Eye movement sequence analysis using electrooculogram to assist autistic children

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ABSTRACT

The present work proposes a system for assistance of Autistic children by analysis of eye movements. Autism is a disease characterized by abnormal eye movements and an inability to follow a pattern of object movement in different directions. Eye movement data is recorded from normal individuals over a period of five days using an Electrooculogram signal acquisition system developed in the laboratory. Hjorth Parameters are used as signal features. Eye movement directions in response to a visual stimulus for tracking an object are classified using ensemble classifiers based on bagging and adaptive boosting algorithms. Maximum classification accuracies of 83.09%, 90.27%, 80.75% and 92.27% were achieved on Hjorth Parameters as features using Bagging Ensemble classifier while tracking four different sequences. The individuals are trained by repeated tracking of the sequences such that there is an improvement in tracking over time. The system is designed to measure the tracking accuracy of following four different sequences of movement of an object in different directions as shown in a cue in a predetermined interval of time. The average tracking accuracy over ten normal subjects considering all the four sequence stimuli improves from 78.64% to 90.96% in five days which is accompanied with a decrease in staring errors from 6.36% to 1.29%. This would enable convenient detection of eye fixations/staring errors in Autistic people along with the provision of gradual improvements when the tracking sequences are not followed in 50% of the cases through consequent training.

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1. Introduction

Autism is a neurological disorder featuring lack of social interaction and communication abilities [1,2]. The onset of the disease is detected in children prior to 3 years of age. The affected children show restricted and repetitive behavior and avoid eye contact. Execution of core activities involving eye movement tasks such as reading, concentrating on a pattern etc. helps in improving visual discrimination, strengthening of memory, tracking and focusing abilities of such individuals that never reaches typical adult levels.

Eye movement detection can be done using 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 Electrooculography (EOG) [3,4]. EOG has proved to be the simplest of all these techniques. An EOG system is fairly easy to construct using surface electrodes that are placed around the eye socket and is simple to work with in real time. Thus we can employ an electrooculographic system to predict the presence of diseases whose symptoms are heavily characterized by eye movements in a cost-effective and simple way.

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]. Different characteristics of EOG reveal its potential to be implemented for controlling different rehabilitation aids. EOG is important for both clinicians and scientists as it provides abundant neuropathological information. EOG is also an efficient alternative for HCI without speech or hand movements.

The main applications of EOG signal include 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]. Drowsiness detection and cognitive process modeling are also different applications of EOG analysis [9]. Eye movement controlled
human computer interfaces based on EOG are the major interests of recent HCI research. Several instances of EOG based control of neuro-prosthetic devices are found in the literature [4,10], including controlling motion of computer cursor [11] and controlling wheelchair system for rehabilitation [12]. There have been different strategies of analyzing [13] and implementing EOG in the field of robotics [14,15]. Researchers have shown blink detection using various methods with applications in different events like fatigue monitoring, consciousness analysis during driving, etc. [16–18].

The present work proposes a scheme to assist autistic children having abnormalities in eye movement related to continuous tracking of an object using EOG analysis. EOG is recorded using a two channel data acquisition system from ten subjects over a period of 6 min each for 5 days using a visual stimulus. Hjorth Parameters are extracted as features from the acquired EOG. Ensemble (Bagging and Boosting) classifiers are trained to distinguish eye movements in different directions as well as fixed gaze. The trained classifiers are used to classify different eye movement directions using a test visual stimulus that involves tracking a ball on the computer screen. The performance of the ensemble classifiers in distinguishing the eye movement directions is analyzed. The best classifier is then used to find the tracking accuracy of an individual where successful tracking of a complete sequence is considered. If the tracking accuracy is lesser than 50%, it can be concluded that the person cannot trace the movement of the ball and is likely to be affected by autism. If a subject is detected to be Autistic, he/she is asked to use the system daily until the tracking accuracy improves more than 50% and the staring errors decreases below 20%.

The rest of the paper is structured as follows: Section 2 explains the principles and methodology concerning EOG, the features and classifiers used. In Section 3 the entire method followed to build the proposed system has been discussed. Section 4 covers the experimental results. Finally, in Sections 5 and 6 the discussions are provided and conclusions are drawn respectively.

2. Principles and methodology

This section accounts the different attributes of the EOG signal and the algorithms used for feature extraction and classification.

2.1. Electrooculogram

Electrooculogram (EOG) signal [19,20] is the electrical potential which is generated due to the movement of the eyeballs in the surrounding region of the eye. It is acquired noninvasively using surface electrodes placed on the region surrounding the eye socket.

The amplitude of the EOG signal changes depending on the angle through which the eyeball is moved. When the eye ball is moved either side, the voltage changes from positive to negative and returns to zero when looking straight. When measuring vertical movement, the potential caused by horizontal movement on the vertical electrodes is less significant compared to vertical potential and vice versa. The pulse produced by leftward movement is nearly the same as produced by rightward movement in both amplitude and pulse duration. The signal potential remains the same even with the eyes closed. EOG signal has pulse duration of approximately 200 ms on average. The signal shows a particular pulse shape for eye ball movement in either direction. Signal magnitudes changes from 5 to 20 μV for a degree of eye ball movement typically. The main disadvantage of EOG signal is that head or body movement alters the DC level of the signal.

2.2. Feature extraction

Hjorth Parameters, namely activity (A), mobility (M) and complexity(C) [21–23] are time domain features extracted from a signal. For an input signal x(n) of length N, these can be defined by (1)–(3).

\[
A(x) = \text{var}(x) \quad (1)
\]

\[
M(x) = \sqrt{\frac{\text{var}(x)}{\text{mean}(x)}} \quad (2)
\]

\[
C(x) = \frac{\text{mean}(x)}{M(x)} \quad (3)
\]

where \(x\) denotes the first derivative of the signal \(x(n)\) and \(\text{var}(x)\) denotes the biased variance of signal \(x(n)\) with mean value \(\bar{x}\) given by (4).

\[
\text{var}(x) = \frac{\sum_{n=1}^{N}(x(n) - \bar{x})^2}{N} \quad (4)
\]

Hjorth Parameters are relevant in case of biosignals because they help in reducing the non-stationarities and capturing the stationarities through the use of higher order derivatives of the input signal [21]. In order to represent the stationarities, Hjorth Parameters are computed over small overlapping windows of equal lengths and then for a particular instance, all the parameters over all windows for that instance are averaged. For each instance from each of the two channels of the EOG signal, we have obtained three values corresponding to activity, mobility and complexity representing the Hjorth Parameters. Concatenating the features per channel we obtain six features per instance. For our work, the length of the window is experimentally chosen to be 16 i.e. Hjorth Parameters are evaluated over 16 instants of an observation, at a time, followed by moving the window over the next set of 16 instants considering 50% overlap with the previous window.

2.3. Classification

Ensemble classifier [24–29] is a family of classifiers whose individual predictions are combined (weighted voting) to decide the class of the test samples. It is more accurate to rely on the decision that is made by a group of classifiers rather than by a single classifier. So, we use ensemble classifier in our work. Two important criteria must be satisfied in selecting the classifiers: the classifiers must be accurate (error rate better than random guess; also called weak learners) and diverse (different error on new dataset). We have used ‘tree’ classifier as the weak learner in this work. Each node of the tree classifier operates on each of the features in the dataset to predict the class of a sample. There are several algorithms to implement the ensemble classifiers. Two such popular methods are bagging and boosting [25–28] which have been used in this work.

In case of bagging, classifiers are trained by dataset obtained from bootstrapping the original dataset. While bootstrapping, a subset of the dataset is created by randomly drawing (with replacement) \(n\) samples from the original dataset. The diversity among the weak classifiers is obtained by resampling procedure. The resampling is decided to take place \(T\) times. Finally, majority voting is employed to infer the class of an unknown sample.

AdaBoost refers to adaptive boosting. If the process is iterated \(T\) times, each time AdaBoost creates a new weak classifier using the whole dataset and the weights for all samples are updated, which is initially equal for all instances. The weights of the samples misclassified are increased and the weights of the samples correctly classified are decreased. It is called adaptive because it is focuses on those samples which are misclassified in previous iterations. The weighted voting mechanism decides the class of a new sample.
For our work, the value of $T$ in both the algorithms is taken to be 100. The bootstrap size ($n$) for the bagging algorithm is considered to be 30% of the total dataset. AdaBoostM1 extension of the AdaBoost algorithm is chosen for the concerned application and the classification is performed in a one-versus-one framework.

3. Autism assistance

A brief description of the circuit used for acquiring the data and the different steps taken in the course of experimentation in a laboratory environment are briefly outlined in this section.

3.1. Data acquisition

The layout of the data acquisition module and the total arrangement for gathering the data for the experiment has been addressed to in this section.

3.1.1. Data acquisition system

From the characteristics of EOG signal it is known that the frequency range of the signal is 0.1–20 Hz and the amplitude lies in between 100 and 3500 μV [5]. Hence a voltage gain of minimum 2000 is needed to further processing of the raw signal.

The data acquisition system is shown in the experimental setup in Fig. 1. The collected signal from the electrodes is fed to instrumentation amplifier (implemented using IC AD620) having high input impedance and CMRR (−90 dB) followed by a second order low pass filter with a cut off of 20 Hz and a high pass filter of 0.1 Hz cut off to eliminate unwanted data. For filter designing IC OP07s are used. Gain is applied in various stages. Amplifier has a gain of 200 and 10 gain is provided by the filters. Thus an overall gain of 2000 is reached.

For biosignal acquisition isolation is an important factor to be considered for patient’s safety as well as for instrument’s safety. Power isolation is provided by the use of a dual output hybrid DC to DC converter (MAU 108) and signal isolation is obtained by optical coupling the amplifier/output signal with the next stage. To achieve this HCNR 200 is used. EOG signal is acquired at a sampling frequency of 256 Hz using 5 Ag-AgCl disposable electrodes, two for the horizontal channel, two for the vertical channel and one as reference. This circuit is interfaced with the computer using a National Instrument Analog to Digital Converter of word length 12 bits.

3.1.2. Experimental setup

The EOG data is collected from twenty subjects, ten male and ten female in the age group of 25 ± 3 years. The electrode placement is illustrated in Fig. 1. 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 to the eyes of 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.

We consider four different visual cues in the form of the movement of a ball in a specified path. In the first cue the displayed sequence is right, down, left, up followed by a stare in the middle. In the second one, the previous cue is back tracked i.e., down, right, up, left and stare. The third cue traces a ‘Z’ in the screen where the ball moves in the right side in the top of the screen, then, coming down along the off diagonal and again, moving in the right side in the bottom of the screen followed by a stare i.e. right, off-diagonal down, right, stare. The fourth cue is just opposite of the third one, where the ball moves in the order left, off diagonal up, left, stare. The first and the third cues are illustrated in Fig. 2(a) and (b), respectively. For each sequence of pattern, a particular direction of movement is of duration 2 s. Each stimulus is traced ten times by each subject with sufficient rest periods in between to produce a dataset of large number of instances for training/testing. Data was acquired in an airy room where the stimulus was shown on a screen using a projector.

3.2. Filtering

In the present experiments it was found that the EOG power spectrum showed significant variations below 10 Hz which concludes that no necessary information is prevalent in the 10–20 Hz region. To eliminate undesirable noise and obtain EOG in the frequency range of 0.1–10 Hz, the range where maximum information

![Fig. 1. EOG signal acquisition and experimental setup.](image1)

![Fig. 2. Visual cues showing the path of the ball along the sides of a rectangle and stare at the center for the sequences corresponding to (a) stimulus 1: Right, Down, Left, Up, Stare and (b) stimulus 3: Right, Off Diagonal Down, Right, Stare.](image2)
is contained [10,30], we implement band pass filtering using a Butterworth band pass filter in the specified frequency range.

3.3. Training of classifier

EOG for eye movements over an interval of approximately 6 min are recorded and processed for training the classifiers. Experiments are carried out using Hjorth Parameters as the signal features. Different ensemble classifiers are trained for classification. Classification is carried out using 5-fold cross-validation and following a one-versus-one strategy. After classification, percentage accuracy (5) is noted as a performance metric using the number of samples classified as true positive (TP), true negative (TN), false positive (FP) and false negative (FN) according to the resulting confusion matrix.

\[
\text{accuracy} = \frac{TP + TN}{TP + TN + FN + FP} \times 100\%
\] (5)

3.4. Assistance to the autism affected

Ten new subjects, who are unaware of the pattern in the visual cue, are asked to provide data in a manner similar to the previous case. The trained classifiers are used to classify the gaze direction. The resulting classification accuracy gives a measure of how correctly the sequence is tracked and is termed as tracking accuracy, henceforth. The number of eye movements (left, right, up, down or diagonals) misclassified as looking straight is referred to as staring errors.

After consulting with professionals working with autistic children, taking a safe margin we have set the value of greater than 50% tracking accuracy and less than 20% staring error for healthy individuals in properly conditioned light and air in following the sequence of movements as shown in the visual cues. Hence we can say that autistic people will fail to follow a pattern in 50% of the cases and mostly maintain a fixed gaze at the screen where the cue is shown.

We understand that the opinion of professionals, not being based on any objective study, is likely to have a subjective component. Therefore, the actual threshold values for determining tracking accuracies and staring errors may differ from the values set in our study and we also intend to find them out through experiments with autistic children in future. Thus the threshold values may be modified accordingly. The proposed methodology to be followed during assistance to autistic persons been illustrated in Fig. 3.

4. Experimental results

The EOG signal acquired while tracking the first sequence once is plotted against time in Fig. 4(a) and (b). The obtained signal is then filtered using a band pass Butterworth filter. The filtered signal is shown in Fig. 4(c) and (d).

![Flowchart depicting course of work.](image_url)
The time required to execute each eye movement is 2 s. Such eye movement tracings of the four different stimuli separately have been illustrated in Fig. 5(a)–(d) showing the horizontal and vertical channel signals in each case. From these plots it is observed how the horizontal channel data discriminates between the right/left directions and the vertical channel data discriminates the up/down or diagonal up/down movements clearly. For example the pattern in Fig. 5(a) clearly illustrates the tracing of right (a high positive horizontal signal)-down (a high negative signal)-left (a high negative horizontal signal)-up (a high positive vertical signal)-stare (almost zero amplitudes in both channels) with respect to the time axis.

The average classification accuracy along with the timing complexity over 20 subjects obtained while training the classifier is noted in Table 1. As we note from Table 1, classification using Bagging outperforms the other and hence is considered further. To bring out the relevance of the use of Ensemble methods rather than standard procedures, a statistical validation test is carried out to rank Ensemble (Bagging and Boosting), Support Vector Machine (SVM) [31], Naive Bayes [31,32] and k nearest neighbor (k-NN) [32] classifiers with respect to their Accuracy (%) in classification.

All classifications are carried out in one-versus-one method and average results are used. For SVM a Radial Basis Function (RBF) kernel is used with the width of the Gaussian taken as 1 and it is tuned with a cost parameter of 100. The Naive Bayes classifier is used with the assumption that the features have a normal distribution whose mean and covariance are learned during the process of training. For k-NN the value of k is taken as 3 and Euclidean distance as the distance measure with majority voting is used for determining the class of the test samples. All these parameters are determined experimentally after noting the best performances on an average. Friedman Test [33] has been carried out taking the mean classifier accuracy for each classification algorithm used, as shown in Table 2.

![Fig. 5. EOG signals acquired from Subject 1 for different eye movements while tracking (a) stimulus 1, (b) stimulus 2, (c) stimulus 3 and (d) stimulus 4.](image)

| Table 1 Classification results: average over twenty subjects. |
|---|---|---|---|---|
| Stimulus | Ensemble classifier | Classification Accuracy (%) | Time (s) |
| 1 | Bagging | 83.09 | 17.6976 |
| 2 | Boosting | 74.91 | 49.736 |
| 3 | Bagging | 90.27 | 17.3454 |
| 4 | Boosting | 77.26 | 48.3352 |
| 5 | Bagging | 80.75 | 20.1218 |
| 6 | Boosting | 79.59 | 60.1906 |
| 7 | Bagging | 92.27 | 19.6406 |
| 8 | Boosting | 89.32 | 60.1380 |

| Table 2 Table for classifier comparison through Friedman test. |
|---|---|---|---|---|---|
| Test parameters | Classifier | Ensemble bagging | Ensemble boosting | SVM | kNN | Naive Bayes |
| Mean accuracy (%) | 86.60 | 80.27 | 78.25 | 72.66 | 75.84 |
| Mean rank | 1.25 | 2 | 3.50 | 4 | 4.75 |
Table 3
Eye movement analysis results for day 1.

<table>
<thead>
<tr>
<th>Sequence</th>
<th>Tracking accuracy (%)</th>
<th>Staring errors (%)</th>
<th>Tracking accuracy (%)</th>
<th>Staring errors (%)</th>
<th>Tracking accuracy (%)</th>
<th>Staring errors (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Right, Down, Left, Up, Stare</td>
<td>65.45</td>
<td>9.72</td>
<td>72.31</td>
<td>6.91</td>
<td>83.45</td>
<td>3.63</td>
</tr>
<tr>
<td>Down, Right, Up, Left, Stare</td>
<td>69.5</td>
<td>5.67</td>
<td>79.55</td>
<td>5.97</td>
<td>73.55</td>
<td>13.23</td>
</tr>
<tr>
<td>Right, Off Diagonal Down, Right, Stare</td>
<td>74.17</td>
<td>6.32</td>
<td>82.01</td>
<td>2.54</td>
<td>71.23</td>
<td>8.24</td>
</tr>
<tr>
<td>Left, Off Diagonal Up, Left, Stare</td>
<td>72.45</td>
<td>3.87</td>
<td>81.45</td>
<td>9.67</td>
<td>72.43</td>
<td>8.1</td>
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<tr>
<td></td>
<td>73.17</td>
<td>5.57</td>
<td>80.92</td>
<td>7.89</td>
<td>78.5</td>
<td>7.89</td>
</tr>
<tr>
<td></td>
<td>79.84</td>
<td>7.8</td>
<td>77.78</td>
<td>5.48</td>
<td>77.89</td>
<td>5.13</td>
</tr>
<tr>
<td></td>
<td>72.34</td>
<td>4.92</td>
<td>78.34</td>
<td>9.21</td>
<td>79.7</td>
<td>8.27</td>
</tr>
<tr>
<td></td>
<td>74.89</td>
<td>5.72</td>
<td>79.49</td>
<td>7.63</td>
<td>80.45</td>
<td>7.33</td>
</tr>
<tr>
<td></td>
<td>69.82</td>
<td>7.47</td>
<td>80.16</td>
<td>5.82</td>
<td>78.71</td>
<td>8.09</td>
</tr>
</tbody>
</table>

The null hypothesis states that all the classification algorithms are equivalent. The Friedman statistic is given by (6).

\[
\chi^2_F = \frac{12N}{K(K+1)} \left[ \sum_{j=1}^{K} \frac{R_j^2}{K(K+1)^2} \right] - \frac{K}{4} \tag{6}
\]

It is distributed according to \( \chi^2 \) with \( K - 1 \) degrees of freedom. Here \( K \) is the number of algorithms used which in our case is 5. The null hypothesis is rejected if evaluated \( \chi^2_F > \chi^2_{0.05, K} = 9.49 \), which indicates, for 4 degrees of freedom, the null hypothesis is correct to an extent of only 5%. The test is carried out on the twenty databases corresponding to the twenty subjects and the ranks are evaluated with respect to the average classification accuracies over all stimuli presentation. In this case \( \chi^2_F \) is found to be 91 hence the null hypothesis is rejected and the classifier performance is evaluated by its rank, showing the superiority of the bagging ensemble classifier followed by boosting ensemble classifier.

Tracking accuracy measures the percentage of occasions when a complete sequence is correctly identified out of total number of such sequences followed by the subject. Staring error is defined as the percentage of occasions when a non-stare class is classified as a stare. The tracking accuracy and the staring errors are mentioned in Table 3 when the proposed system was tested on healthy individuals for a single day. The tracking accuracy should be high so as to indicate a good ability to track a specified sequence. A low value of staring error indicates the absence of unnecessary staring and hence is mandatory to prove that the person is free from autism.

As observed from Table 3, the high performance of the proposed system indicates its applicability for the mentioned purpose of assisting Autistic children. Table 4 illustrates the gradual improvement in tracking all the four stimuli in average over a period of 5 days while training 10 normal individuals using the proposed system. There is evident improvement in tracking in healthy individuals according to the obtained results. However, when the system will be used on autistic persons, the accuracies are likely to deteriorate with larger amounts of staring errors. But it can be justifiably claimed that the trend in improvement with time will exist.

5. Discussions

In our previous works [20,34–36] we have successfully demonstrated EOG signals for classification of different types of eye movements using various features and standard pattern classifiers achieving high accuracies. In [37] a microprocessor based control of motors using EOG based commands has been illustrated. Such works show that EOG can successfully be utilized in eye movement recognition. In [38] EOG signal analysis has been used for assisting the improvement of speed and accuracy of visual attention. This has been implemented by predicting the gaze positions while subjects play a computer game through wavelet denoising and subsequent target position estimation by least squares error from the linear transformation of EOG data into target positions. However, the present work, to the best of the authors’ knowledge, for the first time incorporates extensive experimental procedures to determine the relations of EOG signals with tracking four specific eye movement sequences and implements the results to estimate the improvements in tracking accuracy of subjects over time, achieving remarkable results.

6. Conclusions

The present work proposes a simple scheme to provide assistance by ocular training to the autistic children by studying the eye movements by classifying EOG to assess the correct tracking of four different sequences over a period of time. Feature extraction was accomplished by Hjorth Parameters. Multiclass classification was performed to distinguish between different directions eye movements or fixed gaze using ensemble classifiers employing bagging and boosting algorithms. The maximum classification accuracies of 83.09%, 90.27%, 80.75% and 92.27% were achieved on Hjorth Parameters as features using Bagging Ensemble classifier for the four different tracking sequences. The average tracking accuracy over ten normal subjects and four different stimuli increases to 90.96% at the end of fifth day of training from 78.64% in the first day whereas the staring errors decrease from 6.36% to 1.29% at the end of five days.

Hence, the proposed methodology can be utilized in developing an intelligent automatic concept for behavioral intervention system for autistic children based on EOG signal analysis for cost-effective assistance in eye movement based sequence following training. The final strategy has to be designed working with autistic children. Moreover, the system needs to be made portable and wireless so that it can be useful to use at home also.

Table 4
Average improvements observed over ten subjects.

<table>
<thead>
<tr>
<th>Performance parameters</th>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tracking accuracy (%)</td>
<td>78.64</td>
<td>84.09</td>
<td>87.78</td>
<td>89.53</td>
<td>90.96</td>
</tr>
<tr>
<td>Staring errors (%)</td>
<td>6.36</td>
<td>5.95</td>
<td>3.78</td>
<td>3.50</td>
<td>1.29</td>
</tr>
</tbody>
</table>
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