Electrooculogram Based Blink Detection to Limit the Risk of Eye Dystonia

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***Abstract*—In this paper a system for detecting the possibility of eye dystonia, a neural disorder that causes a person to blink excessively, by eye movement analysis is proposed. The designed system counts the number of blinks for a particular time interval and thus detecting the risk of eye dystonia. Electrooculogram (EOG) signal is recorded to collect eye movement data using a laboratory developed acquisition system. Radial Basis Function(RBF) kernel Support Vector Machine (SVM) classifier and Feed forward neural network classifier is used to classify blinks from other types of eye movements using combinations of Wavelet coefficients, Autoregressive (AR) parameters and Hjorth parameters with Power Spectral Density (PSD) as signal features. A maximum average accuracy of 95.33% over all classes and participants is obtained using RBF-SVM classifier with a feature space of AR parameters of order 5 and PSD taken together.**

Keywords—Autoregressive Parameters(AR); Blink Detection; Electrooculogram (EOG); Eye Dystonia; Hjorth Parameters; Power Spectral Density (PSD); Support Vector Machine (SVM); Wavelet Transform.

I. INTRODUCTION

Eye dystonia is known as a neural disorder where eye blinking frequency increases. A disease that causes involuntary muscular contractions in a particular body part is called Focal dystonia. A type of focal dystonia that affects the human eyes, and is characterized by excessive blinking and involuntary closure of the eyelids is termed as Blepharospasm, popularly known as eye dystonia [1-2].

Many techniques such as Infrared Video System (IRVS), Infrared Oculography (IROG), Search Coil (SC), Optical-type Eye Tracking System, Purkinje dual-Purkinje-image (DPI) and Electroculography (EOG) [3-4] can be used to record eye movement data. The simplest of all these techniques is EOG. Using surface electrodes that are placed around the eye socket EOG signal is easy to acquire and process in real time. To predict the presence of diseases whose symptoms are heavily characterized by eye movements and blinks in a cost-effective and simple way, an electrooculographic system can be applied.

EOG signal is a measure of the potential difference between the front and back of the eye ball. Experiments reveal that there exists a linear relation between eye movement and EOG amplitude up to a certain degree. EOG can thus be used for detection of eye movements and blinks [5]. EOG is important for both clinicians and scientists as it provides abundant neuro-pathological information. EOG is also an efficient alternative for HCI without speech or hand movements. Moreover, Different characteristics of EOG reveal that it has the potential to be implemented to control different rehabilitation aids.

Detection and assessment of many ophthalmological diseases such as Retinitis Pigmentosa [6] and Best's disease [7] as well as degenerative muscular disorders and neural diseases like Parkinson' s disease [8] are the main applications of EOG signal. Different applications of EOG analysis can be found in Drowsiness detection and cognitive process modeling also [9]. EOG based Eye movement controlled human computer interfaces are the major interests of recent HCI research. Several instances of EOG-based control in Human Computer Interactions are found in the literature [10-12], including controlling motion of computer cursor [13] and controlling wheelchair system for rehabilitation [14]. There have been different strategies of analyzing [15, 18] and implementing EOG in the field of robotics [16]. Researchers have shown blink detection using various methods with applications in different events like fatigue monitoring, consciousness analysis during driving, etc [17, 19].

A scheme to detect the number of blinks of an individual, over a certain period of time using EOG analysis and thus predicting whether the individual is likely to be affected by eye dystonia has been proposed in this work. A two-channel data acquisition system is used to record EOG from ten subjects over a period of 30 minutes each for 5 days. Wavelet Coefficients, Auto-regressive parameters, Hjorth parameters and Power Spectral Density are extracted as features from the acquired EOG. Feed forward neural network and Radial Basis Function Kernel Support Vector Machine (RBF-SVM) classifiers are implemented to detect the eye blinks. After classification, the number of blinks is counted and if the number of blinks is found to be greater than 900 in 30 minutes it is possible that the person is likely to be affected by eye dystonia and is referred to an ophthalmologist for further tests and consequent treatment.

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The rest of the paper is structured as follows. Section II explains the principles and methodology concerning EOG, the features and classifiers used. In section III the entire method followed to detect blinks has been discussed. Section IV covers the experimental results. Finally in section V the conclusions are drawn.

II. PRINCIPLES & METHODOLOGY

This section describes the different stages of EOG signal processing to detect the risk of eye dystonia.

A. Electrooculogram (EOG)

Electrooculography (EOG) is a method of measuring the potential difference between the front and back of the eye ball [6-7]. When the eyes are kept fixed straight ahead, a steady baseline potential is measured by electrodes placed around the eyes. 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 in potential difference 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.

Typically EOG signal magnitudes range from 0.05 mV-3.5 mV per degree of eye ball movement with the frequency range of 0.1 Hz to 20Hz. When the gaze is shifted in the upward direction, the positive cornea becomes closer to the upper electrode, which becomes more positive, with zero potential at the electrode below the eye, and vice versa resulting negative and positive output voltage respectively. The pulse produced by upward movement is nearly the same as produced by downward movement in both amplitude and pulse duration. Even with the eye closed, the potential is observed to be the same. Blinks, on the other hand, are short duration pulses, having comparatively high amplitude.

B. Feature Extraction

1) 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.

2) Hjorth Parameters: Hjorth Parameters, namely activity (A), mobility (M) and complexity(C) [25] are time domain features extracted from a signal. For an input signal x (n) of length N, these can be defined as follows:

$$A(x) = \mathrm{var(x)} \tag{1}$$

$$M(x) = \sqrt{\frac{A(x')}{A(x)}} \tag{2}$$

$$C(x) = \frac{M(x')}{M(x)} \tag{3}$$

Where $\mathrm{var(x)}$ denotes the variance of signal x (n) with mean value $\bar{x}$, given by:

$$\mathrm{var}(x) = \frac{\sum_{n=1}^{N}(x(n)-\bar{x})}{N} \tag{4}$$

For each signal component of each of the two channels of the EOG signal, we have obtained three values corresponding to activity, mobility and complexity representing the Hjorth Parameters. Thus, horizontally concatenating the hjorth parameters (in the above order) for the horizontal and the vertical channel we get each feature vector of dimension of 1×6 and thereby a feature space is constructed.

3) Auto-Regressive (AR) Model : The AR model is used to describe a stochastic stationary time-series. A wide-sense stationary series has a constant mean and the autocorrelation depends only on the time lag (5).

$$< x_t >= \text{constant}; \quad < x_t x_{t+k} >= r_k \tag{5}$$

The autoregressive model of order p, AR (p), is given by (6).

$$x_t = \sum_{i=1}^{p} a_i x_{t-i} + \varepsilon_t \tag{6}$$

Where a_i is the AR coefficient, x_t is the series under observation having zero mean and ε_t is the zero-mean Gaussian white noise. In the present work AR coefficients have been calculated by the Yule-Walker Method.

In Yule Walker method (6) is multiplied by x_{t-d}, where d is the delay; then the result is averaged and normalized. Repeating the process for d=1 to p, the following set of linear equations called the Yule-Walker equations are obtained [23]. The matrix form of the Yule-Walker Equations is given by (7)

$$\begin{bmatrix} 1 & r_1 & r_2 & \cdots & r_{p-1} \\ r_1 & 1 & r_1 & \cdots & r_{p-2} \\ r_2 & r_1 & 1 & \cdots & r_{p-3} \\ \vdots & \vdots & \vdots & & \vdots \\ r_{p-1} & r_{p-2} & r_{p-3} & \cdots & 1 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_p \end{bmatrix} = \begin{bmatrix} r_1 \\ r_2 \\ r_3 \\ \vdots \\ r_p \end{bmatrix} \tag{7}$$

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

In our work, we have fitted the data using an AR (5) model on segments of EOG signal assumed to be stationary, thereby obtaining 5 coefficients for each data point.

4) Power Spectral Density : In the present work we have computed the parametric Power Spectral Density (PSD). Parametric power spectral density estimation [24] involves fitting the data to an appropriate model and a parametric estimation method to calculate the values of the model parameters. Then the frequency response of the model is evaluated to estimate the PSD of the data.

From (6), we can write

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

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

$$\Rightarrow H(f) = \frac{1}{1 - \sum_{i-1}^{p} a_i e^{-ji(2\pi f)T}} \tag{8}$$

Eq. (8) states the transfer function of the system where the AR coefficients, a_i, are given by the Yule-Walker Equation (7). The power spectrum, $P_x(f)$, of the time series x_t is given by (10), where $P_\varepsilon(f)$ is the power spectral density of the white noise, given by its variance σ^2.

$$P_x(f) = |H(f)|^2 P_\varepsilon(f) = \frac{\sigma^2}{\left| 1 - \sum_{i=1}^{p} a_i e^{-ji(2\pi f)T} \right|^2} \tag{9}$$

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

C. Classification

1) Support Vector Machine : Support vector machine (SVM) is a well-known supervised machine learning algorithm for classifying data into two different classes [26].

Linear SVM (LSVM) works on the principle of separating two classes of data by constructing a hyper plane within the training data points. The hyperplane is defined by the 'support vectors'. These are the training data points closest to the hyperplane that belong to two different classes. The hyperplane is constructed so as to maximize the distance margin between the support vectors, and thereby maximally separating the two classes. However, use of Linear SVM is limited to situations where the data are linearly separable. This limitation of Linear SVM can be overcome by mapping the data into a larger dimensional space using a kernel function, *K(x,y)*, to make the data points linearly-separable. The frequently used kernel functions are polynomial and radial basis function (RBF) kernel [27-28]. The polynomial kernel is defined by (10) where d is the order of the polynomial and c is a constant trading off the influence of higher-order versus lower-order terms in the polynomial.

$$K(x, y) = (x^T y + c)^d \tag{10}$$

The RBF or Gaussian kernel is defined by (11) where σ denotes the width of the Gaussian.

$$K(x, y) = \exp\left(\frac{-\|x - y\|^2}{2\sigma^2} \right) \tag{11}$$

2) Feed Forward Neural Network: 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.

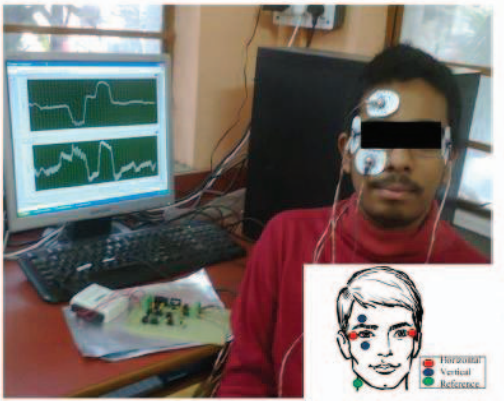
In the present work we have used a feed forward network with 10 hidden layers where weight adaptation is done on the basis of Levenberg-Marquardt method [21].

III. Possibility of Eye Dystonia: Blink Detection

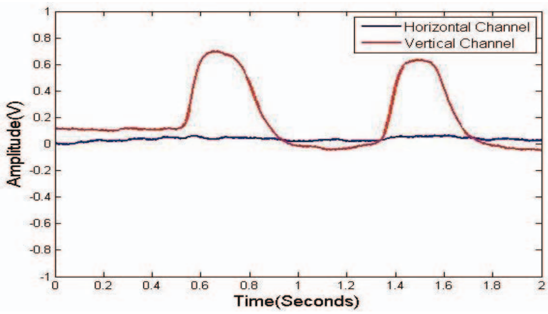
A. Data Acquisition

1)Data Acquisition System : EOG signal has been acquired through a two channel data acquisition (DAQ) system developed in the laboratory (comprising of a horizontal and a vertical channel)[22]. The system makes use of Ag/AgCl disposable surface electrodes [18]. 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, a 12 bit Analog to Digital Converter (manufactured by National Instruments) is used with the circuit and the data is taken at a sampling frequency of 256 Hz.



(a)



(b)

Fig. 1. EOG Acquisiton (a) Designed Data Acquisition System & Electrode Placement (b) Blink signal

Five electrodes are used in our experiment to measure the EOG signal. One of these five electrodes acts as the reference electrode and is placed at earlobe. The other four electrodes are placed above, below, to the left and to the right of the eye socket (as shown in Fig. 1(a)).

2) Experimental Setup : The EOG data is collected from fifteen subjects, ten female and five male in the age group of 50-60 years. The electrode placement is illustrated in Fig. 1(a). Though the designed system has two channels, the data collected from the vertical channel is further processed, as blinks are detected in this data.The data acquisition is done for 5 days with one day interval in between, to include any variation caused by the weather, the surrounding environment as well as possible allergy or temporary infections on the subjects. After explaining the procedure and the objective of study, a consent form is signed by all the subjects. An audio visual stimulus is shown to the subjects for acquiring EOG data for classification. As the EOG signal from the vertical channel can discriminate blinking from staring, looking up and looking down, we consider the cue in the form of blink, followed no-blink (stare/up/down alternatively) i.e. in the sequence blink-stare-blink-up-blink-down. The data is acquired in a properly lit and airy room. In Fig.2, the methodology of work has been illustrated.

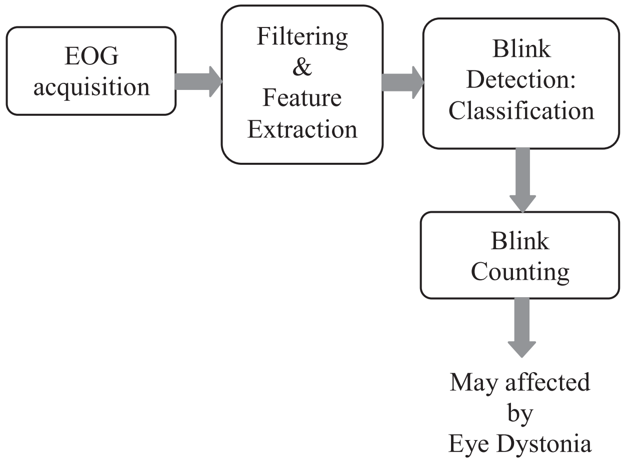


Fig. 2. Flowchart depicting course of work

B. Filtering

To eliminate undesirable noise and obtain EOG in the frequency range of 0.1 to 15Hz, the range where maximum information is contained, we implement band pass filtering. A Elliptical band pass filter in the specified frequency range has been used for this purpose.

C. Detection of Blinks

EOG for eye movements over an interval of approximately 30 minutes (30×60=1800seconds) are recorded and processed for feature extraction. Experiments are carried out using three different features, Wavelet coefficients, AR parameters, and PSD. Two feature spaces are constructed. The first feature space is constructed from Wavelet coefficients + PSD, the second feature space is constructed from AR (5) parameters + PSD and the third feature space is constructed from Hjorth parameters + PSD. The two classes in which the data is classified are Blink and No-Blink. RBF-kernel SVM and feed forward neural network classifiers are trained for binary classification. For RBF kernel the value of σ is taken as 1. From the resulting confusion matrix after classification, several performance indicators are calculated.

The number of blinks made by each subject is counted from the results of classification. A healthy individual in properly conditioned light and air blinks 18-22 times in a minute while at rest [29]. So taking a safe margin, we can assume that people afflicted by eye dystonia have increased blink rate of around 30 blinks per minute. If the count of blinks for the classification of EOG data in 30 minutes exceeds 900 (30×30=900), it is concluded that the person is likely to be afflicted by eye dystonia.

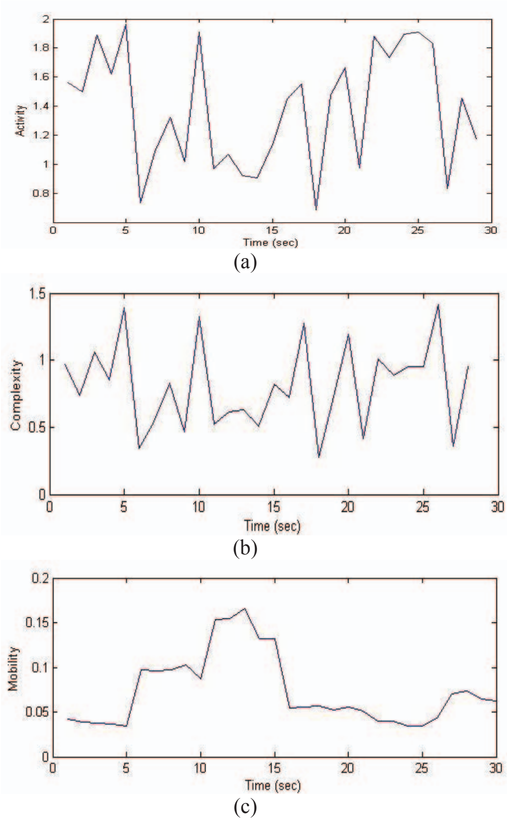


Fig. 3 Hjorth parameters of EOG signal
[Activity (a), Complexity (b) and Mobility (c)]

D. Performance Analysis

A confusion matrix is constructed from each classification result to evaluate the accuracy (12), sensitivity (13) and specificity (14) as performance metrics.

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \times 100\% \tag{12}$$

$$Sensitivity = 1 - \frac{FN}{TP + FN} \tag{13}$$

$$Specificity = 1 - \frac{FP}{TN + FP} \tag{14}$$

In (12-14), TP, TN, FP and FN represent the number of samples classified as true positive, true negative, false positive and false negative respectively. Ideally the accuracy should be close to 100%, while the sensitivity and the specificity should be 1.Sensitivity specifies how much perfectly the classifier can identify a blink as blink. While the precision with which a non-blink movement of the eye is classified as no-blink is indicated by Specificity.

IV. Experimental Results

The EOG data acquired for 30 minutes has alternates of blink and no-blink eye movements. The acquired EOG signal of two such observations is plotted against time in Fig. 3(a). The obtained signal is then filtered using a band-pass Elliptical filter. The filtered signal is shown in Fig. 3(b). The results of classification in terms of the average value of the performance metrics along with the timing complexity over 10 subjects are noted in Table I.

TABLE I. Classification results

Feature	Classifier	Accuracy (%)	Sensiti-vity	Specifi-city	Time (sec)
Wavelet + PSD	Feed Forward Neural Network	66.67	0.70	0.8	1.2579
	RBF-SVM	73.20	0.83	0.7	1.1276
AR + PSD	Feed Forward Neural Network	81.50	0.85	0.9	1.1483
	RBF-SVM	**95.33**	0.9	1	1.1169
Hjorth + PSD	Feed Forward Neural Network	75.21	0.75	0.8	1.1463
	RBF-SVM	86.67	0.8	0.8	1.0386

As we note from Table I, feature-set produced with AR (5) +PSD and classified using RBF kernel SVM outperforms the other algorithms considered.

V. Comparison with Related Works

In [16], assistance for the paralyzed using eye blink detection has been done with 84%. 95.3% accuracy has been achieved for eye blink detection in drivers using novel color and texture segmentation algorithms [17]. A statistical modeling based system in digital cameras [20] has been 94% accurate in blink detection. In our proposed method an accuracy of 95.33% has been obtained. In our prevous work [19] also, this combination of feature and classifier has given good results.

VI. Conclusions

This work proposes a simple scheme to detect the possibility of eye dystonia. Here EOG is classified to detect blinks and then by counting the number of blinks over a period of time, possibility of dystonia is calculated. Feature extraction was accomplished by Wavelet coefficients, AR parameters and Power Spectral Density. Three acquired feature sets (Wavelet+PSD), (AR+PSD) and (Hjorth+PSD) are used for binary classification to distinguish between blinks and non-blink eye movements using Radial Basis Function (RBF) kernelized Support Vector Machine (SVM) classifier and feed forward neural network classifier. Using AR (5) +PSD feature space and RBF-SVM as the classifier, the best classification accuracy of 95.33% was achieved.

The present work has been carried out on normal individuals, and future scopes include implementation of this scheme to patients suffering from eye dystonia for cost-effective assistance in diagnosis of the disease.

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