Classification of Eye Movements Using Electrooculography and Neural Networks

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Abstract

Electrooculography is a technique for measuring the cornea-retinal potential produced by eye movements. This paper proposes algorithms for classifying eleven eye movements acquired through electrooculography using dynamic neural networks. Signal processing techniques and time delay neural network are used to process the raw signals to identify the eye movements. Simple feature extraction algorithms are proposed using the Parseval and Plancherel theorems. The performances of the classifiers are compared with a feed forward network, which is encouraging with an average classification accuracy of 91.40% and 90.89% for time delay neural network using the Parseval and Plancherel features.

Keywords: Electrooculography, Human Computer Interaction, Parseval features, Plancherel Features, Feed Forward Network, Time Delay Neural Network.

1. INTRODUCTION

Today there is an increasing need for assistive technology to help people with disabilities to attain some level of autonomy in terms of communication and movement. People with disabilities, especially total paralysis are often unable to use the biological communication channels such as voice and gestures hence digital communication channels are required. Research on Human Computer Interaction (HCI) is striving to help such individuals to convert human intentions into control signals to operate devices. Electrooculography (EOG) signals of eye movements are one of the bio-signals which can be used in designing multistate HCI systems. People daily make lots of eye movements that allow them to do different tasks such as reading, writing, learning new things, acquiring information about the environment, handling objects and communicating with other [1]. The ability of humans in controlling their eye movements help in designing HCI systems [2].

Eye movements are behaviors that can be measured and their measurements provide the sensitive means of learning about cognitive and visual stimuli. This study concentrates on identifying and classifying eye movements suitable for designing HCI systems. The motivation behind the study is to create a multistate HCI based on eye movements, eleven eye movements commonly used by individuals to express and emphasis their intent are used. In recent years many researchers have used EOG signals for variety of applications such as mobile robot control

[3], mouse cursor control [4], tooth-click controller [5], infrared and ultrasonic non-contact head controllers [6], hospital alarm system [7], multifunction myoelectric control system [8], brain-computer interface [9], controlling mouse pointer position using an infrared head-operated joystick [10] and electrical wheelchair control [11], all the above studies have used four eye movements. Previous study details are explained in section 2, EOG and its characteristics are explained in section 3, while section 4 details the experimental protocol, acquisition, spectral analysis, preprocessing, feature extraction and signal classification techniques. The experimental results are presented and discussed in section 5 and section 6 provides the conclusion.

2. BACKGROUND

Research on HCI based on EOG has been undertaken in the last decade, some of the prominent studies are given below. Human Machine Interface based on EOG proposed by Barea et al, implements a wheel chair, guidance system which uses a four state system to guide a wheelchair to move forward, backward, right and left. The results obtained in this study shows that disabled people usually require about 10-15 min to learn to use this system [11]. Park et al, propose an HCI device using EOG for patients with ALS, using data from two channels for four directional eye movements namely right, left, up, down. The result showed that 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 [12]. Another study by Tsai et al, concentrates on eye writing system using EOG signals of eye movements corresponding to pattern recognition of ten Arabic numerals and four mathematical operators and attain 95% accuracy comparable to the other eye writing system [13]. A HCI to control a computer mouse is proposed by Arslan and Jehanzeb, which uses eye controlled cursor system for left, right, up, down eye movements. The result shows that a higher value is achieved when the eyes move upward and the lower value is achieved when the eyes move downward [14]. Usakli et al, propose the use of EOG for HCI with two passive electrodes to identify horizontal and vertical eye movements, a neural network algorithm is used to classify EOG signals. The output signal is applied to a virtual keyboard to count the characters. The speed is five letters per 25 seconds and 105 seconds with EEG based device [15]. An eight state HCI using EOG is proposed by Aungskan et al, in which uses two channel EOG system to extract the eight eye movements. A non pattern recognition algorithm based on threshold analysis and the domain features are proposed by the authors. The result showed that classification accuracy reached 100% for three subjects during testing [16]. Literature on EOG classification reveals that very limited work has been done on classifying the EOG signals using neural network and most of the research focus on two or four movements only. In this study, we explore the possibility of recognizing eight movements (events) and three (non events) movements using neural networks. Performance of a dynamic network is compared with a static feed forward network to validate the results.

3. ELECTROOCULOGRAPHY

EOG is the technique of sensing eye movements by recording the cornea- retinal potential that exists between the front and the back of the human eye. To measure eye movements, a pair of electrodes is typically placed above and below the eye and to the left and right of the eyes. The eye acts as a dipole in which the anterior pole is the positive and posterior pole is negative [17]. The potential of the EOG varies from 50 to 3500µV. 20µV changes are seen for changes in each degree of eye movement. 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 [18].

EOG can be used to track the eye movements. Eye tracking is a process of electronically locating the point where people look or follow the movement. Eye blinking is the contraction of sets of muscles of the eye and produces an electrical activation of the eyelid muscles. The duration of such signal lasts for a fraction of seconds. The eye blinks can be divided into reflex blink, voluntary blink and involuntary blink. The range of frequency for blinks is from 1 Hz to 10 Hz. Other important terms related to eye movements are saccades and fixation. Simultaneous movements of both eyes in the same direction are called saccades. Fixation is referred to as the time between two saccades during which the eyes are relatively stationary [18].

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 make 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 [19]. In this study, however eye blinks, open, close, stare are not considered as an event as most subjects have difficult in voluntarily controlling blinks for a quick duration.

The relationship between horizontal and vertical channels of the EOG signal and the corresponding movement of the eyeball is quite significant which helps in identifying a particular movement. For angular displacement of the eyeball within 45 degrees either side of the central position, the EOG voltage varies linearly with angle. The frequency characteristics of the EOG are effectively determined by the physical dynamics of the eyeball. The amplitude of the signal is relatively the same (15-200µV), the relationship between EOG and eye movements is linear, and the waveform is easy to detect [20]. Saccadic movements describe quick jumps of the eye from one fixation point to another. Smooth movements are slow, broad rotations of the eye that enable it to maintain fixation on an object moving with respect to the head. The angular motion is in the range of 1 - 30°/s. The parameters commonly employed in the analysis of saccadic performance are the maximum angular velocity, amplitude, duration, and latency. The path and velocity of saccades cannot voluntarily be altered. The magnitude of the corneoretinal potential is in the range 0.4-1.0 mV [21]. Fig.1. illustrates the measurement of horizontal eye movements by the placement of a pair of electrodes on the outside of the left and right eye for subject 7. The opposite effect results from a rotation to the left, as illustrated below.

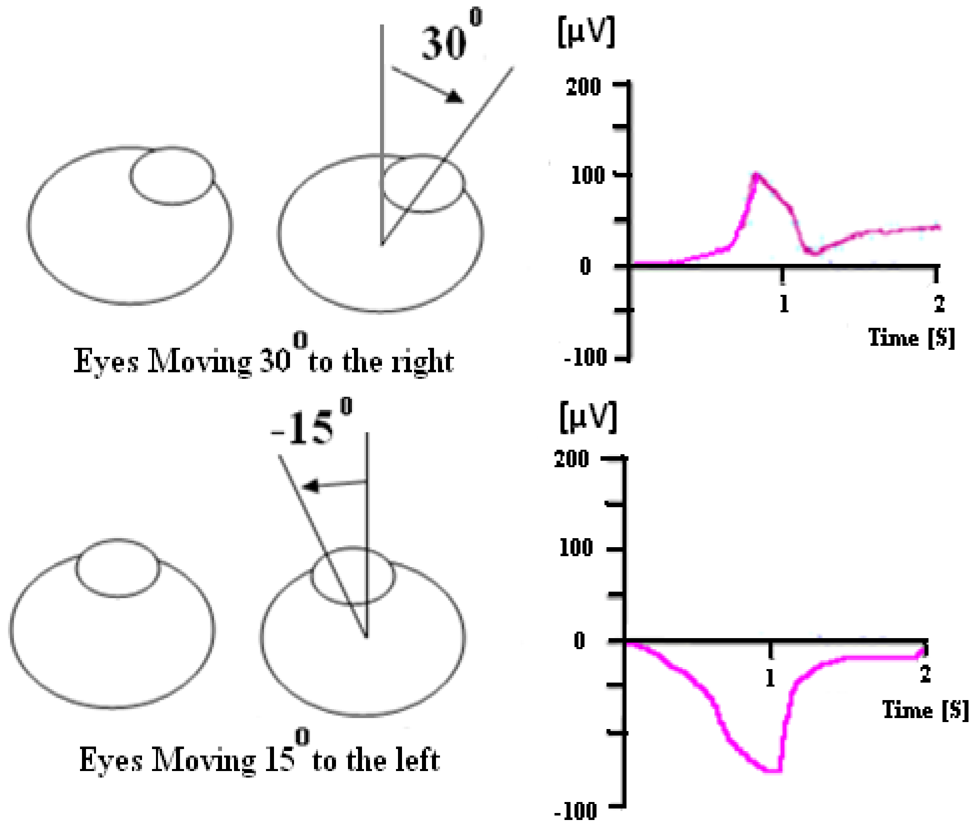


FIGURE 1: EOG Signal generated for Horizontal Movement for subject 7.

4. METHODS

Eleven eye movements are chosen for this study after an initial experimentation with sixteen eye movements. Preliminary studies showed that movements like open, close, stare could not be voluntarily controlled by all subjects during acquisition. Hence, eight event related eye movements and three non event eye movements detailed below are used in this study. The protocol for signal acquisition for each task is also detailed.

Right: The subjects are to move both the eyes synchronously and symmetrically in the right direction to achieve this moment.LR and MR muscles are involved in this task.

Left: This movement is achieved by moving both eyes synchronously and symmetrically in the left direction. MR and LR muscles are responsible for this movement.

Up Right: The Subjects are instructed to move both the eyes synchronously and symmetrically in the upper right direction to complete the task. SR and IO muscles are in charge for this movement.

Down Right: This movement is accomplished by moving both the eyes synchronously and symmetrically in the down right direction. IR and SO muscles are accountable for this task.

Up Left: The subjects are requested to move both the eyes synchronously and symmetrically in the upside left direction. IO and SR muscles are occupied in this task.

Down Left: The subjects are requested to move both the eyes synchronously and symmetrically in the down left direction. SO and IR muscles are 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 are requested to move both the eyes synchronously and symmetrically in the same direction quickly and repeatedly. MR and LR muscles are responsible for this task.

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

Open: The external, visible portion of the organ called eyelids are open slowly together to focus is called open. The subjects are requested to open both the eyes slowly together. SR and IR muscles are engaged in this movement.

Close: The external, visible portion of the organ called eyelids is closed slowly together to cut off the focus is called close. SR and IR muscles are involved in this movement.

Stare: The subjects are instructed to maintain the visual gaze on a single location to complete the task. SR and IR muscles are implicated in this movement.

4.1 Signal Acquisition

EOG signals of the eight eye movements (events), Right (R), Left (L), Upright (UR), Downright (DR), Upleft (UL) , Downleft (DL), Rapid Movement (RM), Lateral Movement (LM) and three eye movements (non events), Open (O), Close (C), Stare (S) are acquired using a two channel AD Instrument Bio-signal amplifier. Five gold plated, cup shaped electrodes are placed above and below the right eye and on the left eye and right side and left side of the eye and ground electrode is placed on forehead as shown in Fig.2. The subjects execute eleven different eye movement tasks while remaining in a totally passive state. Subjects are seated in a comfortable chair in front of marked wall and are requested not to make any overt movements during data acquisition. The room used for the experiments does not have any special acoustic lighting control. Subjects are 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. During signal acquisition a notch filter is applied to remove the 50Hz power line artifacts. EOG signals evoked by all the eleven tasks stated above are recorded from twenty subjects. Each recording trial lasts for two seconds. Ten trials are recorded for each task. Subjects are given a break of five minutes between trials and data are collected in two sessions, each session has five trials per task. All trials for a single subject were conducted on the same day.110 data samples are collected per subject and 2200 data samples for all subjects. 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.

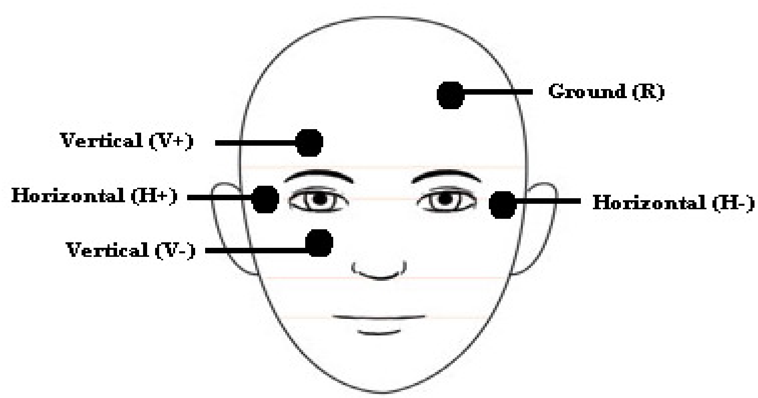
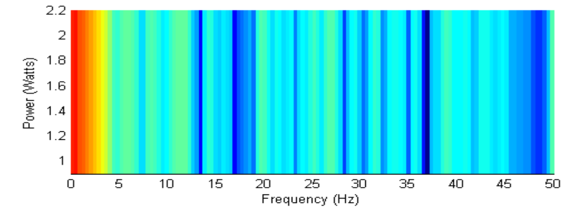


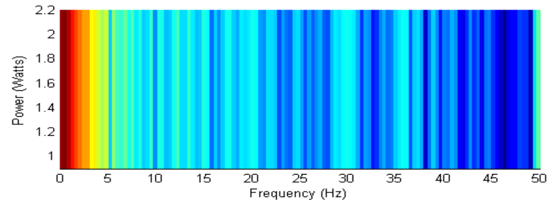
FIGURE 2: Electrode Placement for EOG signal acquisition.

4.2 Spectral Analysis

The spectral of the raw signals is studied using Short-Time Fourier Transform (STFT) to determine the frequency components for each eye movement. STFT algorithm is used to determine the sinusoidal frequency and phase content of a signal as it changes over narrow time intervals [22]. From the spectral analysis the frequency components for each task is inferred, the spectrum of all the eight event tasks and three non event task signals is shown in Fig.3 for subject 7.



(a)



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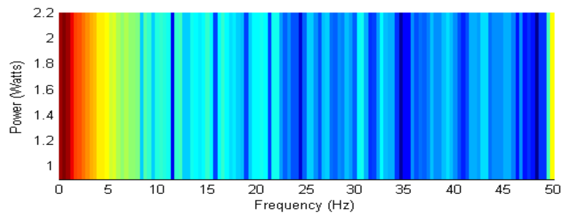

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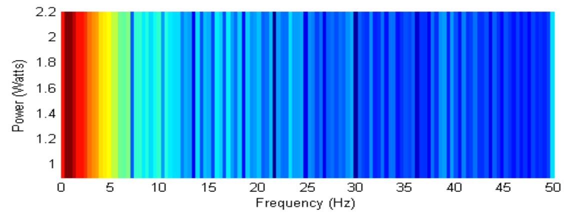

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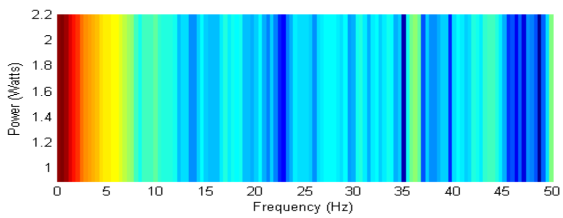

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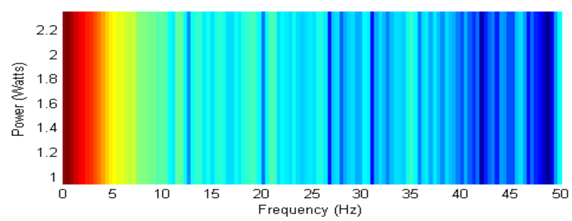

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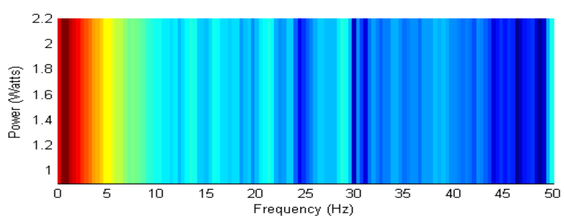

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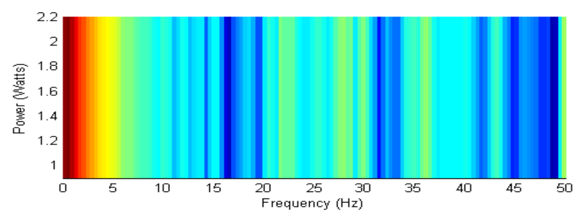

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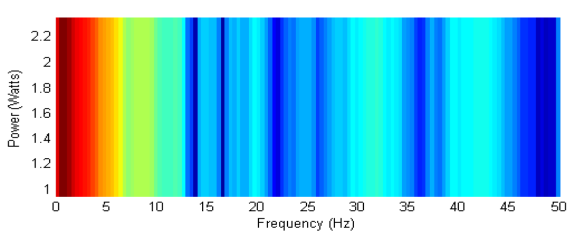
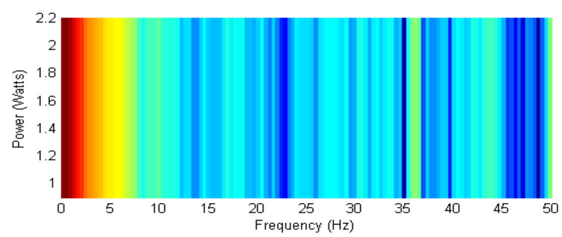
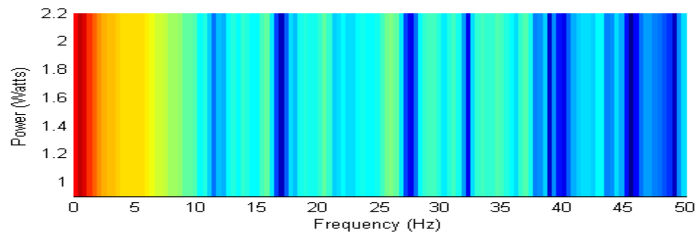


(i)



(j)



(k)

FIGURE 3: Spectral Analysis for Different Eye movement (a) Right, (b) Left, (c) Up Right, (d) Down Right, (e) Up Left, (f) Down left, (g) Rapid Movement, (h) Lateral Movement, (i) Open, (j) close, (k) Stare of subject 7.

The eight movements chosen as events were found to have frequency components in the range of 5-8 Hz while the non event eye movements frequency components in the range of 6-9 Hz as shown in Table 1.

Task	Average Frequency in (Hz)
Right	5-6
Left	5-6
Up Right	7-8
Down Right	6
Up Left	7-8
Down Left	7
Rapid Movement	8
Lateral Movement	6
Open	9
Close	6-8
Stare	8-9

TABLE 1: Average Frequency of twenty subjects.

4.3 Preprocessing and Feature Extraction

The raw EOG signals are processed to extract the features. As the EOG signals related to this study fall in the range of 5-9 Hz. A bandpass filter is used to extract the frequency. This process also removes the artifacts due to EMG signals which have higher frequencies. Chebyshev bandpass filters are used to split 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. Feature extraction algorithm based on the Parseval and Plancherel theorems are proposed to extract the features from each band. The energy features from each segmented signal is extracted using the Parseval theorem which states that the total energy contained in a signal $x(t)$ summed across all of time *t* is equal to the total energy of the summed Fourier Transform *X*(*f*) signal's across all of its frequency components *f* [23]. Parseval theorem for non periodic signals often written as

$$\int_{-\infty}^{\infty} |x(t)|^2 dt = \int_{-\infty}^{\infty} |X(f)|^2 df \quad (1)$$

$$X(f) = \mathcal{F}\{x(t)\} \quad (2)$$

$\mathcal{F}\{x(t)\}$ represents periodic time signal for the Continuous Fourier Transform of $x(t)$ and f represents the frequency components of x. For the time signals theorem becomes

$$\sum_{n=-\infty}^{\infty} |x[n]|^2 = \frac{1}{2\pi} \int_{-\pi}^{\pi} \left|X\left(e^{i\emptyset}\right)\right|^2 d\emptyset \quad (3)$$

Were X represents Discrete Time Fourier Transform of x and $\emptyset$ represents the angular frequency. The relation becomes

$$\sum_{n=0}^{N-1} |x[n]|^2 = \frac{1}{N} \sum_{k=0}^{N-1} |X[k]|^2 \quad (4)$$

Where $X[z]$ is the DFT of $x[n]$ [23]. Using the Parseval theorem concept the total energy of the EOG signal is extracted and is used as a feature to train neural network classifiers. The second feature extraction method proposed uses the Plancherel's theorem which states that the integral of the squared modulus of a signal is equal to the integral of the squared modulus of its spectrum. Let $E(x)$ be a signal and E_v be continuous Fourier transform time signal so that

$$E(x) = \int_{-\infty}^{\infty} E_v e^{-2\pi i v t}\, dv \quad (5)$$

$$\bar{E}(x) = \int_{-\infty}^{\infty} \bar{E}_{v^1} e^{-2\pi i v^1 t}\, dv^1 \quad (6)$$

$$\int_{-\infty}^{\infty} |E(x)|^2 dt = \int_{-\infty}^{\infty} E(x)\bar{E}(x)\, dt \quad (7)$$

$$= \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\infty} E_{v\prime} e^{-2\pi i v t} dv \int_{-\infty}^{\infty} \bar{E}_{v'} e^{2\pi i v' t} dv' \right] dt \quad (8)$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} E_v\, \bar{E}_{v'} e^{2\pi i t (v'-v)} dv dv' dt \quad (9)$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \delta\left(v' - v\right) E_v \bar{E}_{v'} dv dv' \quad (10)$$

$$= \int_{-\infty}^{\infty} E_v \bar{E}_v dv \quad (11)$$

$$= \int_{-\infty}^{\infty} |E_v|^2\, dv \quad (12)$$

Where $\delta(x-x_0)$ is the delta function of Fourier transform [24]-[25]. The two feature sets obtained from the above feature extraction methods are individually applied to neural networks as input features to classify the signals into eleven eye movements.

4.4 Signal Classification

To classify the EOG signal extracted from the eye movements two neural network models are used to identify the eleven eye movements. This study uses the Time Delay Neural Network which is a dynamic network to classify the EOG data signals. The results obtained are compared with a static Feed Forward Neural Network [26]. 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 is, 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 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 [27].

The TDNN is trained using Levenberg back propagation training algorithm. The training and testing samples are normalized between 0 to 1 using a binary normalization algorithm. 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, eight hidden neurons and four output neurons to identify the events 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.

The FFNN is trained using Levenberg back propagation training algorithm. The training and testing samples are normalized between 0 to 1 using a binary normalization algorithm. 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, eight hidden neurons and four output neurons to identify the events 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.

5. RESULT AND DISCUSSION

Eighty network models are designed using the two features proposed and the two networks chosen in the study to design a nine state HCI system with eight events and three non events. Data was collected from twenty subjects for all the eleven tasks. For each subject a network is modeled to evaluate the suitability of designing nine state HCI system. The classification performance results of the TDNN is shown in Table 2 and Table 3 for the two different features proposed respectively. From the Tables it is observed that the performance of the network is marginallyy better using the Parseval features in comparision to the Plancherel features.

S.no	Sub	Mean Training Time (sec)	Mean Testing Time (sec)	Classification Performance for TDNN in %			
				Max	Min	Mean	SD
1	S1	24.47	0.59	94.55	89.09	91.32	1.76
2	S2	24.70	0.70	94.55	87.27	91.18	2.04
3	S3	24.37	0.70	94.55	89.09	90.87	1.39
4	S4	25.30	0.63	94.55	89.18	92.02	1.50
5	S5	24.68	0.65	94.55	87.27	91.05	1.87
6	S6	24.54	0.68	94.55	89.09	91.59	1.60
7	S7	24.63	0.61	94.55	87.27	90.93	1.75
8	S8	24.19	0.61	93.64	89.09	91.23	1.42
9	S9	24.45	0.67	94.55	89.09	91.22	1.51
10	S10	24.53	0.66	93.64	86.36	90.68	1.53
11	S11	24.28	0.63	94.55	89.09	91.26	1.37
12	S12	24.30	0.64	94.55	87.27	91.17	1.94
13	S13	24.57	0.64	94.55	87.27	91.48	1.95
14	S14	24.52	0.64	96.36	90.00	92.65	1.69
15	S15	25.18	0.63	94.55	88.18	91.45	1.60
16	S16	24.86	0.72	94.55	89.09	91.42	1.67
17	S17	24.67	0.75	96.36	88.18	91.88	2.10
18	S18	24.48	0.69	94.55	89.09	91.54	1.48
19	S19	24.53	0.76	93.72	88.18	91.27	1.40
20	S20	24.54	0.70	94.55	89.09	91.91	1.68

TABLE 2: Classification Performance of TDNN Using Parseval features.

S.no	Sub	Mean Training Time (sec)	Mean Testing Time (sec)	Classification Performance for TDNN in %			
				Max	Min	Mean	SD
1	S1	24.51	0.63	93.78	87.27	91.04	1.74
2	S2	24.00	0.63	93.64	87.27	91.03	1.42
3	S3	24.28	0.60	92.73	85.45	90.30	2.04
4	S4	24.61	0.63	93.64	86.36	91.09	1.61
5	S5	24.46	0.63	92.73	88.18	90.49	1.25
6	S6	24.10	0.59	94.55	87.27	91.03	1.76
7	S7	24.35	0.65	93.64	88.18	90.81	1.69
8	S8	24.26	0.64	93.64	88.18	90.77	1.57
9	S9	24.32	0.57	94.55	89.09	90.90	1.64
10	S10	24.37	0.57	93.64	86.36	90.04	1.90
11	S11	24.39	0.63	92.73	88.18	90.49	1.25
12	S12	24.20	0.65	93.64	86.36	90.66	1.90
13	S13	24.65	0.62	94.55	86.36	91.14	2.11
14	S14	24.81	0.63	95.45	90.00	92.22	1.63
15	S15	24.66	0.59	92.78	87.27	90.94	1.39
16	S16	24.69	0.60	93.78	89.09	91.01	1.40
17	S17	24.43	0.57	94.55	84.55	90.84	2.37
18	S18	23.97	0.57	93.64	87.27	90.99	1.77
19	S19	24.24	0.58	92.78	86.36	90.62	1.82
20	S20	24.49	0.65	95.45	89.09	91.50	2.01

TABLE 3: Classification Performance of TDNN Using Plancherel features.

A comparision is also made with the static FFNN with the two features to verify the performance of the dynamic and static networks. The performance results of the FFNN is illustrated in Table 4 and Table 5 for the two features respectively. On observation of the results it is observed that mean classification accuracy of the dynamic network is comparatively better to the static networks which shows highest standard deviation compared to dymamic networks.

The performance of the nine state HCI system designed for each subject is verified through single trail analysis to determine the predictive power analysis of the HCI system. From the result it was observed that for subject 8 the acceptance rate was high at a mean of 90% for events and 85% for non events. However it was seen that the mean accuracy of nine state HCI was around 80% only for other subjects. Though the feasibility of designing a nine state HCI is evident better algorithms have to be studied to improve the efficiency of the HCI. Bit Transfer Rate [28] of 59.07 was achieved using the TDNN. The results validate that dynamic networks are more suitable for designing HCI systems. It is also evident that more training samples are required to designing HCI system.

S.no	Sub	Mean Training Time (sec)	Mean Testing Time (sec)	Classification Performance for FFNN in %			
				Max	Min	Mean	SD
1	S1	12.87	0.63	94.55	85.64	90.13	2.17
2	S2	12.79	0.60	93.64	88.18	90.95	1.51
3	S3	12.62	0.63	94.55	82.73	90.14	3.01
4	S4	12.48	0.61	95.45	87.27	91.27	2.54
5	S5	12.57	0.60	95.45	86.36	90.72	2.29
6	S6	13.00	0.68	94.55	85.45	91.27	1.83
7	S7	13.70	0.67	94.55	87.27	90.12	2.06
8	S8	12.65	0.64	93.64	83.64	90.01	2.86
9	S9	13.60	0.70	94.55	88.18	91.09	1.71
10	S10	12.57	0.62	92.73	83.64	87.19	2.47
11	S11	12.83	0.63	94.55	86.88	90.67	2.13
12	S12	12.77	0.64	93.64	87.00	90.70	1.96
13	S13	12.81	0.62	94.55	86.36	91.16	2.26
14	S14	12.86	0.61	96.36	90.00	92.36	1.71
15	S15	12.64	0.64	94.55	85.45	91.00	2.45
16	S16	12.80	0.76	94.55	85.45	90.81	2.21
17	S17	12.77	0.71	93.64	87.27	91.14	1.96
18	S18	13.07	0.68	93.64	84.55	90.95	1.98
19	S19	12.94	0.78	93.64	84.55	90.72	2.14
20	S20	12.95	0.66	94.55	84.55	90.49	2.59

TABLE 4: Classification Performance of FFNN Using Parseval features.

S.no	Sub	Mean Training Time (sec)	Mean Testing Time (sec)	Classification Performance for FFNN in %			
				Max	Min	Mean	SD
1	S1	12.81	0.62	95.45	85.45	90.45	2.88
2	S2	12.60	0.65	94.55	86.36	90.01	2.23
3	S3	12.87	0.64	93.64	84.55	90.00	1.03
4	S4	12.56	0.61	93.64	87.27	90.72	1.99
5	S5	12.73	0.58	93.64	84.55	90.23	2.35
6	S6	12.64	0.58	93.66	85.45	89.54	2.40
7	S7	12.47	0.62	92.73	88.18	90.53	1.25
8	S8	12.80	0.60	92.73	84.55	89.95	2.07
9	S9	12.78	0.56	94.55	84.55	89.83	2.70
10	S10	12.73	0.57	93.64	83.64	87.17	3.14
11	S11	12.71	0.59	93.64	85.45	90.04	2.63
12	S12	12.84	0.69	93.64	84.55	89.36	2.64
13	S13	12.89	0.61	94.55	86.36	90.46	2.39
14	S14	13.03	0.63	95.45	87.27	91.54	1.80
15	S15	12.84	0.61	93.64	86.36	90.45	2.12
16	S16	12.80	0.59	94.55	84.55	89.87	2.89
17	S17	12.62	0.57	94.55	84.55	90.26	2.03
18	S18	12.60	0.58	93.64	86.36	90.77	2.01
19	S19	12.88	0.59	92.73	84.45	89.81	2.16
20	S20	12.79	0.64	94.55	84.72	90.33	3.15

TABLE 5: Classification Performance of FFNN Using Plancherel features.

6. CONCLUSION

In this paper a study was conducted to design a nine state HCI using EOG signals. Data was collected from twenty subjects for eleven tasks related to eye movements of which eight were considered as voluntary events and three were considered as non events. Two feature extraction algorithms were proposed using the Parseval and Plancherel theorems. The HCI system was designed using the dynamic time delay neural network. The results were compared with the performance of static network also. The experimental results validate the feasibility of designing a nine state HCI using the dynamic networks. An average acceptance rate of 85% was obtained. The focus of our future research will be on the development of better feature extraction and classification algorithms to improve the performance of the HCI system. Further study is required to verify the applicability of the HCI system in real time.

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