in the range of 0.05mV to 3.5mV, and the frequency range between 0.1Hz to 40Hz. The EOG is one of the most used techniques due to its low cost and intuitive use [5].

Feature extraction methods, distinguishing patients intents through EOG, have been published with expressive rating results [6], [4]. In the study [6], a set of filtered EOG signals were classified using fuzzy distinction rules with a classification rate around 90%, whereas in [4] the recognition solution enables the identification of characteristic peak amplitudes associated with eye saccades, blinks or winks by using a classifier based on a set of fuzzy logic rules and a deterministic finite automaton, with an accuracy of 95,63% .

The Electroencephalogram (EEG), the Event Related Potential (ERP) and EOG recognition methods consist mainly in performing feature extraction and classification, in which the feature extraction has an important role for the classification. The significant features of a particular EEG, ERP (this electrophysiological recording reveal transient information contained in EEG), or EOG signal, which characterize the translation of the patient's intent, generally can be extracted from the measured signal and then be compressed into a few parameters [7]. Using a smaller number of parameters to represent the EOG signal is a crucial step for recognition algorithms, mainly in real time system applications.

This paper proposes the use of algorithms based on peak detection and correlation analysis to interpret eye movements and verify the feasibility of its use in HCMI applications, with a resulting classification accuracy comparable with the studies [6] and [4]. Eye movement signals are acquired by a data acquisition module configured for EOG measuring. The algorithms employ the discrete wavelet transform (DWT) as a compression tool, representing the signal in less coefficients, so as to increase mathematical and computational performance of an application while keeping most relevant information of the signal. In addition, classification algorithms were used to identify the best thresholds for identification of eye movement.

This paper is divided into 6 sections. In section II, the EOG acquisition module used in this paper is described. In section III, the suggested recognition methodologies are presented. Section IV presents the results of the data set simulations, comparison and discussion of the efficiency of the methods. Finally, in section VI conclusion about this paper is exposed.

II. EOG Acquisition System

The EOG signal is obtained by detecting the potential variation of the ocular dipole through surface electrodes [5]. The EOG is used in several device control projects and

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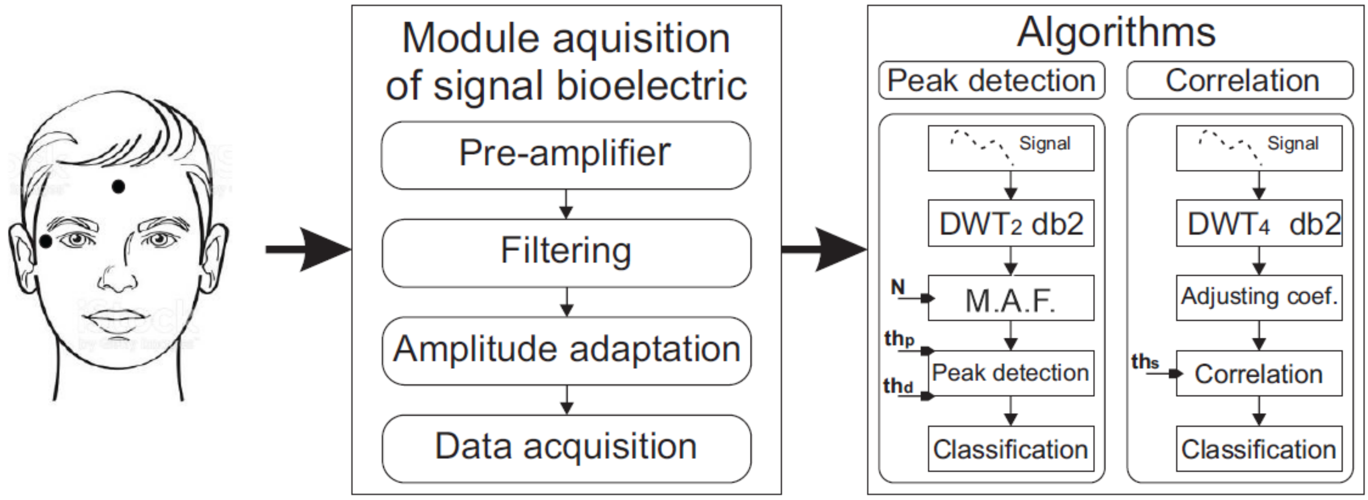

Fig. 1. EOG signal flow chart.

rehabilitation of people with disabilities. Due to the fact that the EOG signals have very low amplitude, there is a great concern with artifacts that can incorporate the signal and damage the measurement process. The main noise factors found in bioelectrical signals are: 50Hz or 60Hz component of the electrical grid, electrode impedance fluctuation, cable routing, electrode damage and bioelectric variations caused by other body parts other than the one being inferred.

There are several already published platforms developed for processing bioelectrical signals and more specifically for EOG analysis [6], [5], [8]. All studies present as main stages of signal processing the signal amplification, frequency selection and signal sampling.

Fig. 1 shows the adequate position of the electrodes to measure EOG signals [8], [5]. A first electrode should be positioned on the side of the eye (active signal) and a second, on the center of the forehead (reference signal). In the module developed for this paper, the measured signal is then treated by an analog processing module of bioelectrical signals, which consists in the following stages: pre-amplification, filtering, amplitude adaptation, and data acquisition. Each of these steps will be briefly detailed below.

1) Pre-amplification: The device that presents the best characteristics for this stage is the instrumentation amplifier (AI) [6], [8], [5]. Its high input impedance, high common mode rejection and easily adjustable gain characteristics are desirable for such application. The AI used is the INA121 fabricated by Burr Brown. The gain applied to this stage is 100V/V.

2) Filtering: The filters were designed so as to select the relevant range of frequencies for the EOG signal. Since the module was originally developed to capture both EEG and EOG signals, the frequency range of the device is designed to reject signals with frequencies below 0.5Hz and above 100Hz and to eliminate the influence of the electric grid (60Hz).

The high-pass filter (H.P.F.) was designed as a second order Sallen-Key active filter with a cutoff frequency of 0.5Hz and a gain of 1.2V/V in the passband. Meanwhile, the low pass filter (L.P.F.) was designed as a second order Sallen-Key active filter with a gain of 1.2V/V in the passband and a cutoff frequency of 100Hz. The reject band filter, used to eliminate the 60Hz frequency component, was the Fliege Notch filter (F.N.F.) due to its fast and satisfactory degree of rejection [9]. This filter was designed to provide a unity gain in its passband.

3) Amplitude adaptation: This step is set according to the capacities and limitations of the analog-to-digital (A/D) converter used. The A/D used was the one presented in the microcontroller PIC18F4550 fabricated by Microchip, which has an input range of 0 to 5V. This stage was designed to adapt the signal range to the voltage range of 5V, since its average value after the HPF is zero. The total gain after the FNF output is of 144V/V. Analyzing the theoretical signal range (0 - 3.5mV) and the A/D operating range (0 - 5V), we obtain that the necessary gain of the conditioning circuit should be of approximately 1430V/V. Furthermore, in order to adapt the measured signal range to the A/D range, it is equally necessary to add an offset to the signal at a value of 2.5V (average value of the A/D range). To perform such procedures, an addition and amplifier circuit were used to insert an a signal offset and the appropriate gain.

4) Data acquisition: The PIC18F4550 microcontroller was used for this stage, due to its complete functionality and to its communication and A/D conversion characteristics. The programming mode used to record the code in the microcontroller was ICSP (In-Circuit Serial Programming) mode. The microcontroller was also responsible for sending the converted data to the computer via serial communication through an USB port.

For a signal to be reconstructed through its samples the signal sampling rate must be at least twice as large as the largest frequency component of the signal [10]. To assure a good representation of the EOG signal, the sampling rate was chosen to be 480Hz, that is, 12 times higher than the maximum frequency of the typical EOG signal.

III. Proposed Recognition Methods

Based on time-domain characteristics of the measured EOG signals, we propose two distinct methods for motion detection and classification: peak detection and correlation analysis. These methods are detailed below.

A. Peak detection

This method consists on detecting a characteristic sequence of peaks and valleys of the signal, which can be translated into eye movement codes. Such correspondence between the signal shape and eye movement can be seen in the Table I.

TABLE I

Correspondence between measured signal and eye movement.

Eye movement	Signal shape
Center-Right-Center (CRC)	Peak + Valley
Center-Left-Center (CLC)	Valley + Peak
None of the cases	Other combinations

The algorithm of peak detection consists in 4 steps, as seen in Fig. 1:

1) Compression: the Wavelet Transform is employed in order to compress the measured signal and therefore reduce computational costs in signal processing;
2) Filtering: a simple moving average filter (M.A.F) of order N is used, so as to soften and put the peaks/valleys of the signal in evidence;
3) Peak detection: the derivative of the filtered signal is taken, and the points of absolute value inferior to a certain threshold th_d are considered to be critical points. These points are then classified into maximum or minimum points based on a threshold th_p comparison, which results in a coded sequence of peaks and valleys;
4) Classification: this sequence is finally translated into actual eye movements (center-right-center, center-left-center or none), according to Table I.

An example can be seen in Fig. 2, where we have the original Center-Right-Center signal, the compressed signal, the filtered signal and the identified critical points.

All three parameters (filter order N, the derivative threshold th_d and peaks threshold th_p) are optimized according to a classification score, which will be discussed in section IV.

B. Correlation analysis

The correlation analysis method consists on calculating the cross-correlation coefficients between the signal one wants to identify and a known reference signal.

Therefore a calibration process is necessary, where the user must perform the reference eye movements at the beginning of the acquisition procedure. The method can be described through the following steps:

1) Calibration: a reference signal for each movement one wishes to identify must be measured;
2) Compression: once again we use the Wavelet Transform decomposition so as to compress the measured signal and reduce computational costs;

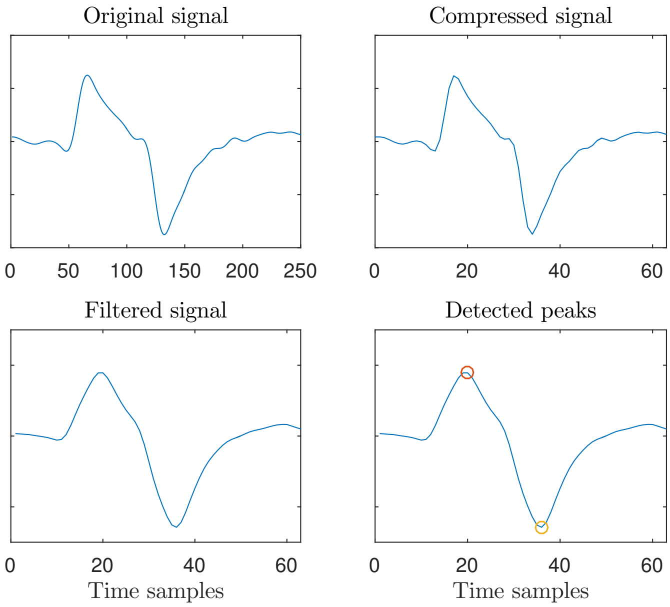

Fig. 2. Peak detection algorithm example.

3) Correlation analysis: the correlation coefficients between the EOG signal and the reference signals are calculated;
4) Classification: a threshold of similarity th_s is chosen in order to classify whether or not the signal is similar to a given reference signal, based on the correlation coefficients previously calculated. This threshold th_s will be optimized as well according to the classification score discussed in IV.

Fig. 1 shows the block diagram representing the signal flow up to its classification.

IV. Recognition Algorithms Validation

A. Signal database

In order to validate the algorithms proposed in section III, both algorithms have been tested over an EOG signal database. This database has been built in two stages:

1) Single user: A single user was instructed to follow a simple sequence of eye movements: look forward, look to the right, look forward again (center-right-center eye movement), this procedure was performed ten times. Similarly the same user has performed tentests for the eye movement center-left-center, amounting to a total of 20 EOG signals.

2) Multiple users: Four other users were required to perform the same movements and with the same rest procedure. Each person executed 2 to 3 times both eye movements (center-right-center and center-left-center), summing up to 21 other signals.

In both cases the tests were performed on men, aged between 20 and 25 years, with no apparent motor or psychological abnormality. In-between tests, the subject was required to relax and concentrate for the execution of the next movements. The duration of the rest time was defined by the subject's orientations.

B. Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) has been used to compress the measured EOG signals. In order to do so, the One-Dimensional Discrete Wavelet Analysis Tool from MATLAB [11] has been employed. Such tool decomposes the signal using the DWT of a certain order. For the EOG application, we have considered the DWT of type *Daubechies* 2. This function was chosen due to its deflection characteristics, which are similar to the EOG signal's ones. Consider an EOG signal, for instance. Using the DWT, we obtain a series of detailed signals, each with lesser samples than the original one. If we take its decomposed signal of order n, it presents 2^n times less samples than the original signal.

Because of the particularities of the recognition methods, different orders of DWT decomposition will be used. For the peak detection method, a maximum DWT order of 2 is necessary so the compressed signal represents properly the original signal. However, a DWT order of 3 is largely enough to employ the correlation analysis method, since this method uses the DWT characteristics to perform the noise filtering digitally.

C. Evaluation of classifiers

To analyze the methods' results, it is desirable to quantify the success rate of the predictions performed by the two algorithms for the signal database available. In order to do so, concepts of evaluation of classic classifiers, such as *precision*, *recall*, and the F-measure score were used.

Let's consider the example illustrated in the confusion matrix given in Fig. 3, in which we have three possible classes, A, B and C.

	R_A	R_B	R_C
P_A	T_A	F	F
P_B	F	T_B	F
P_C	F	F	T_C

Fig. 3. Example of confusion matrix.

In Fig.3, the terms R_A, R_B and R_C correspond to the number of objects belonging to classes A, B and C respectively. Also the terms P_A, P_B and P_C correspond to the number of objects that the evaluated algorithm classified as belonging to class A, B and C respectively.

The term T_A corresponds to the number of elements of class A, which are actually classified as belonging to that class. Likewise, the term T_B is defined for class B, and T_C, for class C. The other F terms correspond to objects whose classification was incorrect.

We then have the following definitions [12]:

$$recall_i = \frac{T_i}{R_i} \qquad precision_i = \frac{T_i}{P_i} \tag{1}$$

where i represents classes A, B and C. Therefore $recall$ is a form of evaluating the amount of objects from a class which are correctly identified, whereas $precision$ quantifies how reliable are the prediction results provided by the algorithm [13].

From the harmonic mean of both $recall$ and $precision$, we define the F-measure index (or F1 Score), which will allow us to evaluate both aspects of the classifier performance for each of the classes.

$$F1_i = \frac{2\ recall_i \cdot precision_i}{recall + i + precision_i} \tag{2}$$

where again the index i represents classes A, B and C.

The average evaluation index F1 for all classes A, B and C will then be used for the purpose of optimizing the parameters N, th_d, th_p, th_s of the classification algorithms, in a similar way as performed in [14].

V. Analysis and Results

For the peak detection method, the F1 Score was calculated through a sweep in all three parameters: $th_d \in [0.5, 2.0]$ (derivative threshold), $N \in [1, 15]$ (order of the moving average filter), $th_p \in [1, 15]$ (threshold value). For the signal database used, the configuration found to me optimal was for $th_d = 2.0$, $N = 8$ and $th_p = 8$. The corresponding F1 Score surface, with fixed $th_d = 2.0$ is shown in Fig. 4, where the maximum point is highlighted for $N = 8$ and $th_p = 8$.

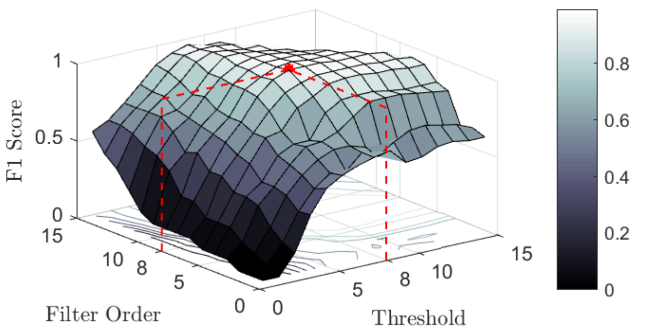

Fig. 4. F1 Score surface for a fixed $th_d = 2.0$ and bounded N and th_p.

The maximum F1 Score achieved was of 0.9878 for the scenario $th_d = 2.0$, $N = 8$ and $th_p = 8$.

Now for the correlation method, the threshold th_s (similarity coefficient) was optimized within the interval $th_s \in [0.51, 0.70]$. The optimal th_s value was chosen in order to maximize the calculated F1 score. The resulting curve of the optimization can be seen in Fig. 5, as well as the highlighted optimal point.

The highest value of the F1 Score (0.9459) was reached for a value of $th_s = 0.59$. In other words, signals whose cross-correlation with a reference signal results higher than this value were considered strongly correlated.

For the optimal tuning of the peak detection method and the correlation analysis method, the corresponding confusion matrix can be seen in Fig. 6, with identification classes

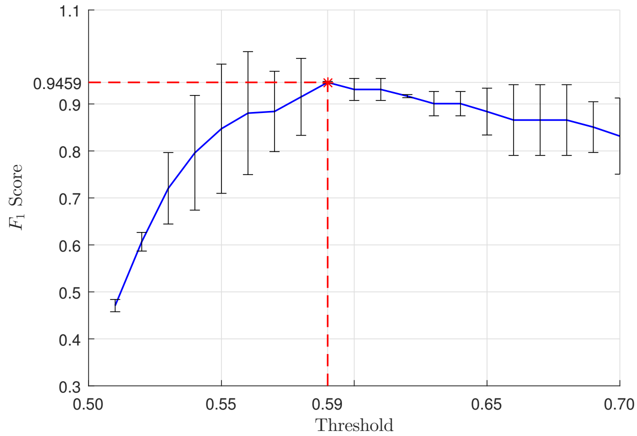

Fig. 5. F1 Score curve for a bounded th_s.

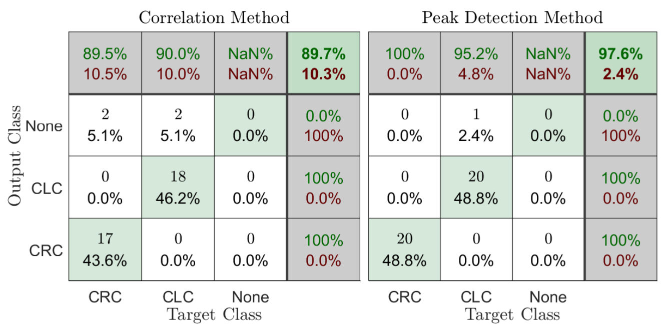

Fig. 6. Confusion matrices for the best scenario of application of the correlation and the peak detection methods.

CRC (center-right-center movement), CLC (center-left-center movement) and None.

We should observe in the correlation method's matrix in Fig. 6 that only 39 signals are analyzed, instead of 41. This is justified by the fact that the correlation analysis method depends on having one reference signal for each movement (CRC and CLC). These reference signals were drawn from the database arbitrarily.

By comparing both confusion matrices, we realize that the peak detection method reaches a higher success rate of 97,6%, whereas the the correlation analysis method presents a 89,7% success rate for the EOG signal database considered. This difference is justified by the fact that the correlation analysis depends on the similarity between the analyzed signal and a reference signal. Therefore, if both signals do not belong to the same user, we expect the correspondence between them to be smaller. Meanwhile, the peak detection method depends only on the dynamics of peaks and valleys which are typical of any EOG signal.

In the paper [6] the data acquisition system is similar to the one described in this paper, and similar accuracy results were achieved as well. The accuracy of over 90% achieved in [6] reveals to be very close to the 89,7% accuracy obtained by the correlation analysis method described in this paper, and below the 97,6% achieved with the peak detection method. Although comparison is difficult, since data acquisition experiments are of different nature, the resulting rates provide motivation to improve the algorithms proposed.

In [4], more types of eye movement were investigated and distinguished. The classification results of the method presented in [4] was of 95.63% accuracy, again very close to the rate achieved in both methods presented in this paper.

VI. Conclusion

In this paper, we described the EOG signal acquisition module used, as well as the methodology to generate the signal database. Two eye movement recognition algorithms were proposed using DWT tools and classification evaluation. Using the previously created database, the peak detection and the correlation analysis methods were validated resulting in an accuracy rate of 89,7% and 97,8% respectively. Finally a comparative analysis was performed between the two proposed methods and those presented by [6] and [4]. Future developments for this work should include vertical eye movements detection as well as a robustness analysis for a more diversified signal database.

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