Feature selection in categorizing activities by eye movements using electrooculograph signals

S.Mala

Research Scholar, Department of CSE
Anna University, BIT Campus,
Tiruchirappalli,Tamil Nadu, India
scholarmala@gmail.com

K.Latha

Assistant Professor, Department of CSE
Anna University, BIT Campus,
Tiruchirappalli, Tamil Nadu, India
erklatha@gmail.com

Abstract—**Eyes are the windows to the brain and the eye movements are a rich source of information in information processing. The aim of this paper is to select the features with CBFS Feature selection algorithm using eye movements by ElectroOculoGraph (EOG) signals during reading and writing task. The objective is to impart the fundamental functionality to get an extensive understanding of how EOG signals can be applied in human computer interaction(HCI) and what can be inferred from those signals using feature selection and data mining classification techniques. This paper first identifies the importance of eye movements and EOG signals then analyze EOG signals by CBFS (clearness based feature selection), mRMR (minimum redundancy maximum relevance) feature Selection methods and the third section demonstrates the performance of data mining classification in EOG signals.**

Keywords—Eye Movements; Feature Selection; CBFS; mRMR; Classification.

I. INTRODUCTION

Eye movements can be recorded by using a wide variety of methods [1-2]and are extremely informative as a data source for analysis of human cognition. Eye movements are used as one of the rich source of information in information processing. There are broadly two types of eye movements' namely voluntary and involuntary movements of the eyes. Some of the interfaces used for detecting eye movements are listed in Table 1.

TABLE I. VARIOUS EYE TRACKING TECHNIQUES

Eye Tracking Technique	Source	Comments
ElectroOculoGraphy (EOG)	Geoffrey Arden (Arden et al. 1962).	This can be manufactured at low price. Installation of electrode is easy, noninvasive. Can be used for long time. Simple and Cost effective
Sclera search coil method	Robinson, 1963;Collewijn, van der Mark & Jansen, 1975	Determined with high accuracy, but needs particular contact lens, Invasiveness to subject is high and experimental time is limited to around 30 min
InfraRedOculoGraphy (IROG)	Kumar&krol, 1992	Head Mounted and Limbus tracking. Special and Temporal resolution will be high but blink is the downside.
VideoOculoGraphy (VOG)	Chan, chang, sang and won, 2006	Non invasive but expensive and large dimension device.

II. ELECTROOCULOGRAPH (EOG) SIGNALS AND ITS APPLICATIONS

Electrooculograph Signals relates to several research communities such as Human Computer Interaction, Activity Recognition, Visualization and Data Mining.

A. Eye movements and EOG

The EOG may be detected with the eye in total darkness and/or with the eyes closed. It is quite unrelated to light incentive. Emil du Bois-Reymond observed that the cornea of the eye is electrically positive relative to the back of the eye, and described eye as a fixed dipole with positive pole at the cornea and negative pole at the retina.An electrooculograph is a device that measures the voltage between two electrodes placed on the face of a subject so it can detect eye movements. Electrooculography (EOG) is a technique for measuring the resting potential of the retina, and the resulting signal is called the Electrooculogram. Elwin Marg named the electrooculogram in 1951 and Geoffrey Arden in 1962 created the first clinical application. The main applications are in ophthalmological diagnosis and in recording eye movements. The Fig.1 outlines the sample EOG Horizontal signals on eyes moving right and left and the Fig. 2. It shows the electrodes placements for measuring EOG signals.
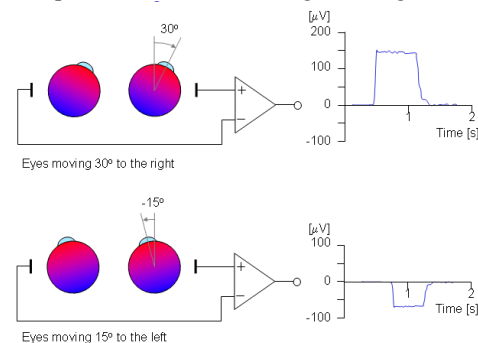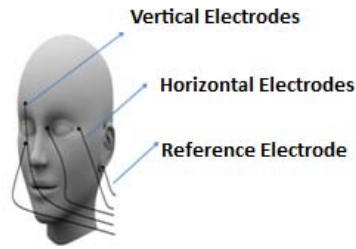

Fig. 1. A Sample EOG by horizontal movement of the eyes[i]

Fig. 2. Electrode Placements for EOG

B. EOG in HCI

For instance, researchers have studied eye movements to understand user behaviour in basic interface tasks, to reveal how clients encode and process information, and to infer user intent in real-time interfaces. However, with notable exceptions [3], Eye movements can be recorded by using several methods, some of them are listed in Table 1. Eye movements are extremely informative as a data source for analysis of human cognition.

The use of EOG signals as control signal for HMI/HCI plays a vital role in understanding characterization and classification of eye movements. These signals can be applied to wide range of applications including virtual mouse, key board control electric power wheelchairs and industrial assistive robots.

The EOG and blinking signals are utilized as a part of Human-Computer Interfaces in;

- The Vehicle Control [4]
- The Video compression driven by eye-interest
- The Driver Drowsiness Detection System
- The ergonomics, the advertisement analysis
- The Wearable machines [5]
- The Human-Computer-Interaction (HCI)system[e.g.Virtual keyboard [6]]
- The game and operating a TV remote control [7]
- The Visual navigation interface [8]
- The Online Vigilance Analysis [9]
- The Multitask gadget control [10]
- The electric wheelchair [11]

C. Advantage of EOG

EOG signal is one of the efficient electro-physiological signals to be deployed in Human Computer Interface [12]. In recent years dedicated Human Computer Interfaces / Human Machine Interfaces have been developed for people with disabilities like Parkinson, Quadriplegia, armless people and people who suffer from a motor skill disability but not a cognitive one, Amyotrophic Lateral Sclerosis or Motor Neuron Disease that leave them with no possibility to communicate, although the brain and eyes activities are not affected, among the few ways of communication in these cases is the detection of the eye movements. The advantages of EOG than other eye tracking methods are

✓ Reduces the complexity and cost.
  ■ EOG can be made with cost effective electrodes, data acquisition card and appropriate software.
✓ Eye Closure is Permissible
  ■ The EOG can beused to record eye movements when the eye is shut, for example during rest.
✓ Head Movements are Permissible
  ■ The EOG has the advantage that the signal recorded is the actual eyeball position with respect to the head. Therefore for frameworks intendedto measure relative eyeball position to control switches (e.g. looking up, down, left and right could translate to four separateswitch presses) head movements will not hinder accurate recording.
✓ Non-invasive
  ■ Unlike techniques such as the magnetic search coil technique, EOG recordings do not require anything to be fixed to the eye which might cause discomfort or interfere with normal vision. EOG electrodes are affixed externally to the skin.
✓ Real-Time
  ■ The EOG can be utilized in real-time as the EOG signal responds instantaneously to a change in eye position. The eye position can be quickly inferred from the change.

III. ACTIVITYRECOGNITION AND EYE MOVEMENTS

Most of the researches in activity recognition have focused on gait, posture, and gesture. The recognition of activities such as reading and writing are investigated during stationary and mobile settings using different eye tracking techniques. Eye movements are linked to a number of cognitive processes of visual perception such as visual memory, learning or attention. Eyes are therefore called a window to mind and brain. The cognitive aware systems are able to sense and adapt to a person's cognitive state [13].

Activity recognition has become an important topic for a broad range of real-life applications. In surveillance systems, patient monitoring systems and a variety of systems that involve interactions between persons and electronic devices such as human-computer interfaces activity recognition places a significant role. A rich source of information for activity recognition is the movement of the eyes [14]. This work demonstrates the machine recognition of reading and writing activities using EOG signals and reduces the computational complexity which mainly occurs during the feature selection.

IV. METHODOLOGY

EOG signal classification is mapping EOG signals into predefined classes. The characterization includes some essential principlessuch as representation where features of the signals are extracted, generalization which is training andevaluating the classifier. The vital role of classification is feature extraction and feature selection.In this paper, two different feature selection techniques (mRMR, CBFS) have

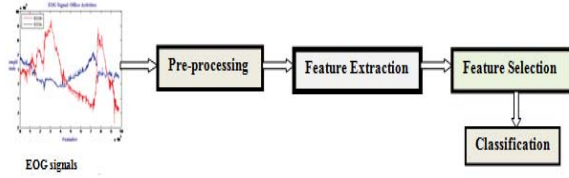been utilized to represent EOG signals. Fig. 3: illustrates basic EOG signal classification framework.

Fig. 3. General EOG Signal Classification Framework

A. EOG Data Collection

The initial process is data collection. The data used in this study are collected from the Andreas Bulling "RECOGNITION OF OFFICE ACTIVITIES"[1] data set. The data collection of this work included two major offices-based activities - reading a printed paper, taking handwritten notes. The columns of data found in mat files representing the time, voltage readings of EOG signals during reading and writing activities are used in this work.

B. Preprocessing

The median filter performed denoising best; it preserved edge steepness of eye movements, retained EOG signal amplitudes, and did not present any artificial signal changes. For baseline drift removal this work employedlevel nine 1-D wavelet decomposition using Daubechies wavelets. Fig. 4 outlines the EOG signal after using median filtering and removing base line drifts.
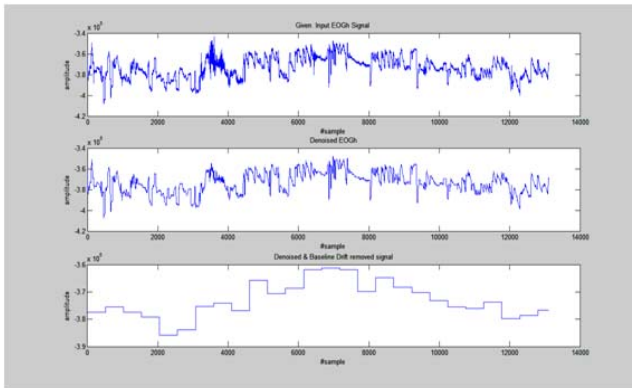

Fig. 4. Preprocessed EOG Signal

C. Feature Extraction

The job of feature extraction is to obtain the most usefulinformation from the original data. Feature Selection represents the information in a fewer dimension space.This work concentrate on improving the feature extraction (in EOG signals) stage by selecting efficient subset of features. 13

[1] https://www.andreas-bulling.de/datasets/recognition-of-office-activities/

features from a database of EOG signals are extracted. These features are used in efficient identification of reading and writing Activity. This work used Minimum Redundancy Maximum Relevance (mRMR) [15] and Clearness Based Feature Selection (CBFS) [16-17] techniques to select the features and also recommend good features for recognizing activities.

D. Basic Eye Movement Characteristics

Basic eye movements such as Saccades, Fixations and Blinks can be detected from the preprocessed EOG signals. Basic eye movement's features such as Mean, Trim means Median, Variance, Standard deviation, z-score, sigh-rank, kurtosis, sample entropy, HFD (Higuchi's Fractional Dimension) can be detected from the processed Horizontal and Vertical EOG signals.

E. Feature Selection

Feature selection is important in many pattern recognition problems for excluding inappropriate and tautological features. Feature Selection improves recognition accuracy by reducing system complexity and processing time. Feature selection is a search problem for finding an optimal or suboptimal subset of m features out of original M features. Many feature subset selection algorithms have been proposed. These algorithms can generally be classified as wrapper or filter algorithms according to the criterion function used in searching for good features. The simplest feature selection methods select best individual features. A feature evaluation function ranks the individual features, then the highest ranked features(m) are selected. These methods can exclude irrelevant features, but they often include redundant features.

1) Minimum Redundancy MaximumRelevance:

The minimal-redundancy-maximal-relevance (mRMR)algorithm is a sequential forward selection algorithm. It uses mutual information to analyze relevance and redundancy. The mRMR scheme selects the features that correlate the strongest with a classification variable and combined with selection features that are mutually different from each other have high correlation and it is denoted by (1). The selected features with relevance score are listed in Table 3.

$$J(X_n) = I(X_n;Y) - \frac{1}{|S|}\sum_{X_i \in S} I(X_n;X_i)$$

(1)

Where $I(X_n;Y)$ -measure of dependence between feature X_n and target Y.

$J = I(X_{1n};Y) - I(X_{1n-1};Y)$ - Change in information with and without X_n.

S- Feature Set |S| - number of features

2) Clearness Based Feature Selection:

CBFS calculates the distance between the target sample and centroid of each class, and so compares the class of the closest centroid with the class of the target sample (Seo 2012). The matching ratio of all samples in a feature turns into a clearness value for the feature.

Clearness based feature selection (CBFS)algorithm which can be classified as a filter method. Clearness means the separability between classes in a feature. If (clearness of feature *f2*) > (clearness of feature *f1*), then *f2* is more advantageous to classification than *f1*.

Step 1:

The centroid for read and write is calculated by average operation. It is the median point of a class. Med (*fi, j*) denotes the median point of class *j* in the feature *fi,* which is computed by (2):

$$Med(fi, j) = \frac{1}{k} \sum_{r=1}^{k} (Xri \in classj)$$

(2)

Where k is a number of samples of class j.

Step 2:

For each xij in sample predicted class label is calculated. After calculating the distance between *xij* and Med (*fj,ci*) for all classes, this work takes the nearest centroid Med(*fj, s*) and *s* is a predicted class label for *xij*. The length between *xij* and Med(*fj, t*) is computed by (3):

$$D(x_{ij}, Med(f_j, t)) = | x_{ij} - Med(f_j, t) |$$

(3)

Step 3:

Calculate *n × m* matrix M2 which contains a matching result of predicted class label and correct class label in *CS*. M2(*i,j*) is calculated by (4):

$$M_2(i, j) = \begin{cases} 1 if M_1(i, j) = C_i \\ 0 if M_1(i, j) \neq C_i \end{cases}$$

(4)

Step 4:

Calculate CScore (*fi*).initially we calculated CScore (*fi*) by (5):

$$CScore(f_i) = \frac{1}{n} \sum_{r=1}^{n} M_2(r, i)$$

(5)

The range of CScore (fi) is [0, 1]. If CScore (fi) is close to 1, this shows that classes in feature fi are clustered well and elements in fi can be clearly classified. The Table 2 list all the features with its clearness score.

TABLE II.   CLEARNESS SCORE FOR EACH FEATURE

S.No	Feature	CScore(fi)
1.	Mean	0.75
2.	Trim mean	0.75
3.	Inter quartile range	0.675
4.	Median absolute deviation	0.625
5.	Standard deviation	0.625
6.	Variance	0.675
7.	Median	0.75
8.	z-score	0.625
9.	sign-rank	0.5
10.	Hurst Exponent	0.575
11.	Higuchi's Fractional Dimension (HFD)	0.6
12.	Sample Entropy	0.625
13.	Kurtosis	0.725

The Table 3 list the score for selected features by CBFS feature selection and mRMR feature selection.

TABLE III.   FEATURE SELECTION METHODS WITH ITS SELECTED FEATURES

Feature Selection Method	Order	Fea.No	Feature Name	Score
CBFS	1	1	Mean	0.75
	2	2	Trim mean	0.75
	3	7	Median	0.75
Max Relevance	1	7	Median	1.439
	2	2	Trim mean	1.439
	3	13	Kurtosis	0.588
mRMR	1	7	Median	
	2	2	Trim mean	
	3	11	HFD	

CScore (fi) measures the clearness of the feature whereas the mRMR scores the features based on mutual information. The selected features by CBFS, mRMR feature selection algorithm is shown in Table 2 with its CScore. The selected features alone can clearly classify the activities such as read and write in EOG signals effectively and efficiently. This is shown by few traditional classifiers. The accuracy is used as a function of the feature subset size evaluation using few traditional classifiers in Weka.

V.   CLASSIFICATION

Classification plays an important role in many real time applications. It is important to automate the classification process since hand processing is often not a viable option [18]. The goal of EOG signal classification is to identify an input pattern with a category or class, which is a set of patterns grouped together based on similarity measures [19]. The similarity depends on the concept of interest: it may be abstract that is detecting all patterns produced by same event or more quantitative that is matching an EOG signal pattern with a prototype.

TABLE IV. DETAILED ACCURACY BY CLASS WITH CONVENTIONAL CLASSIFIERS

Method	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
CBFS+Naive Bayes (With 3 CBFS Features)	0.500	0.125	0.750	0.7500	0.750	0.708	Read
	0.875	0.500	0.700	0.700	0.700	0.708	Write
	0.714	**0.339**	**0.721**	**0.714**	**0.702**	**0.708**	Average
CBFS+SMO (With 3 CBFS Features)	0.500	0.000	1.000	1.000	1.000	0.750	Read
	1.000	0.500	.727	0.727	0.727	0.750	Write
	0.786	**0.286**	**0.844**	**0.786**	**0.767**	**0.750**	Average
CBFS+Multilayer Perceptron (With 3 CBFS features)	0.500	0.000	1.000	1.000	1.000	0.500	Read
	1.000	0.500	0.727	0.727	0.727	0.500	Write
	0.786	**0.286**	**0.844**	**0.786**	**0.767**	**0.500**	Average

VI. RESULTS AND DISCUSSION

The Table 4 shows the average precision and recall, and the corresponding True Positive, False Positive Rate of features selected for each activity (read/write). The number of features used is only three. The mean True Positive Rate for the task Write is higher than the task read. This shows that the eye movement EOG signals varied much in writing compared to reading. The task of writing may easily be identified than the other task such as reading. The overall average performance of SMO classifier is higher than other two classifiers. Though the precision, recall, F-measure for SMO (a SVM based classifier) is same that of Multilayer Perceptron, the ROC Area is high for SMO. Hence among the three classifiers the Sequential Minimal Optimization algorithm with SVM classifier performs better than others. The existing method used mRMR feature selection with different set of features. The proposed method with CBFS feature selection algorithm the SMO, a SVM based classifier performance is 84.4% precision and 78.6% recall. Thus the classifier performance is improved by using CBFS feature selection algorithm. This work shows that various task like normal and subnormal may be identified by eye movements using EOG signals and CBFS plays vital role in classification.

VII. CONCLUSION

This work recommends good features for recognizing reading and writing in EOG signals and analyze the recognition accuracy as a function of the feature subset size using conventional classifiers. CBFS C_{Score} evaluates each feature based on degree of condensation of samples to the centroid of the class such as read and write, and reduces the validation errors. Additional eye movement characteristics that are potentially useful for activity recognition are still worth investigating in the future as they may carry information that can contribute more in the current work. This work can be extended in various directions such as to explore a line of research that focuses on comparison of different feature selection methods with different set of features from EOG signals of various activities.

REFERENCES

[1] B. Wolfe, D. Eichmann. "A neural network approach to tracking eye position." *International Journal of Human-Computer Interaction*, 1997.

[2] L.R. Young, D. Sheena. "Survey of eye movement recording methods." *Behavioral Research Methods and Instrumentation*, 1975.

[3] Goldberg, D. D. Salvucci. "Identifying fixations and saccades in eye-tracking pro-tocols." *Proceedings of the 2000 Symposium on Eye Tracking Research & Applications (ETRA '00).* 2000.

[4] R Barea, L Boquete,M Mazo,E Lopez. "System for assisted mobility using eye movements based on electrooculography." *IEEE Trans. Neural Syst. Rehabil. Eng.*, 2002.

[5] A Bulling, D Roggen,G Tröster. "Wearable EOG goggles: Seamless sensing and context-awareness in everyday environments." *J. Ambient Intell. Smart Environ*, 2009.

[6] AB Usakli, S Gurkan. "Design of a novel efficient human–computer interface: an electrooculagram based virtual keyboard." *IEEE Trans. Instrum. Meas.*, 2010.

[7] LY Deng, DL Hsu, TC Lin,JS Tuan,SM Chang. "EOG-based human-computer in-terface system development." *Expert Syst. Appl.*, 2010.

[8] Talaba, Doru. "EOG-based visual navigation interface development." *Expert Systems with Applications Elsevier*, 2012.

[9] Ruo-Fei Du, Ren-Jie Liu, Tian-Xiang Wu, Bao-Liang Lu. "Online Vigilance Analysis Combining Video and Electrooculography Features." *ICONIP.* 2012.

[10] T Gandhi, M Trikha , J Santhosh,S Anand. "Development of an expert multitask gadget controlled by voluntary eye movements." *Expert Syst. Appl.*, 2010.

[11] Hiroki Tamura, Takao Manabe, Takafumi Goto, Yuki Yamashita, Koichi Tan-no. "A Study of the Electric Wheelchair Hands-Free Safety Control System Using the Sur-face-Electromyogram of Facial Muscles." *ICIRA.* 2010.

[12] A Ubeda, E Ianez, JM Azorin. "Wireless and portable EOG-based interface for assisting disabled people." *IEEE/ASME Trans. Mechatron*, 2011.

[13] S Aungsakun, A Phinyomark , P Phukpattaranont, C Limsakul. "Robust eye move-ment recognition using EOG signal for human-computer interface." *ICSECS.* 2011.

[14] A Bulling, JA Ward, H Gellersen,G Troster. "Eye movement analysis for activity recognition using electrooculography." *IEEE Trans. Pattern Anal. Mach. Intell.*, 2011.

[15] H. Peng, F. Long,C. Ding. "Feature Selection Based on Mutual Information Criteria of Max-Dependency, Max-Relevance,and Min-Redundancy." *IEEE Trans. Pattern Analysis and Machine*, Aug. 2005: 1226-1238.

[16] M Seo, S Oh. "CBFS: High Performance Feature Selection Algorithm Based on Feature Clearness." *PLos ONE 7(7): e40419*, 2012.

[17] S. Mala, K. Latha,. "Efficient Classification of EOG using CBFS Feature Selection Algorithm." *ERCICA'13.* Bangalore: Elsevier, 2013. 800-806.

[18] Kamber, J. Han. *Data Mining: Concepts and Techniques.* Elsevier, 2006.

[19] A Güven, S Kara. "Classification of electro-oculogram signals using artificial neural network." *Expert Syst. Appl.*, 2006.