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Development of BCI Based Wheelchair Using Steady State Visual Evoked Potential

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Abstract**—**This paper shows a Steady State Visual Evoked Potential (SSVEP) based Brain Computer Interface (BCI) framework to control a wheelchair in forward, in reverse, left, right and in stop positions. Four diverse glinting frequencies in low recurrence area were utilized to evoke the SSVEPs and were shown on a Liquid Crystal Display (LCD) screen utilizing LabVIEW. The Electroencephalogram (EEG) signals recorded from the occipital district were initially fragmented into 1 second window and elements were removed by utilizing Fast Fourier Transform (FFT). Three distinct classifiers, two in light of Artificial Neural Network (ANN) and one taking into account Support Vector Machine (SVM) were planned and contrasted with yield better exactness. Ten subjects were taken part in the analysis and the precision was figured by considering the quantity of right location delivered while performing a predefined development succession. One-Against-All (OAA) based multiclass SVM classifier indicated preferred exactness over the ANN classifiers.

Keywords*- Artificial Neural Network (ANN); Brain Computer Interface (BCI); Steady State Visual Evoked Potential (SSVEP); Support Vector Machines (SVM).*

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I. INTRODUCTION

Brain Computer Interface (BCI) is a framework, that can obtain and make an interpretation of the brain signs to give an immediate correspondence channel between the brain and a computer. For individuals experiencing serious neuromuscular issue, for example, spinal string harm, brain stem stroke or Amyotrophic Lateral Sclerosis (ALS), a BCI framework can give an option, augmentative correspondence and control alternatives to reestablish the cooperation with their encompassing surroundings, without utilizing fringe nerves and muscles [1].

Electroencephalography (EEG) is a non-obtrusive method for obtaining brain signals from the surface of human scalp. It is broadly acknowledged in the BCI frameworks because of its ease, straightforward and safe methodology. A portion of the brain exercises that can be viably recorded from the scalp by utilizing EEG are Event Related Potentials (ERPs), Slow Cortical Potentials (SCPs), P300 possibilities and Steady-State Visual Evoked Potentials (SSVEPs) [3]. Among them SSVEPs are pulled in because of its favorable circumstances of requiring less or no preparation, high Information Transfer Rate (ITR) and usability [4].

SSVEPs are the reactions that are inspired in the brain when the individual is outwardly centering his/her consideration on a Repetitive Visual Stimulus (RVS) that is flashing at recurrence 6Hz or above [4].

These signs are solid in occipital district of the brain and are almost sinusoidal waveform having the same key recurrence as the boost and including some of its music. By coordinating the crucial recurrence of the SSVEP to one of the boost frequencies displayed, it is conceivable to identify the objective chose by the client.

Numerous exploration gatherings are creating SSVEP based BCI frameworks. Lalor et al. [5] built up the control for an immersive 3D amusement utilizing SSVEP signal. Muller and Pfurtscheller [6] utilized SSVEPs to control two-pivot electrical hand prosthesis. Cecotti [7] built up a self-managed and adjustment less BCI speller taking into account SSVEP discovery. As of late, Lee et al. [8] proposed a SSVEP based BCI framework to control a little mechanical auto in three bearings.

A portion of the fundamental variables that can decide the execution of a BCI framework incorporate the sort of the brain signal used to exchange the goals, highlight extraction techniques, grouping calculations to get the control summons and so on. In this study, we explore the impact of three diverse order techniques in improving the execution of a SSVEP based wheelchair control framework. This framework can control a wheelchair in forward, right, left, in reverse and in stop positions. The classifiers, two in view of Artificial Neural Network (ANN) and one taking into account Support Vector Machine (SVM) are contrasted and each other.

II. MATERIALS AND METHODS

A. System Configuration

Fig.1 delineates the piece graph of the proposed SSVEP based wheelchair control framework, which incorporates visual boosts created utilizing LabVIEW and showed on a Liquid Crystal Display (LCD) screen, EEG obtaining unit, signal preparing unit with highlight extraction and order calculations, equipment interface and a wheelchair model.

B. Subject

Ten right gave solid subjects (seven guys and three females, matured 22-27 years), with ordinary or redressed to typical vision took part in the test. None of them had past BCI experience. Earlier beginning, subjects were educated about the method of the analysis and required

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to sign an assent structure.

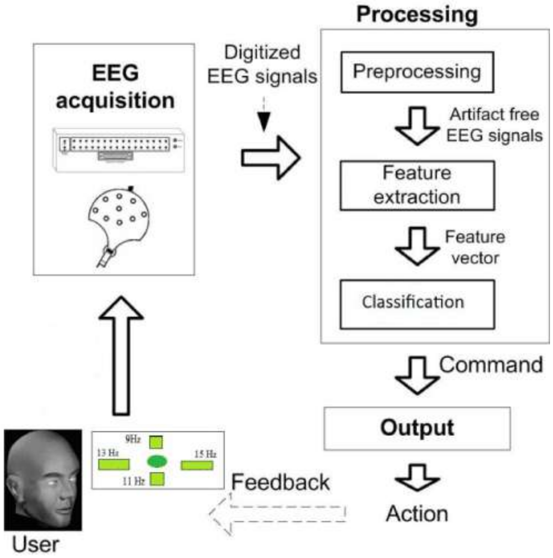

Figure 1. Conceptual block diagram of the proposed SSVEP based wheelchair control system.

C. Visual Stimuli

The RVS for evoking SSVEP reactions can be introduced on an arrangement of Light Emitting Diodes (LEDs) or on a Liquid Crystal Display (LCD) screen [9]. In this study RVS was planned by utilizing LabVIEW programming (National Instrument Inc., USA) and shown utilizing LCD screen. The visual boosts were square (4cm×4cm) fit as a fiddle and were set on four corners of the LCD screen. Four frequencies 7, 9, 11 and 13 Hz, in the low recurrence extent were chosen, as the reviving rate of LCD screen is 60 Hz [10] and the high adequacy SSVEPs are acquired at lower frequencies [11].

D. Experimental setup

The subjects were situated 60cm before the visual stimulator. EEG signs were recorded utilizing NEXUS-10 EXG securing gadget (Recorders and Medicare System, India). The SSVEP potential recorded from occipital locale utilizing Ag/AgCl anodes were increased and associated with the connector box through head box. Connector box comprise the hardware for sign molding and further associated with the computer by means of USB port. This framework can record 10 channels of EEG information. The cathodes were put according to the global 10-20 framework. The skin-cathode impedance was kept up underneath 5KΩ. The EEG signs were separated by utilizing a 3-50 Hz band pass channel and a 50 Hz step channel. Signs were examined at 512 Hz and the affectability of the framework was chosen as 7.5μV/mm.

In training session the electrodes were placed at the O_1, O_2 and O_z regions of the scalp. The reference anodes were put on the privilege and left ear cartilage (A1 and A2) and ground terminal on Fpz. The subjects were required to close their eyes for recording 2 minutes of benchmark sign and afterward given 5 minutes to adjust to the flashing boost put before them

The subjects were coordinated to concentrate on a specific recurrence for 5 second span took after by 5 second rest period. Amid centering the subjects were told to maintain a strategic distance from eye developments or squinting. The occasion markers were utilized to demonstrate the beginning and closure time of every recurrence. In a solitary trial, each of the four frequencies was performed three times and the same system was rehashed for another three trials. 5 minutes break was given in the middle of every trial. The ideal opportunity for finishing the entire session was around 30 minutes.

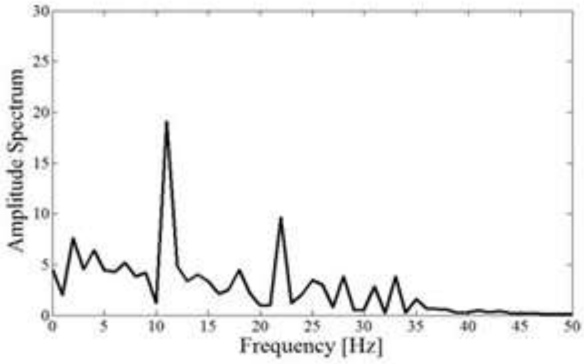

Figure 2. Amplitude spectra of SSVEP in response to 11 Hz, recorded from O_z -A_2 channel of subject 4. First and second harmonics can be found clearly.

E. Feature Extraction

The recurrence components of SSVEPs can be separated utilizing Fast Fourier Transform (FFT) [12]. The EEG signals recorded from every channel were digitized and portioned into 1 second time window in at regular intervals. MATLAB was utilized for building up the FFT calculation. Fig. 2 demonstrates the plentifulness spectra of SSVEP affected by 11 Hz incitement. From the FFT of all the associated channels, the information from Oz–A2 was chosen for further framework improvement as most grounded SSVEP was seen at Oz. The coefficients of the crucial and second sounds of all the four target frequencies from the abundancy spectra were considered as the component vector for grouping.

F. Classification

ANN and SVM classifiers were actualized to characterize the component vectors. Two multilayer ANN models, Feed-forward Backpropagation (FFBP) and Cascade-forward Backpropagation (CFBP) were composed. Backpropagation [13] is a managed learning calculation which can be utilized as a part of multilayer ANN. In FFBP, neurons are associated in food forward style from the info layer to the yield layer through the shrouded layers as per backpropagation calculation. CFBP is like FFBP in backpropagation calculation; with a special case that in CFBP every layer has a weight association from the info and past layers and therefore every layer neuron relates all past layer neurons including information layer neurons.

Displaying of the ANN was finished by utilizing MATLAB neural system preparing apparatus. Diverse blends of inside parameters like number of concealed layers, number of neurons in each shrouded layer,transfer capacity of concealed layers and yield layer and so forth were attempted. By considering the eight information parameters i.e. the first and second music of each of the four frequencies, eight neurons were altered in the information layer of the ANN models. Four neurons were settled in the yield layer to get a four digit information yield for every class. Inclination plummet with force weight and predisposition learning capacity was utilized as a part of both ANN models. Diverse variations of the backpropagation calculation were attempted like Bayesian regularization, Levenberg-Marquardt backpropagation, Fletcher-Powell conjugate inclination backpropagation, and Gradient plummet with force backpropagation.

Execution measure of the ANN models was finished by Mean Square Error (MSE) capacity. The Cross Validation (CV) technique [13] assesses the preparation and learning of the ANN model. The CV is executed toward the end of preparing age and uses two free information sets: the preparation set and the approval set for assessing the preparation and learning mistakes.

SVM presented by Vapnik, [14] is essentially a paired classifier that can isolate two classes by utilizing an ideal hyperplane. Bit capacities give an advantageous technique to mapping the information space into a high-measurement highlight space without figuring the non-direct change [15]. Direct, quadratic, polynomial and spiral premise capacity (rbf) parts are a portion of the regular bit capacities.

SVM preparing and arrangement was finished by utilizing Bioinformatics tool stash as a part of MATLAB. As four visual boosts were utilized, it was important to build up a multiclass SVM. One-Against-All (OAA) procedure [14], a multiclass SVM, was received in our trial. The definition of this mode expresses that an information point would be arranged under a specific class if that class' SVM acknowledged it while rejected by all different classes SVMs. In this mode four paired SVMs were prepared, one for every recurrence. In the wake of preparing, a structure was created having the subtle elements of the SVM, showing the quantity of bolster vectors, alpha, predisposition and so forth.

G. *Hardware Implementation*

The wheelchair model is appeared in Fig. 3. Engine driver (IC L293D) was utilized to control two engines (M1 and M2) of the wheelchair. By changing the extremity of the sign given to the engines, through the engine driver IC, it is conceivable to move the engines in both forward and in reverse bearings.

The parallel port of the computer was utilized to convey eight information bits. The initial four information pins i.e. D0, D1, D2, and D3 were utilized to interface the control sign to the engine IC. Positive and negative of the right engine was given through D0 and D1 and that of left engine was by utilizing D2 and D3. Rest of the information pins was not utilized. Interfacing project was created utilizing MATLAB.

The control orders used to change the extremity of the engines for every development of the wheelchair were introduced in Table I. Forward development of both right (M1) and left (M2) engine results in the forward course movement. Left engine forward and stop position of right engine will give right development of the wheelchair.

Figure 3. Wheelchair prototype for SSVEP based BCI control

Table 1. Control Logic for Wheelchair Movement

Right Motor (M_1)		Left Motor (M_2)		Movement Direction
+	-	+	-	
1	0	1	0	**Forward (F)**
0	1	0	1	**Backward (B)**
0	0	1	0	**Right (R)**
1	0	0	0	**Left (L)**
0	0	0	0	**Stop**

The classifier yields for each of the four frequencies and unwind state were appointed to the five unique developments of the wheelchair. For 7 Hz discovery, the yield of the parallel port is [1 0 1 0] and will propel the wheelchair in bearing. 9. . Hz would give [0 0 1 0] and will bring about a right development. 11 Hz location conveys a yield of [1 0 0] and will bring about the left development of the wheelchair. For 13 Hz the parallel port yield is [0 1 0 1] which results in a regressive development of the wheelchair. The classifier result for the unwind condition of the client is [0 0 0] and it will stop the wheelchair.

A. *Performance Evaluation*

It is important to approve the execution of BCI so as to upset the examination experiencing around there and to improve frameworks in both ways quantitatively and subjectively. Different execution assessment parameters are accessible to assess their execution. Among these some are in importance to our exploration region and these are utilized to assess the execution of use control by BCI framework.

The execution of a BCI framework is measured by a few ways. Out of these a basic and most generally utilized metric is characterization exactness or Accuracy Rate. It is characterized as the proportion of the quantity of accurately recognized trials to the aggregate number of trials. This measure is required to gauge the precision of the framework.

$$AccuracyRate = Correctly\ Identified\ Trials \div Total\ Number\ of\ Trials$$

Another measure is blunder rate which is characterized as the proportion of mistakenly distinguished trials to the aggregate number of trials. This measure shows us the rate of mistake required in the trials.

$$Error\ Rate = Incorrectly\ Identified\ Trials \div Total\ Number\ of\ Trial$$

Table 2. Brief summary of trial session

Number of Subjects	10
Trials performed by each subject for Forward movement	10
Trials performed by each subject for Backward movement	10
Trials performed by each subject for Left movement	10
Trials performed by each subject for Right movement	10
Total number of trials performed by each Subject	40
Total number of trials performed by all the Subjects in all the directions	400

Table 3. Accuracy Rate for all type of movements.

Accuracy	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
FORWARD MOVEMENT										
Correct Detections (10)	9	8	8	10	8	7	10	9	9	8
Accuracy (%)	90	80	80	100	80	70	100	90	90	80
BACKWARD MOVEMENT										
Correct Detections (10)	9	8	9	10	9	8	10	9	8	10
Accuracy (%)	90	80	90	100	90	80	100	90	80	100
RIGHT MOVEMENT										
Correct Detections (10)	9	9	9	10	9	9	10	10	10	10
Accuracy (%)	90	90	90	100	90	90	100	100	100	100
LEFT MOVEMENT										
Correct Detections (10)	10	9	8	10	9	10	10	10	10	10
Accuracy(%)	100	90	80	100	90	100	100	100	100	100

Table 4. Calculation of average Accuracy Rate.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
Total correct detections by each subject (Max. 40)	37	34	34	40	35	34	40	38	37	38
Accuracy rate (%)	92.5	85	85	100	87.5	85	100	95	92.5	95
Average number of correct detections by all the subjects								367/400		
Average Accuracy rate (%)								91.75		

This table depicts all out number of fruitful endeavors made out of aggregate endeavors by every subject. On the premise of this we discover their exactness rate. At that point normal number of right discoveries by all the subjects has been figured in request to get normal exactness rate of the framework. The precision rate of 91.75% is accomplished. Precision up to this is considered as great since it demonstrates that the vast majority of the times framework can distinguish the objective precisely. Little misses might be because of different reasons also, for example, absence of client consideration, clamor accessible in the framework and that's only the tip of the iceberg.

IV. CONCLUSION

The key is to take BCI innovation past the exhibit stage to this present reality applications, so that the personal satisfaction for incapacitated patients is made strides. We recognized the adjustments in the EEG designs because of mental undertakings. In this study we explored the

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controlling of a force wheelchair by mental assignments (EEG signals). This was an endeavor to control course of wheelchair by means of brain signs. Every heading (left, forward, right, in reverse and stop) of the wheelchair related to five mental errands (development symbolism, paltry increase, geometrical figure revolution, non –trivial augmentation and unwind). To separate five mental errands, quick fourier change (FFT) was utilized for highlight extraction and Radial premise capacity neural system was utilized for order. The trial result indicated 91.75% precision.

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