Biomedical Signal Processing and Control 14 (2014) 134–140

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Eye movement sequence analysis using electrooculogram to assist autistic children

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ARTICLE INFO

Article history:
Received 21 November 2013
Received in revised form 7 July 2014
Accepted 17 July 2014
Available online 9 August 2014

Keywords:
Autism
Hjorth Parameters
Electrooculogram
Ensemble classifier
Eye movement analysis

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.

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 although 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 Electroculography (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

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http://dx.doi.org/10.1016/j.bspc.2014.07.010
1746-8094/

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).

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

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

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

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

$$var(x) = \frac{\sum_{n=1}^{N}(x(n) - \bar{x})^2}{N} \tag{4}$$

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.