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Classifying Electrooculogram to Detect Directional Eye Movements

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Abstract

Human computer interfaces that can be controlled by eye movements may be used as intelligent rehabilitation aids. Electrooculogram (EOG), the bio-potential produced around eyes due to eye ball motion can be used to track eye movements. This paper presents a comparative study of different methods for Electrooculogram classification to utilize it to control rehabilitation aids. Electrooculogram is acquired with a designed data acquisition system and different signal features are extracted. Those features are used to classify the movements of the eyeball in horizontal and vertical direction. Based on these classified signals control commands can be generated for human computer interface.

Keywords: Autoregressive parameters(AR); classification; electrooculogram(EOG); human computer interfacing(HCI); power spectral density(PSD); wavelet transform.

1. Introduction

Diseases like amyotropic lateral sclerosis, spinal cord injury etc., can cause neuro-motor disabilities leading to difficulty in controlling limb movements. Human computer interfacing (HCI) technology can help to restore the activities of the lost or damaged body part by providing motor, sensory or cognitive modality [1].

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Human Computer Interfaced rehabilitative aids can be implemented by various modalities of bio-signals, Electrooculography (EOG) being an efficient one. It is non-invasive, cost efficient, easy to acquire and can be processed in real time. Eye movement is proved to have a linear relation with EOG amplitude up to a certain degree. EOG-based control of devices can be used for neuro-prosthetic devices [2], controlling motion of computer cursor [3] and controlling wheelchair system for rehabilitation [4]. There have been different strategies of analyzing [5] and implementing EOG [6] for control application [19, 20, 21].

The detection of the actual direction of eye movements is the basic and most important criteria to apply EOG to control devices. The potential of EOG changes, when unintentional eye movement occurs. Hence to generate the control commands of any device from EOG signal the directional eye movements must be accurately classified.

Controlling Human Computer Interface (HCI) by any bio-potential comprises of three main steps: feature extraction, classification, and control signal coding. Previously we have successfully detected horizontal eye movement utilizing only wavelet features [22]. In the present work, PSD, wavelet detail coefficients, Auto Regressive (AR) coefficients and combinations of these are taken as sets of features. After feature extraction, the band pass filtered EOG signals are classified according to different directions of eye movements i.e., right, left, up, down, blink and straight or no movement. These can be used to generate control signals to simulate the movement of rehabilitation aids. The present work has been developed in an offline environment, but it has opened the door towards the real time control of HCI using EOG in future.

2. Electrooculogram(EOG)

Electrooculography (EOG) is a method of measuring the potential difference between the front (positive pole formed by cornea) and back (negative pole formed by retina) of the eye ball [7] and thus can be used for detection of eye movements and blinks. When the eyes are fixated straight ahead, a steady baseline potential is measured by electrodes placed around the eyes.

Usually silver-silver chloride electrodes are used as they show negligible drift and develop almost no polarization potentials. The electrodes should be placed as near the eyes as possible to maximize the measured potential. A change in potential is detected as the poles come closer or move away from the electrodes while moving the eyes. The sign of the change depends on the direction of the movement. EOG measurements can be affected by artifacts arising from muscle potentials and small electromagnetic disturbances due to cables or surrounding power line interference.

3. Experimental Paradigm

3.1. Visual Cue

Experiments were conducted with two females and two males in the age group of 23±2 years as subjects, who were asked to move their eye balls according to a visual cue. In the visual stimulus, a ball in the middle of a screen was displayed in the first 10 seconds. After that they were asked to track the movement of the ball in different directions (left-right-up-down) and blink their eyes when it is displayed to do so in the screen.

3.2. Data Acquisition System

EOG signal has been acquired through a two channel system (comprising of a horizontal and a vertical channel) developed in the laboratory, using Ag/AgCl disposable electrodes at a sampling frequency of 256 Hz. The frequency range of EOG signal is 0.1 to 20 Hz and the amplitude lies between 100-3500 micro volts [8]. A minimum voltage gain of 2000 is necessary.

The signal collected from the electrodes is fed to instrumentation amplifier having high input impedance and CMRR followed by a second order low pass filter with a cut off of 20Hz and a high pass filter of 0.1Hz cut off to eliminate unwanted data. An overall gain of 2000 is achieved. For bio-potential signal acquisition isolation is an important factor to be considered for patients as well as for instrument's safety. Power isolation is provided by the use of a dual output hybrid DC-DC converter and signal isolation is obtained by optically coupling the amplifier output signal with the next stage. The whole system is used for each of the two channels. For conversion of the signal in digital format, National Instruments ADC is used with the circuit and the data is taken in LabVIEW 2012 platform.

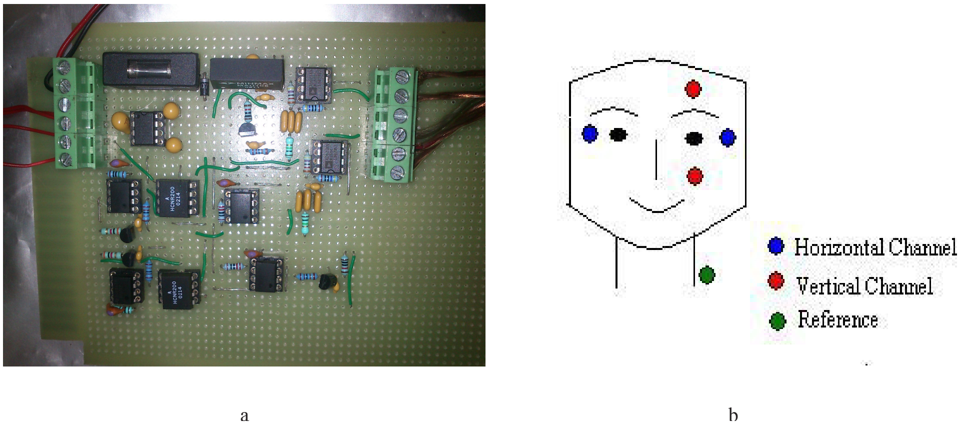

Fig. 1. (a) Designed EOG recording system and (b) placement of electrodes

4. Eye Movement Detection Methodology

The raw EOG data obtained is subjected to the following processes: Filtering, feature extraction and finally classification.

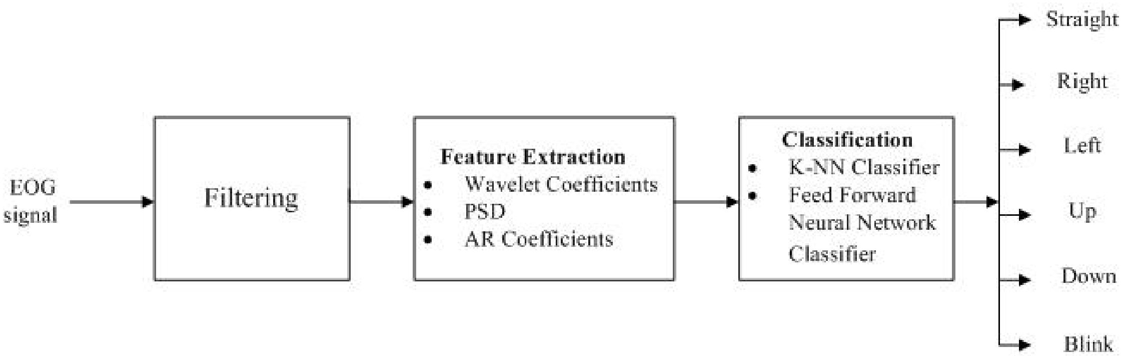

Fig. 2. Flowchart depicting the course of work

4.1. Preprocessing

The raw EOG data is filtered before features are extracted from it, in order to get EOG signal within the frequency range of 0.1 to 15Hz, as it is observed that the maximum information is contained within this frequency range. We have used a Chebyshev band pass filter for this purpose.

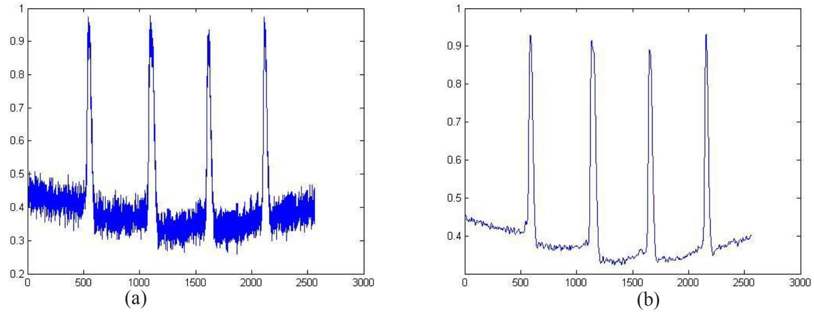

Fig. 3. Raw (a) and Filtered (b) EOG signal of normal blinks of subject 4 of the experiment

4.2. Feature Extraction

Any signal can be represented by means of some attributes. Such attributes can be used as features to distinctly characterize the signal. In the present work we have performed classification with Auto-Regressive parameters, Power Spectral Density (PSD) and Wavelet Coefficients as features of the EOG signal.

4.2.1. Auto Regression (AR) Model

The AR Model can also be called infinite impulse response (IIR) filter or all-pole filter or maximum entropy model. It is used to model any stationary stochastic time-series. Wide-sense stationary means the mean of the data is constant and the autocorrelation depends only on the time lag Eq. (1).

$$< x_t >= \text{constant}; \quad < x_t x_{t+k} >= r_k \tag{1}$$

The autoregressive model of order p, AR (p), is given by

$$x_t = \sum_{i=1}^{p} a_i x_{t-i} + \varepsilon_t \tag{2}$$

Where a_i is the AR coefficients, x_t is the series under observation and ε_t is the residue term which is Gaussian White Noise. By convention, the series x_t is assumed to have zero mean.

For calculating the AR coefficients, among the different methods the two algorithms that we have followed are:

- Yule-Walker Method
- Burg Method

4.2.1.1. Yule Walker Method

The method involves multiplying the Eq. (2) by x_{t-d}, where d is the delay; then averaging and normalizing the result. Repeating the process for d=1 to p, yields the following set of linear equations called the Yule-Walker equations.[9] The matrix form of the Yule-Walker Equations is given by Eq. (3)

$$\begin{bmatrix} 1 & r_1 & r_2 & \cdots & r_{p-1} \\ r_1 & 1 & r_1 & \cdots & r_{p-2} \\ r_2 & r_1 & 1 & \cdots & r_{p-3} \\ \vdots & \vdots & \vdots & & \vdots \\ r_{p-1} & r_{p-2} & r_{p-3} & \cdots & 1 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_p \end{bmatrix} = \begin{bmatrix} r_1 \\ r_2 \\ r_3 \\ \vdots \\ r_p \end{bmatrix} \tag{3}$$

Here, a_i (i=1 to p) are the required AR coefficients for an AR (p) process.

4.2.1.2. Burg Method

If we are provided with N discrete values, we can approximate the values using k coefficients by forward linear prediction Eq. (4) or by backward linear prediction Eq. (5).

$$y_n = -\sum_{i=1}^{k} a_i x_{n-i} \tag{4}$$

$$z_n = -\sum_{i=1}^{k} a_i x_{n+i} \tag{5}$$

The forward prediction and backward prediction selects a_i such that the forward error F_k and backward error B_k are minimized. Eq. (6) & (7)

$$F_k = \sum_{n=k}^{N} (x_n - y_n)^2 = \sum_{n=k}^{N} (x_n - (-\sum_{i=1}^{k} a_i x_{n-i}))^2 \tag{6}$$

$$B_k = \sum_{n=0}^{N-k} (x_n - z_n)^2 = \sum_{n=0}^{N-k} (x_n - (-\sum_{i=1}^{k} a_i x_{n+i}))^2 \tag{7}$$

In Levinson Durbin recursion

$$A_{k+1} = A_k + \mu V_k \tag{8}$$

Where $A_{k+1}= [1\ a_1\ a_2\ \ldots\ a_k\ 0]^T$ and $V_{k+1}=[0\ a_k\ \ldots\ a_2\ a_1\ 1]^T$

In Burg's method, μ is so calculated that F_k+B_k are minimized. With the initial condition of A_0= [1] and iterating Eq. (8) from k=0 to p-1, we can obtain the AR coefficients for an AR (p) process [10].

In our work, we have fitted the data using an AR (4) model. So we have 5 coefficients for each data point.

4.2.2. Power Spectral Density Estimation using Yule-Walker Method

Non-parametric power spectral density estimation involves computing the Fourier Transform of the data or the auto-correlation function of the data. On the other hand, parametric power spectral density estimation involves fitting an appropriate model to the data, a parametric estimation method to calculate the values of the parameters of the model and the frequency response evaluation of the model which gives an estimate of the PSD of the data.

The method, used in this work, is a parametric power spectral density estimation method [11].

Rearranging Eq. (2), we can write

$$x_t - \sum_{i=1}^{p} a_i x_{t-i} = (1 - \sum_{i=1}^{p} a_i z^{-i}) x_t = \varepsilon_t$$

$$\Rightarrow \frac{x_t}{\varepsilon_t} = \frac{1}{1 - \sum_{i=1}^{p} a_i z^{-i}} = H(z)$$

$$\Rightarrow H(f) = \frac{1}{1 - \sum_{i-1}^{p} a_i e^{-ji(2\pi f)T}} \tag{9}$$

This is the transfer function of the system Eq. (9), where the AR coefficients, a_i, are given by the Yule-Walker Equation Eq. (3).

The power spectrum, $P_x(f)$, of the time series x_t is given by Eq. (10). This is related to the power spectral density of the white noise, $P_\varepsilon(f)$, which is its variance, σ^2.

$$P_x(f) = |H(f)|^2 P_\varepsilon(f) = \frac{\sigma^2}{\left|1 - \sum_{i=1}^{p} a_i e^{-ji(2\pi f)T}\right|^2} \tag{10}$$

We have used a 129-point discrete approximation of the power spectrum.

4.2.3. Wavelet Features

Wavelet transform [12, 13], an efficient technique to represent the characteristics of a signal, is based on small waves called wavelets having variable frequency and limited duration. The discrete wavelet transform (DWT) analyzes the signals by decomposing the signal into approximation and detail information, called approximation and detail coefficients respectively.

The outputs of the first decomposition level provide the detail D1 and approximation A1 coefficients, respectively. The first approximation A1 is further decomposed into second approximation A2 and detail D2 and the process continued, until the desired result is obtained.

In the present study, Daubechies (db) mother wavelet of order 4 have used. After trials with the filtered EOG data, the detail coefficients from level 5 are selected as features.

4.3. Classification

Classification is carried out on each of the different feature spaces obtained from the raw EOG signal as described above using two different classification techniques: k-NN Classifier and a feed- forward neural network and the corresponding classification accuracies are compared.

4.3.1. k-NN Classifier

K Nearest Neighbour is a classification algorithm where a test point is put into the class which is the most common among its k nearest neighbours [14, 15]. The measure of nearness is some form of distance which can be calculated using different methods, such as Euclidean distance, Mahalanobis distance, Manhattan distance etc.

In our experiments, k-NN algorithm has been run with different values of k ranging from 2 to 7. Euclidean distance with k=5 have been selected as it produces the best results.

4.3.2. Feed Forward Neural Net Classifier

Artificial Neural Networks [16, 17] comprise of artificial neurons following the principle of biological neural networks. A feed forward neural network consists of a number of layers of neurons connected such that information can flow only in the forward direction. The initial layer is the input layer and the final layer is the output layer. All the other layers are hidden layers. For each neuron the weighted sum of the inputs are passed through some non-linearity to obtain the outputs. According to the principle of supervised learning, during the training phase, for an initial set of weights of the neural network, the output is calculated and the error is computed for a known target. According to the computed error the weights are adapted. The process is continued as long as the error is reduced below a certain predetermined small value.

In the present work we have used a feed forward network with 10 hidden layers where weight adaptation is done on the basis of Levenberg-Marquardt method [18].

4.4. Performance Analysis

The classification results obtained are compared in terms of the classification accuracies and the computational time for each classification method. The classification accuracies are computed using confusion matrices.

Table 1 and Table 2 show the classification performance using Wavelet Detail Coefficients and Power Spectral Density (PSD) as features respectively.

Table 1. Classification Results for Wavelet Detail Coefficients as Features

	k-NN with k=5		Feed Forward Neural Network	
	Classification Accuracy	Time (Sec)	Classification Accuracy	Time (Sec)
Subject 1	56.67%	0.5634	70.00%	25.0183
Subject 2	56.67%	0.5792	72.00%	26.3662
Subject 3	56.67%	0.5951	70.00%	34.8541
Subject 4	56.67%	0.5766	73.30%	34.8165
Average	56.67%	0.578575	71.33%	30.26378

Table 2. Classification Results for PSD as Features

	k-NN with k=5		Feed Forward Neural Network	
	Classification Accuracy	Time (Sec)	Classification Accuracy	Time (Sec)
Subject 1	66.67%	1.5175	83.30%	86.6939
Subject 2	73.33%	0.5901	83.30%	126.3032
Subject 3	60.00%	0.6731	70.00%	92.3123
Subject 4	66.67%	0.6899	76.70%	78.2909
Average	66.67%	0.86765	78.33%	95.90008

Table 3. Classification Results for Wavelet Detail Coefficients + PSD as Features

	k-NN with k=5		Feed Forward Neural Network	
	Classification Accuracy	Time (Sec)	Classification Accuracy	Time (Sec)
Subject 1	60.00%	0.6398	70.00%	287.3973
Subject 2	70.00%	0.6554	76.70%	259.3699
Subject 3	56.67%	0.6734	76.70%	284.115
Subject 4	66.67%	0.6575	77.70%	296.0901
Average	63.34%	0.656525	75.28%	281.7431

Table 3 shows the classification results when both Wavelet Detail Coefficients and PSD are used to construct the feature space. A feature vector from the feature space representing the two channels of EOG signal formed by only Wavelet Detail Coefficients, only PSD and Wavelet Detail Coefficients + PSD have dimensions of 1×172, 1×258 and 1×430 respectively. As is clear from these three tables, the average classification accuracy is increased to 63.34% for k-NN classifier when Wavelet Detail Coefficients and PSD are together used as features.

Table 4. Classification Results for AR Coefficients (Yule Walker Method + Burg Method) as Features

	k-NN with k=5		Feed Forward Neural Network	
	Classification Accuracy	Time (Sec)	Classification Accuracy	Time (Sec)
Subject 1	51.00%	0.6647	90.00%	5.1052
Subject 2	53.33%	0.6899	73.30%	4.967
Subject 3	50.00%	0.648	73.30%	4.9705
Subject 4	56.67%	0.6491	83.30%	5.0177
Average	52.75%	0.662925	79.98%	5.0151

Table 4 shows the classification results obtained by taking the AR coefficients as features. The feature space is constructed by concatenating the feature spaces obtained from calculating AR coefficients by Yule Walker method and Burg Method respectively, the corresponding feature vector having dimension of 1×20.

Table 5 shows the classification results obtained by taking AR coefficients from Yule Walker method and PSD together to form the feature space so that a feature vector in this case would have a dimension of 1×268.

Table 5. Classification Results for AR Coefficients (Yule Walker Method) + PSD as Features

	k-NN with k=5		Feed Forward Neural Network	
	Classification Accuracy	Time (Sec)	Classification Accuracy	Time (Sec)
Subject 1	63.33%	0.6495	80.00%	105.5567
Subject 2	80.00%	0.6111	86.70%	105.839
Subject 3	66.67%	0.6498	73.30%	91.762
Subject 4	66.67%	0.651	80.00%	123.87
Average	69.17%	0.64035	80.00%	106.7569

There is clear improvement of classification accuracy in the latter case. It is increased 69.17% for k-NN classifier and 80% for the Neural Network Classifier.

5. Conclusion & Future Scope

In the present work the different types and directions (straight, up, down, right, left, and blink) of eye movement has been classified from acquired EOG signal by k-NN and feed forward Neural Network classifiers. The features used for classification are Wavelet Detail Coefficients, PSD and AR Coefficients and combinations of these. It has been observed that in all cases the neural network classifier performs better with average classification accuracies greater than 65%.

In future we aim to design real time systems that can be operated from eye movements that can find potential applications in rehabilitation and military purposes.

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