Idendifying Eye Movements using Neural Networks for Human Computer Interaction

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ABSTRACT
Electrooculography based bio signals have been used and applied as a control signal in several Human Computer Interactions. 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. This paper proposes algorithms for identifying eleven eye movement signals acquired from twenty subjects using static and dynamic networks. Convolution technique is used to extract the features. These features are trained and tested with two neural networks, namely time delay neural network and feed forward neural network. The results obtained are compared with Singular Value Decomposition features for same networks. Classification accuracies varied from 90.99% and 90.10% for convolution features and 90.88% and 89.92% for SVD features using time delay neural network and feed forward neural network respectively. From the results it is observed that Convolution features using Time Delay Neural Network has better classification rates in comparison with SVD features.

Keywords
Electrooculography, Human Computer Interaction, Convolution Features, Singular Value Decomposition, Feed Forward Neural Network, Time Delay Neural Network, Multi Layer Perceptron, Fast Fourier Transform.

1. INTRODUCTION
Human beings always have the intention to control every process or incident occurring around them so that they can lead a comfortable life. 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 makes life easier for patients and therefore improves 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]. A basic goal of HCI is to improve the interactions between users and computers by making computers more usable and receptive to the user's needs. An ultimate goal of HCI is to design systems that minimize the barrier between the human's cognitive model of what they want to accomplish and the computer's understanding of the user's task [4].

The reason behind this study is to develop a human machine interface for people with disabilities and setting up multistate communication between a machine and a human body that offers improved operation and simple user friendly setup without compromising the performance by using individuals commonly used eye movements. In recent years, many researchers have used EOG signals for a variety of applications such as robotic arm [5], eye controlled joystick [6], Virtual Keyboard [7], mouse cursor control [8], tooth-click controller [9], infrared and ultrasonic non-contact head controllers [10], lip movement control system [11], vision based multiple gestures [12], brain-computer interface [13], controlling mouse pointer position using an infrared head-operated joystick [14] and Eye controlled mouse [15]. All the above studies have used only four different eye movements. This paper explores the development of a neural network based nine state HCI using eight event based and three non-event eye movements.

This paper has been organized as follows: Earlier research works are reviewed in section 2, section 3 explains EOG and Extraocular muscles and section 4 details the experimental protocol, acquisition, preprocessing, feature extraction and signal classification techniques. Experimental results and discussion is specified in Section 5. Finally conclusion about the work is presented in Section 6.

2. BACKGROUND
HCI based on EOG has been successfully and widely used in biomedical applications to develop assistance for elderly disabled. Many efficient HCI have been developed in the last decades, some of the prominent studies are given below. Usakli *et al*, presented EOG based HCI to operate a virtual keyboard using Euclidean distance and nearest neighbor algorithm were used to extract outstanding features and classify the EOG signals acquired from ten human subjects. The performance of the EOG system is relatively good, since 5 letter word can be written by the patients on average in 25 seconds and 105 seconds with EEG based device with an accuracy of 95% [16]. Tsai *et al,* had developed a EOG based communication system by collecting EOG signals from eleven human subjects aged from 20 to 28 with five electrode systems and recognized ten Arabic numerals and four mathematical operations. Tsai *et al* model attained an accuracy of 95% [17]. Barea *et al*, controlled a wheelchair using neural network based dimensional bipolar model EOG model, recognized the four states for controlling the forward,

backward, right and left movements of the wheel chair. Results demonstrate that users require about 10-15 minutes to learn to and use this system [18]. Aungskan *et al*, implemented eight states HCI using two channel EOG systems and extracted the features from the EOG signals. A robust classification algorithm based on onset analysis, first derivative technique and threshold analysis were proposed by the authors. Using the optimal threshold values and conditions, the result showed that classification accuracy reached 100% for three subjects during testing [19]. Guven and Kara the authors recorded EOG signals from 32 normal and 40 subnormal subjects and developed an eye disease diagnosing system using feedforward neural network models and distinguished normal and subnormal eye. It has been reported that the developed model has a positive prediction of 94.1% with a sensitivity of 94.1 % and a specificity of 93.3%.[20]. Arslan and Jehanzeb, presented a novel idea to control a computer mouse cursor movement using eye movements such as left, right, up, down. Experimental design showed that a 95.6 % is achieved when eyes moved upwards and the lower value is achieved when the eyes were moved downwards [21]. A communication interface controlled by eye movements and voluntary eye blink has been developed by Hori *et al*, to control the cursor movements using the virtual keyboard. A feature extraction technique based on threshold was proposed to extract prominent features. Experiments were performed with five healthy subjects. Based on this threshold method a classification accuracy of 94.16% with false operation rate of 1.68% was obtained [22]. Park *et al*, suggested a HCI device by utilizing EOG to develop an alternative means of communication, especially for ALS patients using data from two channels for four directional eye movements namely right, left, up, down. Feature extraction technique based on 2D wavelet transform was used to extract the features. The obtained results has an accuracy of 91.7% for up, 95% for down, 97.5% for left, 98.3% for right and 87.5% for blink for each eye movement for 120 trials [23]. Much of the research has been done on classifying the EOG signals using neural network and most of the research works focused on two or four states movements only. This paper, investigated the possibility of recognizing eleven eye movements using two classification algorithms namely feed forward neural network and Time delay neural networks. Performances of the two feature extraction techniques are compared using static and dynamic network to validate the results.

3. ELECTROOCULOGRAPHY AND EXTRAOCULAR MUSCLES

EOG technique allows identifying the eye movements by measuring the potential difference between cornea and retina. Human eye acts as an electrical dipole between the cornea (positive potential) and the retina (negative potential). Any rotation of the eye causes a change in the direction of the vector corresponding to the dipole that can be measured. EOG signals are usually between 50 and 3500μV with a frequency range of about 0–100 Hz between the vitreous lamina and the cornea. They have a practically linear behavior for gaze angles between $\pm 50^0$ for horizontal movement and $\pm 30^0$ for vertical movement and 20μV changes are seen for changes in each degree of eye movement [24]. Artifacts can occur in the EOG signal due to EEG, EMG of the facial muscles, position of the electrodes, head and facial moments, lighting conditions and blinking etc [25].

Eye position and motion are controlled by six muscles in each eye. The six muscles are Medial Rectus (MR), Lateral Rectus (LR), Superior Rectus (SR), Inferior Rectus (IR), Superior Oblique (SO) and Inferior Oblique (IO). MR muscles perform the movement of moving the eye inward, toward the nose. LR moves the eye outward, away from the nose. SR muscles primarily moves the eye upward, secondarily rotates the top of the eye toward the nose, tertiarily moves the eye inward. IR muscles primarily execute the eye downward, secondarily rotate the top of the eye away from the nose, tertiarily moves the eye inward. SO primarily rotates the top of the eye toward the nose, secondarily moves the eye downward, tertiarily moves the eye outward and IO muscles mostly rotate the top of the eye away from the nose. Secondarily moves the eye upward, tertiarily moves the eye outward. Each movement that elevates or depresses needs the participation of a minimum of 2 muscles of the axis of the orbit and also the muscles visual axis. The primary function of the four rectus muscles, namely SR, MR and IR, LR are used to control the eye movements from left to right and up and down. Top and bottom rotations are controlled by the SO and IO. These six tiny muscles that surround the eye and control its movements are known as the extra ocular muscles [26]. In this study, however Right (R), Left (L), Upright (UR), Downright (DR), Upleft (UL), Downleft (DL), Rapid Movement (RM), Lateral Movement (LM) are considered as events and Open (O), Close (C), Stare (S) is considered as non events because most subjects have difficulty in voluntarily controlling blinks for a quick duration of 80ms.

4. METHODS

Eleven eye movements were chosen for this study after an initial experimentation with sixteen eye movements. Since some of the eye movements are quite difficult to be performed by a few subjects. 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 non event 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 symmetrically in 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.

4.1. Signal Acquisition

EOG signals of the eight eye movements (events) and three eye movements (non events) 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 as shown in Figure 1. All subjects who participated in the experiments are university students and staff aged between 21 and 44 years and voluntarily participated in the studies. It was ensured that all subjects were healthy and free from illness during the acquisition. The subjects were asked to excute eleven different eye movement tasks while remaining in a totally inactive state. Subjects were seated in a comfortable chair in front of marked wall and requested not to make any overt movement during data acquisition. Subjects were given the eleven eye movement tasks to be executed by moving their eyes as per the protocol given for each task. 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 [27]. 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 EOG signals was formulated. The data sets of all the subjects were combined and a master data set consisting of 2200 trials of EOG signals was formulated.

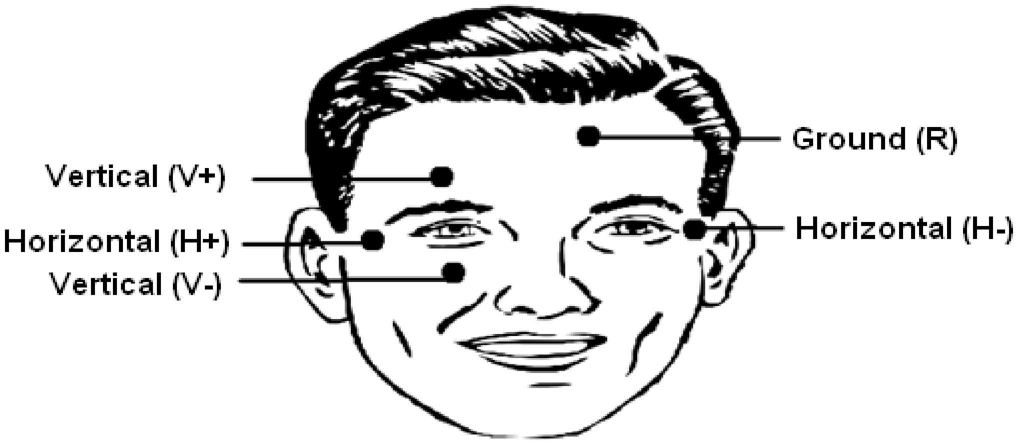

Fig 1: Electrode Placement for EOG signal acquisition.

4.2 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 non event eye movement frequency components in the range of 6-9 Hz which was studied in our previous work. The raw EOG signals have to be further processed to isolate the event and the non event frequency range. Since artifacts due to EEG, EMG of the facial muscles, position of the electrodes, head and facial moments, lighting conditions and blinks in the signal can be removed by a bandpass filter. The band features are extracted from the entire 2 second signals. Each 2s data signal is segmented into 0.1 s segments with an overlap of 0.25s. Hence, eight frequency bands are extracted using a Chebyshev bandpass 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. The energy features from each segmented signal is extracted using the Convolution theorem and SVD. Convolution theorem states that a mathematical operation on two signals X_b^j and R_b^j 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 F_1 and R_1 is written $F_1 * R_1$, where * denotes the convolution operator.

$$\mathrm{X}_\mathrm{b}^\mathrm{j} = \left\{\mathrm{x}_\mathrm{bi}^\mathrm{j}\right\}_{\mathrm{i}=1,2,\ldots\ldots..100,\ \mathrm{b}=1,2,\ldots\ldots,8} \quad (1)$$

$$\mathrm{R}_\mathrm{b}^\mathrm{j} = \left\{\mathrm{x}_\mathrm{bi}^\mathrm{j}\right\}_{\mathrm{i}=100,\ 99,\ldots\ldots..1,\ \mathrm{b}=1,2,\ldots\ldots,8} \quad (2)$$

$$F_1 = F\left\{\mathrm{X}_\mathrm{b}^\mathrm{j}\right\} \quad (3)$$

$$R_1 = F\left\{R_b^j\right\} \quad (4)$$

Let F denote the Fourier Transform, so that $F\left\{\mathrm{X}_\mathrm{b}^\mathrm{j}\right\}$ be a Fourier signal and $F\left\{R_b^j\right\}$ be a reverse and shifted Fourier signal of the Fourier transform of F_1 and R_1 respectively. Then

$$F\{F_1 * R_1\} = F\{F_1\}.F\{R_1\} \quad (5)$$

where the dot represents the point wise multiplication. The above equation can also be written as

$$F\{F_1.R_1\} = F\{F_1\} * F\{R_1\} \quad (6)$$

By applying the Convolution equation, we can write

$$F_1 * R_1 = \sum_{n=0}^{N-1}\{\mathrm{F}\{\mathrm{F1}\}.\mathrm{F}\{\mathrm{R1}\}\} \quad (7)$$

Using the Convolution theorem [28] sixteen features are extracted for each task per trial. The features are extracted for ten trials for each task. For each subject, a feature data set consisting of 110 feature vectors was obtained and used to model the network classifier. 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 called singular value

$$\mathrm{M} = \mathrm{U}\Sigma\mathrm{V}^* \quad (8)$$

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 $\Sigma_{i,i}$ of Σ are known as the singular values of M. Such a factorization is called a singular value decomposition of M. Using the singular value decomposition [29] sixteen features are extracted for each task per trial. The features are extracted for ten such trials for each task. 110data samples for one subject are obtained to train and test the neural network.

4.3. Signal Classification

Among several architectures the multilayer perceptron (MLP) is the most widely used in EOG based HCI design. MLP are universal approximators, i.e. when composed of enough neurons and layers they can approximate any continuous function. Added to the fact that they can classify any number of classes, this makes MLP very flexible classifier, consequently MLP has been used to almost all HCI problems such as binary or multiclass, synchronous or asynchronous HCI. However the fact that MLP are universal approximators makes these classifiers sensitive to overtraining, especially with such noisy and non-stationary data. In this paper two neural networks namely time delay neural networks (TDNN) and feed forward neural networks (FFNN) are proposed to classify eleven eye movement task signals. The performances of the proposed algorithms are compared with a static feed forward neural network classifier to validate the suitability of the classifiers in HCI design.

4.3.1.Feed Forward Neural Network

FFNN is a multilayered network with one layer of hidden units. 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. Back propagation algorithm resembles a multilayer feed forward network. The errors propagate backwards from output nodes to the input nodes [30]. Figure 2 shows the architecture of the FFNN used in this study.

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 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.

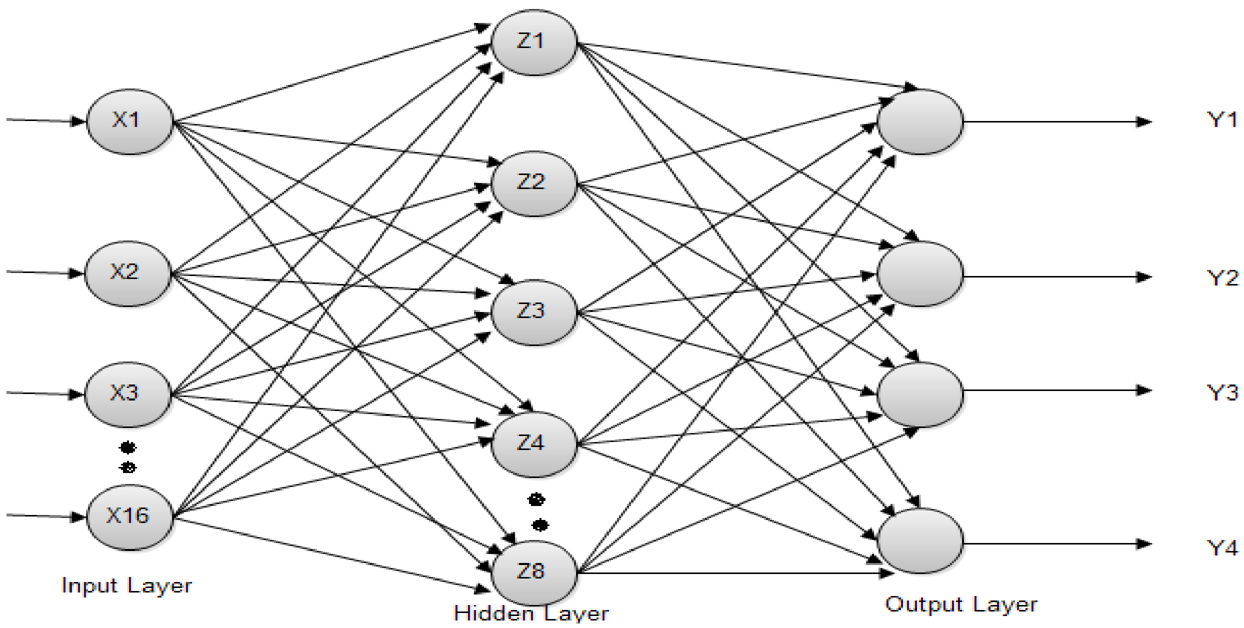

Fig 2: Feed Forward Neural Network Model

4.3.2.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 weight matrix through delay time units such as 0, 1 and 2. These are added in ascending order from left to right to correspond to the weight matrix, when the output is being fed back through a unit delay into the input layer. In order to recognize the pattern TDNN makes a copy of older activation and updates the outgoing connections with original units in each step. These units are fully connected to the following layer called receptive field. Memory limited by the length of the tapped delay line is called a TDNN unit and network, which consists of TDNN units is called Time Delay Neural Network [31]-[32].

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 [33]. 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 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 a maximum iteration limit of 1000 and testing error tolerance is fixed at 0.1.

5. RESULT AND DISCUSSION

Classification performance of the four network models for Convolution and SVD features using TDNN and FFNN is summarized in Table 1 to 4 for twenty subjects respectively. The classification accuracy of the eleven eye movements is shown in terms at mean testing time, mean training time, maximum, minimum, mean accuracy and standard deviation obtained from 110 samples per one subject for twenty subjects. 80 neural network models and their performance are listed in Table 1 to 4 for Convolution features and SVD features using TDNN and FFNN respectively. The result of the Convolution features using TDNN and FFNN classification is shown in Table 1 and 3 and the result of the SVD features using TDNN and FFNN classification is shown in Table 2 and 4 respectively. 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 and standard 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.

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 non events. 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 outperforms 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.

6. 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. 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.

Table 1. Classification Performance of TDNN Using Convolution Features

S.no	Sub	Mean Training Time (sec)	Mean Testing Time (sec)	Classification Performance for TDNN in %			
				Max	Min	Mean	SD
1	S1	25.45	0.66	93.64	87.27	90.90	1.79
2	S2	25.11	0.68	93.64	86.36	90.99	2.30
3	S3	25.09	0.73	93.64	86.36	91.08	1.49
4	S4	24.85	0.72	93.64	86.36	91.07	1.60
5	S5	24.91	0.69	94.55	88.18	90.73	1.46
6	S6	24.69	0.68	94.55	86.36	90.91	2.00
7	S7	25.04	0.66	94.55	86.36	90.68	1.88
8	S8	24.64	0.67	94.55	87.09	91.00	1.94
9	S9	24.49	0.67	94.55	86.36	91.13	2.09
10	S10	25.06	0.72	94.55	85.55	90.41	2.38
11	S11	24.62	0.68	93.64	89.09	90.67	1.49
12	S12	24.96	0.63	94.55	86.36	92.12	2.26
13	S13	24.93	0.65	94.55	86.36	91.09	2.14
14	S14	24.84	0.63	93.64	86.36	91.23	2.15
15	S15	25.00	0.68	93.64	86.36	90.96	1.87
16	S16	24.90	0.63	93.64	86.36	90.90	1.87
17	S17	24.70	0.65	94.55	84.55	90.84	2.37
18	S18	25.01	0.61	93.64	86.36	90.94	1.96
19	S19	25.08	0.61	93.64	85.45	90.90	2.00
20	S20	24.66	0.65	94.55	85.45	91.23	2.15

Table 2. Classification Performance of TDNN Using SVD Features

S.no	Sub	Mean Training Time (sec)	Mean Testing Time (sec)	Classification Performance for TDNN in %			
				Max	Min	Mean	SD
1	S1	24.01	0.61	94.55	88.18	90.72	1.83
2	S2	24.64	0.68	93.74	88.18	91.08	1.83
3	S3	24.63	0.67	95.45	85.45	91.04	2.49
4	S4	24.49	0.65	94.55	87.27	90.92	1.72
5	S5	24.80	0.68	93.64	88.18	90.65	1.70
6	S6	24.74	0.65	94.55	87.07	90.90	1.87
7	S7	27.47	0.84	94.44	88.44	90.50	1.95
8	S8	24.24	0.67	95.44	87.07	90.97	2.18
9	S9	24.62	0.67	94.55	88.18	90.96	1.90
10	S10	24.55	0.62	93.64	86.36	90.27	1.65
11	S11	24.70	0.69	95.45	87.27	92.05	2.17
12	S12	24.58	0.62	94.55	86.36	90.42	2.04
13	S13	24.59	0.64	94.55	87.07	91.05	1.98
14	S14	24.57	0.66	94.55	88.89	91.16	1.97
15	S15	24.93	0.61	92.78	87.88	90.83	1.50
16	S16	24.58	0.68	93.64	87.07	90.80	1.58
17	S17	24.80	0.74	95.45	87.27	90.44	2.16
18	S18	24.43	0.65	93.64	84.55	90.99	2.16
19	S19	24.52	0.65	93.64	85.45	90.85	1.99
20	S20	24.59	0.60	93.82	87.07	91.02	1.80

Table 3. Classification Performance of FFNN Using Convolution Features

S.no	Sub	Mean Training Time (sec)	Mean Testing Time (sec)	Classification Performance for FFNN in %			
				Max	Min	Mean	SD
1	S1	13.07	0.66	93.64	84.44	89.68	2.96
2	S2	12.63	0.75	92.74	85.44	89.85	2.00
3	S3	12.34	0.72	93.64	85.45	89.86	1.36
4	S4	12.27	0.68	93.64	84.55	90.40	2.49
5	S5	12.74	0.66	93.64	84.55	90.05	2.16
6	S6	12.93	0.67	94.55	84.55	89.68	2.91
7	S7	12.91	0.65	93.64	84.55	90.23	2.45
8	S8	12.74	0.64	93.64	84.55	89.90	2.37
9	S9	12.79	0.64	92.73	84.55	89.71	2.14
10	S10	12.65	0.64	93.64	83.33	88.70	2.48
11	S11	13.06	0.72	93.64	85.44	90.26	2.03
12	S12	12.82	0.68	94.55	86.36	91.54	2.54
13	S13	13.07	0.66	94.55	85.36	90.13	2.65
14	S14	12.97	0.64	93.64	87.27	90.72	1.99
15	S15	12.83	0.62	93.64	86.36	90.49	2.05
16	S16	12.88	0.67	94.55	85.44	90.14	2.65
17	S17	12.68	0.64	94.55	85.44	90.03	2.09
18	S18	12.70	0.64	93.64	84.55	90.21	1.94
19	S19	12.69	0.64	93.64	85.45	90.26	2.26
20	S20	12.78	0.64	93.64	85.45	90.32	2.30

Table 4 Classification Performance of FFNN Using SVD Features

S.no	Sub	Mean Training Time (sec)	Mean Testing Time (sec)	Classification Performance for FFNN in %			
				Max	Min	Mean	SD
1	S1	12.75	0.64	93.64	84.55	89.12	2.70
2	S2	12.82	0.67	93.64	86.33	89.84	2.35
3	S3	13.43	0.64	94.55	84.54	89.56	2.72
4	S4	13.33	0.63	93.64	85.45	90.23	2.35
5	S5	12.54	0.66	93.64	85.45	89.63	2.20
6	S6	12.73	0.65	94.55	87.07	90.47	2.09
7	S7	13.77	0.75	94.44	84.55	89.75	2.44
8	S8	13.36	0.69	93.64	86.36	90.15	2.52
9	S9	12.64	0.66	93.64	85.55	89.81	2.18
10	S10	12.58	0.63	94.55	85.56	88.14	2.43
11	S11	12.90	0.62	94.55	87.27	91.35	2.25
12	S12	12.89	0.62	92.73	85.45	89.62	1.94
13	S13	12.76	0.62	94.55	86.36	89.83	2.12
14	S14	12.68	0.63	94.45	85.45	90.68	2.08
15	S15	12.65	0.65	94.55	85.45	90.01	2.46
16	S16	12.74	0.62	94.55	85.45	89.98	2.43
17	S17	12.76	0.63	93.64	87.07	89.79	1.82
18	S18	12.81	0.66	93.64	87.07	90.20	1.80
19	S19	12.62	0.67	93.64	86.36	90.03	1.88
20	S20	12.77	0.59	93.64	84.55	90.23	2.20

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