Eye Movement Analysis using Neural Networks

Anugrah Srivastava
M.Tech Scholar, computer science and engineering department
Rama University Kanpur-209217, India

***Abstract*- Eye movement and their analysis is an effective way to examine visual perception. There is a special need for the design of computer software for the performance of data analysis.EOG is a technique of recording corneal- retinal potential associated with eye movement. An HCI captures and decodes EOG signals and transforms human eye movement into actions. There are two types of neural networks which are used in the analysis of eye movements namely time delay neural network and feed forward neural network. This paper proposes algorithms for identifying eleven eye movement signals and study of neural networks.**

***Keywords*- EOG technique, Electrooculography, Human Computer Interaction, Convolution Features, Singular Value Decomposition, Feed Forward Neural Network,**

1. INTRODUCTION

In day to day life, human has to do certain basic things that need control over their body or some specific body parts. In general to move from a place to another we must have control over our body. But there are persons who are so severely paralyzed that they cannot move of their own. They need someone help to move [1]. Therefore, there is a need for developing an alternative method of communication between human and Computer that would be suitable for the persons with motor impairments and would give them the opportunity to become a part of the society. People with severe disabilities retain their control through eye movements and hence eye movements are used in developing new Human Computer Interface (HCI) systems as a means to communicate with other persons or control instruments. In fact physical energy used up in moving eyes is much lesser when compared to other gestures such as moving head, movement of limbs, speaking, etc. Hence, eye movements can be effectively used for developing assistive devices for the physically disabled. Establishing a new channel without overt speaking and hand/arm motions make life easier for patients and therefore improve their life quality [2]. Assistive robotics can improve the quality of life for disable people. HCI is the study of the interaction between people and computers [3].

2. METHODS

Eleven eye movements were chosen for this study. Preliminary studies showed that the movements like open, close, stare could not be voluntarily controlled by all subjects during acquisition. Eight events related eye movement tasks and three nonevent eye movement tasks performed by each subject during the signal acquisition are detailed below:

Right: Subjects were requested to move both the eyes synchronously and symmetrically in the right direction to achieve this movement. LR and MR muscles were involved in this task.

Left: Subjects were asked to move both the eyes synchronously and symmetrically in the left direction. MR and LR muscles were responsible for this movement.

Up Right: Subjects were told to move both the eyes synchronously and symmetrically in the upper right direction to complete the task. SR and IO muscles were in charge of this movement.

Down Right: Subjects were instructed to move both the eyes synchronously and symmetrically in the down right direction. IR and SO muscles were accountable for this task.

Up Left: Subjects were requested to move both the eyes synchronously and symmetrically in the upside left direction. IO and SR muscles were occupied with this task.

Down Left: Subjects were initiating to move both the eyes synchronously and symmetricallyin the down left direction. SO and IR muscles were engaged in this movement.

Rapid Movement: Rapidly moving both the eyes from left to right and right to left are called rapid movement. The subjects were requested to move both the eyes synchronously and symmetrically in the same direction quickly and repeatedly. MR and LR muscles were responsible for this task.

Lateral Movement: Lateral movement is achieved by moving both eyes slowly from left to right or vice versa. The subjects were told to move both the eyes synchronously and symmetrically in the same direction slowly and repeatedly. MR and LR muscles were involved in this task.

Open: Subjects were instructed to open both the eyes slowly together. SR and IR muscles were engaged in this movement. *Close:* Subjects were requested to close both the eyes slowly together to achieve this task.SR and IR muscles were involved in this movement. *Stare:* Subjects were instructed to maintain the visual gaze on a single location to complete the task. SR and IR muscles were implicated in this movement. Eye movements are shown in fig. 1.

2.1 Signal Acquisition

EOG signals of the eight eye movements (events) and three eye movements (nonevents) were acquired using a two channel AD Instrument Bio-signal amplifier. Five gold plated, cup shaped electrodes were placed above and below the right eye and on the left eye and right side and left side of the eye[5]. The EOG signals are sampled at 100Hz. Since the proposed method has 2.8% reduced data processing time with slight accuracy sacrifice, this will greatly simplify the design and implementation of a microprocessor-based HCI [6]. During signal acquisition a notch filter was applied to remove the 50Hz power line artifacts. EOG signals evoked by all the eleven tasks stated above were recorded from twenty subjects. Each recording trial lasts for two seconds. Ten trials were recorded for each task. Subjects were given a break of five minutes between trials and data were collected in two sessions, each session has five trials per task. All trials for a single subject were conducted on the same day. For each subject, a data set consisting of 110 sets (11 tasks x 10 trials per task) of EOGsignals was formulated.

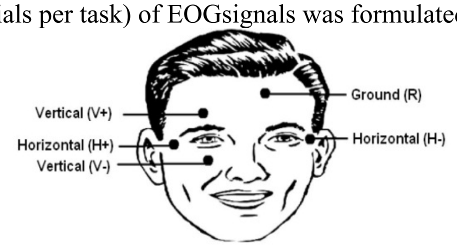

Fig. 1: eye movement signals

2.2 Preprocessing and Feature Extraction

The eight movements chosen as events were found to have frequency components in the range of 5-8 Hz while the nonevent eye movement frequency components in the range of 6-9 Hz. eight frequency bands are extracted using a Chebyshev band pass filters by splitting the signal in the range of two Hz to filter the noisy data. The eight frequency ranges are (0.1-2) Hz, (2-4) Hz, (4-6) Hz, (6-8) Hz, (8-10) Hz, (10-12) Hz, (12-14) Hz, (14-16) Hz. A feature extraction algorithm based on the Convolution theorem and Singular value Decomposition are proposed to extract the features from each band. Convolution theorem states that a mathematical operation on two signals *Xbj*and *Rbj* producing a third signal that is typically viewed as a modified version of one of the original signals, giving the area overlap between the two signals as a function of the amount that one of the original signals is translated. The convolution of $F1$ and $R1$ is written $F1*R1$, where * denotes the convolution operator.

Xbj= xbiji=1,2,……..100, b=1,2,……,8 (1)

Rbj= xbiji=100, 99,……..1, b=1,2,……,8 (2)

$F1$=FXbj (3)

$R1$=$FRbj$ (4)

Let F denote the Fourier Transform, so that FXbjbe a Fourier signal and $FRbj$be a reverse and shifted Fourier signal of the Fourier transform of $F1$ and $R1$ respectively. Then $FF1*R1$ =$FF1$.$FR1$ (5) where the dot represents the point wise multiplication. The above equation can also be written as

$FF1.R1$ =$FF1$ $*FR1$ (6)

By applying the Convolution equation, we can write

$F1*R1$= F{ F1}.F{ R1} $N-1n$=0 (7)

Using the Convolution theorem [11] sixteen features are extracted for each task per trial. The second feature extraction method proposed uses the singular value decomposition which states that a factorization of a real or complex matrix and expresses in the form of m-by-n matrix of non-negative real numbers calledsingular value M=UΣV∗(8) Where U is a signal of $m \times m$ real or complex unitary matrix, Σ is an $m \times n$ rectangular diagonal matrix with non-negative real numbers on the diagonal and $V*$is an $n \times n$ real or complex unitary matrix. The diagonal entries Σi,$i$of Σ are known as the singular values of M. Such a factorization is called a singular value decomposition of M.

2.3 Signal Classification

Among several architectures the multilayer perceptron (MLP) is the most widely used in EOG based HCI design. MLP are universal is used in the testing the network. The FFNN is modeled using sixteen input neurons and four output neurons to identify the event and non event eye movements. The learning rate is chosen as 0.0001.Training is conducted until the average error falls below 0.001 or reaches maximum iteration limit of 1000 and testing error tolerance is fixed at 0.1 proposed to classify eleven eye movement task signals[8].

2.3.1. Feed Forward Neural Network

FFNN is a multilayered network with one layer of hidden units as shown in fig. 2. Each unit is connected in the forward direction to every unit in the next layer. The input layer is connected to hidden layer and output layer is connected by means of interconnection weights. The bias is provided for both hidden and the output layer to act upon the net input. Network activation flow is in one direction only, from the input layer to output layer passing through the hidden layer [7]. The FFNN is trained using Levenberg back propagation training algorithm because it finds a solution even if it starts very far off the final minimum. The training and testing samples are normalized between 0 and 1 using a binary normalization algorithm to fit the data within unity of 1. The network is modeled with 8 hidden neurons, which is chosen experimentally. Out of the 110 samples 75% of the data is used in the training of the network and 100% of the data is used in the testing the network. The FFNN is modeled using sixteen input neurons and four output neurons to identify the event and nonevent eye movements. The learning rate is chosen as 0.0001.

Training is conducted until the average error falls below 0.001 or reaches maximum iteration limit of 1000 and testing error tolerance is fixed at 0.1[12].

2.3.2. Time Delay Neural Network:

The input delay feed forward back propagation neural network is a time delay neural network (TDNN) whose hidden neurons and output neurons are replicated across time where the network required to produce a particular output sequence of inputs. The delay is taken from the top to bottom, hence the network has a tapped delay line to sense the current signal, the previous signal, and the delayed signal before it is connected to the network.

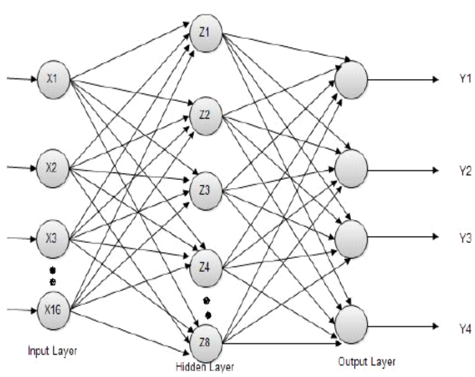

Fig.2: Neural Network

weight matrix through delay time units such as 0, 1 and 2. The TDNN is trained using Levenberg back propagation training algorithm. The training and testing samples are normalized between 0 and 1 using a binary normalization algorithm [10]. The network is modeled with 8 hidden neurons, which is chosen experimentally. Out of the 110 samples 75% of the data is used in the training of the network and 100% of the data is used in the testing the network. The TDNN is modeled using sixteen input neurons and four output neurons to identify the event and nonevent eye movements. The learning rate is chosen as 0.0001. Training is conducted until the average error falls below 0.001 or reaches a maximum iteration limit of 1000 and testing error tolerance is fixed at 0.1.

3. DISCUSSION

Classification performance of the four network models for Convolution and SVD features using TDNN and FFNN is discussed for twenty subjects [12]. The training time for both the network is varied from 24 sec to 12 sec and testing time is around 0.65 sec to 0.67 sec and average maximum accuracy of 97.10% and average minimum accuracy of 93.78 andstandard deviations are varied from 1.96 to 2.25 was achieved. An average performance of the TDNN is 90.99% and 90.88%, while that of the FFNN is 90.11% and 89.92%. The highest mean classification rate is observed for S12 at 92.12% and 92.05% for the TDNN models. For the same subject the FFNN model also records 90.11%and 89.92% for the Convolution and SVD features respectively. It is observed from the four classification tables that the performance of the network model using Convolution features is marginally better than the SVD features [9]. The performance of the nine state HCI system designed for each subject is verified through a single trail analysis to determine the accuracy of the HCI system. From the result it was observed that for subject 2 the acceptance rate was high at a mean of 90% for events and 85% for nonevents. From the result it is observed that feasibility of designing a nine state HCI is possible for some subjects using Convolution features for TDNN and FFNN respectively, while some of the subjects like S5, S6, S14, S15, S19 and S20 the mean accuracy of nine states HCI was around 80% only so it requires more training data. However further training of the subjects could provide improved performance. The experimental results prove that dynamic network is more suitable for designing nine state HCI Examining the performance of all the network models it is seen that performance of the static FFNN models is inferior to that of the dynamic networks with average classification rates at 90.99% and 90.88% for the Convolution features and SVD features respectively. The Convolution features outperform the SVD features in terms of average classification and training time. The TDNN with Convolution features is found to be the best classifier model among the four models with average efficiency of 90.99% and training time of 24.90 seconds [12].

4. CONCLUSION

In this study EOG signals recorded from twenty subjects were used for eleven eye movements. Two new movements, rapid movement and lateral movement are proposed. Two signal processing techniques have been implemented for extracting features from different eye movements. The probability of exploring nine state HCI and recognizing the same using two neural network models was studied. The results show that eye movement classification varies from subject to subject [4]. Recognizing accuracies of 100% were obtained for eye movements like left, down left, rapid movement and lateral movement and 90% accuracy was obtained for movements like right, up right, down right, up left. The experiment results show that the proposed algorithms have an average acceptance rate of 85% was achieved to recognize the ability of recognizing nine states HCI. Our future work will be on exploring better feature extraction and classification models to develop more versatile EOG based HCI. However, in this study, we were able to validate the feasibility of using two unique eye movements as events in the design of an HCI system. Further study is required to verify the applicability of the HCI system in real time.

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