Offline Analysis for Designing Electrooculogram Based Human Computer Interface Control for Paralyzed Patients

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Abstract

Document Sections

I. Introduction

II. Background Study

III. Methods

IV. Classification Technique

V. Discussion

Show Full Outline

Authors

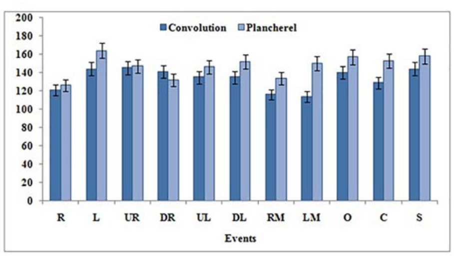
Figures

References

Citations

Keywords

Metrics



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Abstract:

Currently, majority of persons were immobilized and need aid from caretakers due to disability. To reduce and overcome such problem, there was a need for developing human-computer interface (HCI) with the help of biosignals. In this paper, we propose a two-channel elecctrooculograpy (EOG)-based HCI to encourage the contact ability as well as value of life for paralyzed persons who cannot speak or shift their extremity by using 20 subjects with the help of ADT26 Bio amplifier. EOG signals were collected for 11 tasks from both vertical and horizontal eye movement by using gold-platted electrodes. The extracted EOG signals were processed with convolution and Plancherel theorem to obtain the features. Layered recurrent neural network (LRNN) was implemented to analyze the extracted features and then converted into a sequence of commands to control the HCI. A graphical user interface was developed using MATLAB to help a user to convey their thoughts. This paper shows an average classification accuracy of 90.72% for convolution features and 91.28% for Plancherel features. Off-line single trail analysis was also performed to analyze the recognition accuracy of the proposed HCI system. The off-line analysis displayed that Plancherel features using LRNN were high compared to convolution features using LRNN. From this paper, we found that LRNN architecture using Plancherel features was more suitable for developing EOG-based HCI. Single trail analysis was conducted to identify the recognizing accuracy in offline. The off-line results indicated that in comparison with other EOG-based HCI systems, our system was user friendly and needs minimum training to operate.

Topic: New Trends in Brain Signal Processing and Analysis

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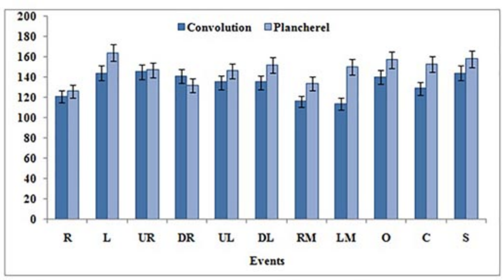

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Contents

SECTION I. Introduction

Paralyzed states, due to neurodegenerative disorders the sufferer may lose the capability to contact with others by verbal communication or movements. In that critical situation, the only remaining and active facility for incapacitate are the eye movements. Using distinct eye movements, the particular can control the interface in order to communicate with others or request the help of the caretaker in case of need and emergency. HCI is an interface technique provides an eye controlled signals to activate and control the external devices with the help of EOG. EOG signals are the electrophysiological signals calibrated by moving eye movement activity. The difference between the eye movements were used to develop HCI system that afford connection

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between the human brain and a digital computer. HCI is technique which helps people like who is paralyzed able to control a machine through control signal generated by individual persons [1]. HCI system was created to assist individuals who are affected by Brainstem Lesion, Stupor, Amyotrophic Lateral Sclerosis and Muscular Dystrophy to drive computers directly by eye movement action moderately than by bodily.

In modern years several researches have been involved in designing and developing HCI systems using Electrooculogram with the help of digital amplifier and electrodes [2]. Conventionally most of the research uses the commonly used eye movements to generate the control signals for designing HCI namely right, left, upright, downright, up and down. According to the eye movement different patterns was generated. Generated patterns were converted in to control commands to command the various devices for paralyzed individuals [3]– [4] [5] [6] [7].Various applications were developed using EOG signal as a control signals to control and command different applications for neural disordered individuals. Some of the prominent devices using EOG were listed below. Hospital alarm system [8], mouse cursor control [9], controlling mouse pointer position using joystick [10], Ultrasonic and Infrared Head Controller [11], eye recognizing System [12], wheelchair control [13], eye exercise recognizing System [14], myoelectric control system [15], eye writing recognition [16], mobile robot control [17], BCI [18] and tooth-click controller [19]. In this investigation we further included five more eye movements' tasks to reveal the nine states HCI by using eleven different tasks. The proposed additional five movements were stare, open, close, rapid movement and lateral movement. Feature extraction algorithms based on Convolution theorem and Plancherel theorem were applied to determine the nine eye movements practicing with dynamic Neural Network models.

SECTION II. Background Study

Early researchers have applied different techniques to develop EOG based HCI. From the previous study a number of most remarkable works were listed below. Postelnicu *et al.* [20] proposed EOG based HCI to navigate a wheelchair in different directions using a fuzzy logic rules and a deterministic finite automaton classifier. The specialized system shows an accuracy of 95.63%, with sensitivity and specificity of 97.31% and 93.65% [20]. Ang *et al.* [21] developed a wearable single channel EOG based cursor control for elderly disabled from eight subjects using NeuroSky Mind Wave headset. During this experiment the study proved that average recognition rate of 84% for indoor use [21]. He and Li [22] developed EOG based speller using single channel for eight healthy subjects with forty button device. From this study the average accuracy of 94.4% with a false positive rate of 0.03/min was obtained [22]. Huang *et al.* [23] created an EOG based wheelchair to move forward, left, right and backward movement, speeding up, speeding down and stopping with the help of healthy subjects. The developed HMI was achieved an average accuracy of 96.7% to 91.7% and a response time of 3.53 sec to 3.67 sec with 0 false positive rates (FPRs) [23]. Chang *et al.* [24] proposed eye-writing system by using EOG signals with the help of eighteen healthy subjects and three unhealthy subjects with amyotrophic lateral sclerosis. The study shows average mean accuracy rates of 95.93% for healthy subjects and 95.00%, 66.67% and 93.33% for three subjects with Amyotrophic Lateral Sclerosis participated in the experiment [24]. Soundariya and Renuga [25] proposed an EOG based interface to determine the happy, sad, angry, fear and pleasant using Multi-class

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Support Vector Machines classifier with Independent Component Analysis feature. Ouyang *et al.* [26], designed reading device using wavelet packet decomposition and saccade detection algorithm to detect the eye blinks for six subjects during the study. Experiential results for six subjects showed that average recognition accuracy ratio of 90.96% [26]. Heo *et al.* [27] designed EOG measurement system for EOG based HCI controlled wheelchair for ALS patient and obtain the mean accuracy of 91.25% and 95.12% respectively. From this survey we concluded that designing HCI using EOG signal was possible, so we planned to validate offline EOG signals for creating EOG based HCI by using twenty subjects.

SECTION III.
Methods

A. Experimental Protocol& Pre-Processing

Twenty subjects were interestingly and voluntarily took part in this experiment. During the study all the subjects were healthy and relax. Electrode placement, data acquisition, room setup, pre-processing were detailed by Ramkumar *et al.* [28]. Five electrode systems with ADT26 bio amplifier with two channel setup were implemented. Each subject was requested to perform the trial for two seconds for each tasks and sampled at 100MHZ and separate the signal range with 2Hz and starts with minimum range of 0.1 Hz to maximum range of 16Hz per trial per tasks. Raw Signal acquired from subject S10 was shown in the Fig.1.

FIGURE 1.
Raw EOG signal acquired from subject S10 for eleven tasks.

B. Feature Extraction

From pre-processed signals, features were extracted by using Convolution and Plancherel theorem techniques. The feature extraction algorithms for Convolution and Plancherel theorem use the following procedure.

1) Convolution Theorem

Convolution theorem defines that a numerical activity on two signals Xbj and Rbj in time domain equals point-wise multiplication in the frequency domain of the original signals translated. The convolution of F1 and R1 is written F1* R1, where * denotes the convolution operator.

$$X_b^j = \{x_{bi}^j\}_{i=1,2,\ldots\ldots 100, b=1,2,\ldots\ldots,8} \tag{1}$$
$$R_b^j = \{x_{bi}^j\}_{i=100,99,\ldots\ldots 1, b=1,2,\ldots\ldots,8} \tag{2}$$
$$F_1 = F\{X_b^j\} \tag{3}$$
$$R_1 = F\{R_b^j\} \tag{4}$$

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Let F denote the Fourier Transform, so that $F(X_b^j)$ be a Fourier signal and $F(R_b^j)$ be a reverse and shifted Fourier signal of the Fourier transform of F_1 and R_1 respectively. Then

$$F\{F_1 * R_1\} = F\{F_1\}.F\{R_1\} \tag{5}$$

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Where the dot indicates the point wise multiplication. The above equation can also be written as

$$F\{F_1.R_1\} = F\{F_1\} * F\{R_1\} \tag{6}$$

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By implementing the Convolution equation [29], [30], we can write

$$F_{1} * R_{1} = \sum_{n=0}^{N-1} \{F\{F1\}. F\{R1\}\} \tag{7}$$

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2) Plancherel Theorem

Plancherel theorem defines that the integral of the squared modulus of a signal was 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 [31]. so that

$$\mathrm{E}(\mathrm{x}) = \int_{-\infty}^{\infty} \mathrm{E_v} e^{-2\pi i v t} dv \tag{8}$$

$$\bar{\mathrm{E}}(\mathrm{x}) = \int_{-\infty}^{\infty} \bar{\mathrm{E}}_{v^1} e^{-2\pi i v^1 t} dv^1 \tag{9}$$

$$\begin{aligned} \int_{-\infty}^{\infty} |\mathrm{E}(\mathrm{x})|^2 dt &= \int_{-\infty}^{\infty} \mathrm{E}(\mathrm{x}) \bar{\mathrm{E}}(\mathrm{x}) dt \qquad (10) \\ &= \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\infty} \mathrm{E}_{v'} e^{-2\pi i v t} dv \right. \\ &\quad \left. \times \int_{-\infty}^{\infty} \bar{\mathrm{E}}_{v'} e^{2\pi i v' t} dv' \right] dt \qquad (11) \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \mathrm{E_v} \bar{\mathrm{E}}_{v'} e^{2\pi i t \left(v' - v \right)} dv dv' dt \qquad (12) \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \delta \left(v' - v \right) \mathrm{E_v} \bar{\mathrm{E}}_{v'} dv dv' \qquad (13) \\ &= \int_{-\infty}^{\infty} \mathrm{E_v} \bar{\mathrm{E}}_v dv \qquad (14) \\ &= \int_{-\infty}^{\infty} |\mathrm{E_v}|^2 dv \qquad (15) \end{aligned}$$

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From each feature extraction techniques sixteen features were collected for every trial per tasks. Totally 110 feature extracted data samples were obtained for individual subjects to test the performance using neural network model. Feature extracted signals for two different technique were shown in Fig.2 and Fig.3.

FIGURE 2.

Feature Extracted Signal from Eleven Different Eye Movements for Subject 10 using Convolution Theorem.

FIGURE 3.
Feature Extracted Signal from Eleven Different Eye Movements for Subject 10 using Plancherel Theorem.

SECTION IV.
Classification Technique

We classified the features using LRNN for the proposed system. LRNN are identical to feed forward networks, apart from that each layer has a recurrent connection with a tap delay related with it. This allows the network to have an unlimited dynamic response to time series input data. This network is similar to the time delay and distributed delay neural networks, which have finite input responses. LRNN has a capacity to solve a simple time series problem efficient than that of other network models [32]. Sixteen input features from feature extracted samples were matched with four output neurons. Input features were normalized between 0 to 1 using binary normalization algorithms. The learning rate was chosen to be 0.0001 experimentally. 75% of the data was used in the training of the network and 100% of the data was used in the testing the network. Hidden layer was chosen experimentally and fixed as ten.

The training error tolerance was fixed as 0.001 and testing error tolerance was fixed at 0.1and Training was carrying out until the average error descends below 0.001 or reaches utmost iteration limit of 1000 [33]. The network architecture applied in this study was depicted in the below mentioned Fig.4

FIGURE 4.
Layered Recurrent Neural Network.

SECTION V.
Discussion

We analyze the activity of each task to verify the patterns collected from all the subjects. Each subject was verified separately using the acquired pattern. From the result, we concluded that EOG signals were slightly varied from subject to subject. From the twenty subjects two were left hander (Subject 12 and Subject14) and eighteen were right hander and assured that all the participants were free from illness. The overall performance accuracies of the proposed technique collected from twenty healthy participants were 90.72% and 91.28% for Convolution and Plancherel features Using LRNN respectively which was shown in Table 1 and Table 2.

TABLE 1 Classification Performance of LRNN Model With Convolution Features

TABLE 2 Classification Performance of LRNN Model With Plancherel Features

The overall mean maximum classification accuracy of 94.06% and 94.12%, the overall minimum classification accuracy of 86.06% and 86.68% were obtained and standard deviation were varied from 1.53 to 2.66 and testing and training time were varied for different feature extraction techniques from 70.93 seconds, 0.88 seconds and 40.69 seconds,0.73 seconds for convolution and Plancherel features using LRNN. We evaluate the result by subject by subject, from this result it was concluded that performance of the left hander was appreciable in comparisons with right hander. During the signal acquisition the left hander performance was highly appreciable. Compared with the performance of right hander with left hander the study proves that left hander can able to perform the entire task very easily and conveniently compared with other subjects participated in this study. They took less amount of time during training. From the two techniques used in this study we analyzed that classification performance for individual subjects using Plancherel features outperforms Convolution features using LRNN model.

From the Table 1 and Table 2 it was seen and that mean recognition accuracy of 90.72% and 91.28% was obtained with ten hidden neurons and the highest average classification accuracy for individual subject were obtained for S12 of 91.72% and 92.46% with ten hidden neurons using Convolution and Plancherel features with LRNN architecture. From Table 1 and Table 2 it was analyzed that S12 shows better classification accuracy rate compared to other subjects. From Table 1 to Table 2 it was observed that Plancherel features using LRNN model shows enhanced classification rate compared to the Convolution features.

From the result we conclude that Plancherel Features with LRNN model shows that better average maximum, minimum, mean classification accuracy compared with Convolution features used in this study was shown in Fig.5. The result outcomes clearly depict that LRNN model was more suitable for classifying the EOG signals for eleven tasks using Plancherel features in comparisons with other network architecture used in this experiment.

FIGURE 5.
Overall Classification accuracy for Convolution and Plancherel features using LRNN.

FIGURE 6.
Single trail performance for Convolution features using LRNN architecture.

Single Trail Analysis

Recognizing accuracy of the individual subjects participated in this experiment was analyzed using Single trail analysis. Single trail performance was analyzed by trial by trial and subject by subject for Convolution and Plancherel features using LRNN architecture were depict in Table 3 and Table 4 respectively. Individual task performance for twenty subjects using Convolution and Plancherel features with LRNN model were displayed in the Fig.7 and Fig.7. From the Table 3 it was concluded that maximum average recognition accuracy of above 83% was able to achieve by the subject S12 and minimum average recognition accuracy of 66% was able to achieved by subject S2 and the remaining subjects average recognition accuracy of 74% was achieved using Convolution features with LRNN architectures. From the Table 4 it was concluded that maximum average recognition accuracy of above 93% was able to achieve by the subject S12 and minimum average recognition accuracy of 72% was able to achieved by subject S4 and the remaining subjects average recognition accuracy of 81% was achieved using Plancherel features with LRNN architectures. During the single trail analysis, we concluded that average recognition accuracy for left hander was marginally greater than that of right hander.

TABLE 3 Single Trail Analysis for Convolution Features Using LRNN

TABLE 4 Single Trail Analysis for Plancherel Features Using LRNN

FIGURE 7.
Single trail performance for Plancherel features using LRNN architecture.

From the result it was depict that average recognition rate was maximum for Plancherel features compared to convolution features using LRNN architecture for all individual trials per task was shown in Fig.8. The experimental result proved that Plancherel features using LRNN model was more suitable for identifying and recognizing EOG signals for eleven eye movement tasks and also, our experiment proved that designing nine states HCI is also possible for some subjects. The control signal can be used to control various devices like wheelchair, keyboard, mouse etc for disabled person.

FIGURE 8.
Overall Single Trail recognizing accuracy for 200 trials per task for twenty subjects.

SECTION VI.
Conclusion

EOG signals collected from twenty subjects were analyzed to determine the possibility of creating EOG based HCI using Convolution and Plancherel techniques with LRNN model. At the end of this study we concluded that developing HCI is possible using Plancherel features with LRNN model because in the classification accuracy as well as the recognizing accuracy using single trail analysis the following method outperforms the other network model used in this experiment. Result was compared with one modeled network with another network model to find out the individual performance of the subjects. After comparisons we concluded that all the subjects using Plancherel features with LRNN was marginally appreciable then that of Convolution features with LRNN and also we made comparisons between performance of right hander as well as left hander during this study. The study proves that subject with left hander outperform the right hander performance during the experiment. We found that during the data collection left hander performed the tasks easily and speedy compared with right hander.

SECTION VII.
Futur Plan

In future we are planned to conduct the study using patients and also we planned to improve the classification accuracy by more training.

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https://www.youtube.com/watch?v=-fOCm467Iz8&t=58s

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