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REVIEW ARTICLE

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A REVIEW ON EEG CONTROL SMART WHEEL CHAIR

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Abstract: People who are impaired from motor movement due to certain diseases like strokes, Multiple sclerosis etc. face constant challenges to move or need constant attention from an assistant to move. In this paper we review different approaches of controlling wheel chair by reading EEG signal from the brain of the subject using a brain control interface. The paper review general technique that is used to translate EEG signal into command for controlling movement of a wheel chair. We also discuss current problems and future research direction in this field.

Keywords: Brain Computer Interface, feature extraction, classification, performance evaluation, EEG control wheel chair

1. INTRODUCTION

The human brain is made up of hundred of thousand of neurons interconnected to each other these neurons communicate with each other resulting in different patterns of neuron activity corresponding to different emotion and thoughts. Activity in the neuron creates an electrical discharge which can be measured by electrode placed on the scalp; since voltage measured at the scalp is small they are usually amplified. Different brain states are the result of different patterns of neural interaction. Brain computer interface are device which can measure this wave and can be used as an input to a computer to perform some action. Brain computer interface are seen recently in controlling character of game, speller application which is used to spell out words, measuring attention and meditation for training the brain and performing recreational activity.

People who are impaired from motor movement due to diseases like Amyotrophic lateral sclerosis, Multiple sclerosis, and people who suffer stroke are impaired from mobility completely. Although wheelchair with joystick are available but it limits to only some people who can use the joystick. These led to the development of Brain Computer Interface (BCI) control wheel chair. The most common research direction in this topic is based on non-invasive BCIs which captured Electroencephalography (EEG) signals from the brain, EEG are voltage fluctuations due to activity in the neurons which may occur due to collaboration of different part of the brain in performing a task or due to different brain dynamics. These signals are used as an input to the wheel chair to classify user intention for controlling the functionality of the wheel chair. Translating this signal requires analyzing different known behavior of brain signal. Most common are ERD/ERS (event related de synchronization or event related synchronization) which occur during motor imagery, ERD are de synchronization due to suppression of MU waves, P300 is a positive deflection in the EEG wave found due to visual or audio stimulus presented to the user it generally occur during odd-ball paradigm where a positive deflection of signal is seen with a delay of usually 300ms after a target stimulus is presented. Steady state visually evoked potentials (SSVEP) are signals that are response to visual stimuli shown at specific frequency usually a spike in power of the stimulus frequency is seen.

2. GENERAL SYSTEM ARCHITECTURE

The main intention of BCI control wheel chair is to control a wheelchair using EEG signal to reach the intended destination easily and with less effort. Fig. 1 is the block diagram of the basic architecture.

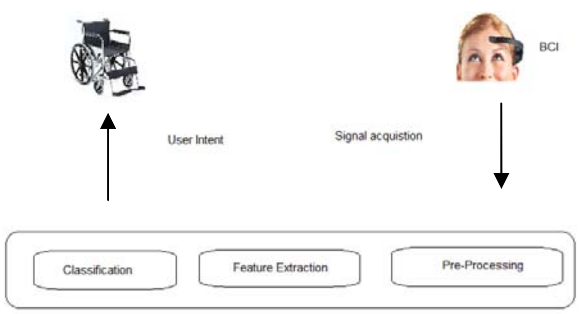

Fig. 1 Basic architecture of brain control interface control wheel chair

A. Signal acquisition

EEG signals acquisition is mainly done by placing electrodes on the scalp. 10-20 system is the most common standard used to place electrode, Fig 2 shows International

10-20 EEG placement system. Some uses five channel bi-polar electrodes [1] while some uses 12 Ag/Cl electrodes [2].More simpler commercial BCI with one electrode and a reference electrode on ear are also used [8].Signal are acquired by placing the electrode in particular location of the brain mostly using 10-20 placement system. Normally for ERD system it is done by imagining certain body part which is active response and for ERP or SSVEP it is done by presenting a stimulus which is reactive response. Sometimes both are used. In [1] electrode is placed using 10-10 system which is much denser electrode placement strategy. Here subject is presented with an arrow pointing to left, right or down which is displayed for 3 seconds during which subject are asked to imagine left hand, right hand or feet movement for 8 seconds. [3] uses a 64 channel device to capture EEG signal the device is sample at 512 Hz with a high pass filter at 1z and subject were ask to execute three mental task left hand imagination movement, rest and words association. [4] Uses 14 electrode to capture EEG signal, and sample at 256Hz. Number of electrode used varies from one research to another usually multiple electrode is favorable.

B. Pre-Processing

EEG data read from electrode contains lots of noise, to eliminate noise in the recorded EEG pre-processing step are required. The most commonly used pre-processing step is filtering the EEG [2] [3][11][17]. CSP (common spatial pattern), PCA are also used to reduce signal to noise ratio. Threshold-based noise rejection and common average reference (CAR) of multiple electrodes is also used to reduce signal to noise ratio [4].Visual inspection of signal and seeing if a signal contains interested signal are also used. In [10] P300 EEG signals are selected by discriminating visually into P300 and Non P300 signal. In [3] signal from 64 channel was spatially filtered using a common average reference before estimating power spectral density of the signal every 62.5 millisecond. In [5] data are average over multiple trials to remove noise then down sampling and principal component analysis is done to reduce data dimension. In [6] band pass filter of 1- 35Hz is used. In [14] signal measured is linearly combined with a optimal weight vector to cancel out noise. In [17] signals are filtered using a band pass filter between 0.1Hz-35Hz

C. Feature Extraction and Classification

Feature extraction in BCI application is the process of extracting feature that can be used to distinguish the EEG signal into different classes. For P300 it is mainly amplitude of the signal in time domain whereas for ERD/SSVEP it is band power or power spectral density of a particular frequency or range of frequency. Simpler approach uses blink, attention, meditation read from commercial BCI as feature. Table I and II shows various feature extraction and classification technique. In [1] two bands from each channel is chosen form five channel as feature so a total of 10 feature is used in the experiment, one vs. rest LDA is used to classify feet, left hand and right hand imagery for switching control between subject control mode and automatic control mode, subject 1 got an accuracy of 75%-80% and for subject 2 around 70%-80% in classifying left vs. rest, right vs. rest, feet vs. rest, another LDA is used to classify left hand vs. right, left hand vs. feet and right hand vs. feet for turning control which subject1 got 85% and subject 2 got 75% for left hand vs. feet , subject1 got 85% and subject2 got 90% for right hand vs. feet and subject1 got 70% and subject 2 got 90 % for left hand and right hand. In [3] feature selection process is based on canonical variant analysis, CVA extracts common discriminate spatial pattern whose difference maximizes the direction in mean spectral power between a given number of classes. Here Gaussian classifier is used as a classifier. In [4] common spatial pattern is used to extract the most discriminative feature which is trained using the recorded EEG data, CSP between left imagination vs. rest, right imagination vs. rest, left imagination vs. rest is performed and used as feature in three SVM one for each CSP performed, then the output of the SVM is normalized to one. In [5] P300 and Non P300 signal obtained is used to train a SVM, the SVM return a score that express the signal in terms of P300 or not, score are average over 8 epochs to avoid wrong classification. In [6] during the recording session, all potential P300-like signal in every 250ms after correct commands flash are averaged and also non P300 signals after every wrong commands flash are also averaged offline. During movement Root mean square of P300 like signal and Root mean square of signal obtained during different command flashes are compared, and average profile of which corresponding RMS value is smallest is selected as command. In [10] data is filtered using moving average technique and down sampled by a factor of 16 and all the data from 16 channel is concatenated creating a single feature vector for classification algorithm and uses a stepwise linear discriminate analysis. In [13] 1 second of EEG data is extracted after each stimulus onset and then filtered using moving average method and down sample by a factor of 16,here the number of channel selected varies from six to ten depending on the participant so if ten channel were selected the feature vector length will be 265/16 *10 channels since it is sample at 265hz, stepwise linear discriminate analysis is used to classify P300 obtaining a performance higher than 90%.In [14] the power of each stimulus frequency is calculated from the acquired brain signal and used a linear classifier to classify in which the subject is focused on, command are considered only when they exceeds a particular threshold and if more than one power have exceeded the threshold, the frequency with the highest power is classified. In [16] context based menus of command are displayed to the user and the menus flashes randomly and then EEG data from10ms to 500ms is extracted and fed into a support vector machine which outputs new score for each button, when the score exceeds the threshold it is issue as a command, when one or more button crosses the threshold the menu with highest score is issued as a command. In [17] the paper uses a GUI that display four buttons and it flicker at 6.0Hz, 6.67Hz, 7.5Hz and 8.7Hz respectively, the paper design P300 detection and SSVEP detection separately, for P300 detection data is filtered between 0.1hz and 10hz then a segment of EEG is extracted for each button flashes then the segment is down sample by a factor of 5 to obtain a data vector and the step is repeated for all 10 channel and concatenated to create a feature vector of length 50,the feature vector is used as a feature in a SVM with label ‘1’ for P300 and ‘-1’ for Non-P300. SSVEP detection is done every 200ms, first the EEG are filtered within the range of 3-20hz using a band pass filter, then segment of EEG is extracted from eight channels in the 3.2s period and use minimum energy combination to combine all the channel then power density spectrum is calculated using DFT. Decision making is done by doing two step, first step is done by calculating the sum of normalized SVM scores and normalized power ratios for each group of buttons and then maximum and second maximum of the four summed value is found. A threshold condition is defined and if the threshold condition is satisfied the system sends a control command, and the second condition is that the same button should both be recognized by both P300 and SSVEP three times and then the command is sent out. In [18] P300 and ERD is combined to control the movement of the wheel chair the EEG signal are first spatially filtered with common average reference and then the signal is filtered using a band pass filter at 8-32 Hz, spatial pattern is computed from the signal using one vs. the rest, common spatial patterns is performed for all the four classes, left hand, right hand, foot and idle state collected before online testing, the logarithmic variance of the projections of the EEG signal from the transformation matrix

TABLE I
Feature extraction technique

Signal Type	***Mechanism to extract feature***	***Feature used***
ERD	Band power of the EEG signal is calculated from 5 channel[1] Uses canonical variant analysis to extract stable frequency[3] Uses CSP(common spatial pattern) to extract the most discriminative feature[4] Uses Discrete wavelet transform to decompose into four principal frequency ranges of the brain waves.[11]	Band power of the EEG signal as feature [1]. Power Spectral Density of the frequency [3]. Common spatial pattern between left and the rest, right and the rest, feet and the rest [4]. Energy of alpha, theta, gamma and beta[11].
P300	From the recorded EEG data, both for P300 and Non P300 average and standard deviation is calculated for each channel[2][6] Identification of P300 signal by visual inspection[10][13]	P300 target signal and Non-P300 target signal [2][5][6][10][13][16]
SSVEP	Spectral density of EEG signal is calculated[14]	Power of each stimulus frequency[14]
Data value from Commercial BCI	-	Blink, Attention ,Meditation Value[8][9][15][7]
Hybrid	(SSVEP and P300) Power spectral Density of signal is calculated for SSVEP[17] (MU and P300) Uses CSP(common spatial pattern) to extract the most discriminative feature[18]	P300 target signal and Non-P300 target signal also power of each stimulus frequency[17] CSP pattern between one versus rest for Mu and P300 signal[18]

TABLE II
Classifier

Classifier	***Paper***	***Output***
Linear Discriminate Analysis	[1][10][13][18]	Switching between Subject Control mode and automatic control mode, Turning left and right[1] ,Target Location[13],Left Turn, Right Turn, Low speed, High Speed, no speed control[18]
Neural Network	[7][11][12]	Left, Right, Forward[7] Left Movement, Right Movement ,Up Movement and Down Movement.[11] Selection of Left or right option of the display[12]
Support Vector Machine	[4][5][16][17][19]	Turning Left, Right and forward [4].P300 and Non P300 signal [5][17].Selection of options displayed on the User interface based on P300 stimulus[16].Accuracy of detecting SSVEP with respect to different color

Classifier	***Paper***	***Output***
Gaussian Classifier	[3]	Left, Right, forward direction[3]
Bayesian Classifier	[2]	Eight direction and stopping[2]

is used as feature in a one vs. rest LDA classifier, for P300 detection 0-600ms data from 15 channel is extracted and down sampled by a factor of 6, for each flash of specific button a vector of 35*15 channels is obtained by concatenating data vector from all channel P300 classification is then done using LDA, left hand motor imagery is used to turn left ,right hand imagery to turn right, foot motor imagery to decelerate, idle state for no command and P300 for acceleration, the mean classification accuracy rate of motor imagery and hybrid task accuracy is found to be 75.6% and 75.4 % respectively.

D. Operation

BCI Control wheel chair can be classified into two categories, Direct control technique where EEG signals from the brain is used to navigate the environment directly and Shared Control technique where EEG signal from the brain with the help intelligent agent is used to navigate the environment in this technique obstacle avoidance and path planning is done by intelligent agent and the BCI is used to convey only the user intent. In Direct Control technique usually a subject is asked to perform mental imagination in case of ERD, a visual stimuli in case of P300 and SSVEP. The EEG signal is obtained while the user is performing the task mentioned above and the task are classified using a machine learning technique, the output of the machine learning algorithm is used as a direct command to steer the wheelchair [4] [11][2][6] whereas in Shared Control Mode usually output of machine learning algorithm and data from the sensor are combined to judged steering path of the wheel chair. In [1] a user can switch between automatic control and subject control, in automatic control the intelligent system take cares of obstacle avoidance in subject control the user takes care of navigating the wheel chair. Some take cumulative decision considering both data from the sensor and machine learning algorithm, in [3] classification output and context based filter output are combined, [14] uses SSVEP to select a command and automatic navigation control perform the task of navigating and obstacle avoidance, [5][10][13][16] uses P300 to select a location based on options presented using familiar environment or target option shown after scene reconstruction using data read from the sensor. Hybrid approach in terms of signal used are also available, [17] uses P300 and SSVEP, presence of P300 is detected using SVM and power ratio of SSVEP after classification are combine to steer the wheel chair,[18] uses P300 and ERD here P300 is used for speed control and ERD is used for turning left and right.

3. RESULT

Performance of BCI control wheel chair are presented normally using metrics such as total correct output command executed, time taken to reach a particular destination, how accurately pattern can be recognized from the EEG data of a known brain dynamics etc. Table III shows various result obtained in different papers. In [1] simulated environment which consist of six rooms and three corridors including some obstacles and specified target in the rooms is used, the job of the wheel chair is to reach the target, subject can issue command with an accuracy of 79.25 % in 8 trials of different length of time which varies from 257s to 364s during automatic control the wheel chair made an error of 1.4 % in average. In [3] two experiment were performed in experiment 1, the two subjects were able to reach 100% (subject 1) and 80% (subject 2) of the final goals along the pre-specified path in their best sessions the result shows that different performances were obtained over time and different path which indicates that EEG signal are non stationary . After four months experiment 2 is performed where subject1 is asked to drive a simulated wheel chair and was able to reach destination with 80% accuracy. In [4] performance is calculated in terms of accuracy and practical running test of the wheel chair, four session were conducted each consist of 12 trials each trial last 4 second and divided into 25 sliding time window each, mean trial accuracy of 82.56% is obtained and average accuracy of sliding time window is 69.92%.In [6] a person is asked to control a wheel chair to a destination which is about eight meters long in trajectory and found that it took about170 second to reach the trajectory and the average delay in choosing a command is about 20 second .In [10] experiment consist of three phase in phase1 two task were performed a screening task to study the P300 response and a training task to calibrate the system and evaluate the online BCI accuracy, the calibration task lasted for only 10 minutes and obtained an accuracy of 100% ,after training the classifier it is tasted online and got an accuracy of 100% and 90 % over a 10 target trials ,in phase two the online BCI accuracy, navigation capabilities its usefulness and ease of reaching a goal is evaluated in two session that consist of three trials accuracy of 84%,81% and 70% is respectively obtained the author claimed that the low accuracy is due to software artifact and after removal of the artifact the BCI got an accuracy of 78% .In contrast to estimated time given by the author of 1372 seconds,910 seconds, and 975 seconds evaluation of the wheel chair obtain 1884 seconds,2021 seconds and 2227 seconds were obtained during traversing path length of 10.99 meters,13.53 meters and 11.84 meters respectively, in phase three the subject had to freely used the functionality for 25 minutes and were successful in doing so. In [13] the experiment consist of three phase the objective of the first phase was to screen the participants for analyzing visual aspect of the interface because p300 are greatly co-related to the visual aspect, in the second phase subject EEG data are recorded and classifier are train on the data, instruction are given to familiarize with the environment simulator test driving are performed before driving the actual wheel chair, in the third phase the navigation capabilities of the system is evaluated and performance of the participants and their ability to accomplish complex maneuverability task is explored, the general performance of brain actuated wheel chair is expressed in terms of Task success ,path length ,time, collisions and BCI accuracy, the experiment performed two task in both the task,100% task success is obtained between mean path length of 15.7 meters in task 1 and 39.3 meters in task two with mean time of 571 seconds and 659 seconds, mean ratio of path length to the optimal path is 1.20 in task 1 and 1.16 in task 2,ratio of the time taken to the optimal time is found to be 5.40 and 2.75 in task1 and 2 respectively, zero collision is obtained with pattern recognition accuracy of 95% and 94 % in task1 and task 2 respectively. In [14] nine subject participated in the experiment and SSVEP pattern recognition accuracy of 93.61% is obtained while the wheel chair is moving the average command issued is 17 during average best time of 3.35 minutes. In [15] Emotive headset is used the mental command detection suite is used to read in and interpret the user thoughts and intent, the paper present emotive mental command suite as a black box and output command such as pull, push, left and right etc this mental command is used to steer the wheel chair with experiment performed with five subjects it has been found that the mental command suite output command corresponding to the user thoughts almost 90%. In [16] error rate which is the ratio of wrongly selected target by number of selection is found to be 10% for large threshold value, response time increases with high threshold, for threshold value lower than the score distribution's centre false acceptance of a p300 signal is found close to 100% and zero for high threshold value the paper suggest that false acceptance around 2.5 % and response time around 20 seconds is favorable. Combining P300 and SSVEP in [17] show that accuracy increases when P300 and SSVEP is combined as oppose to using only P300,accuracy vary from 55%-90% in eight different subject and for SSVEP accuracy varies from 65%-85% while using only using SSVEP as compared to 90%-100%, during online evaluation of the hybrid BCI the average true positive rate, false positive rate and information transfer rate were 14.8 true positives/min,0.49 false positive/min and 2.11 bits/min respectively ,the author also found that occipital channels at O1,Oz and O2 contribute most to the SVM classification, BCI could also send a go/stop command and found out that go command can be sent in an average of 4.12s with 0.48 per min false activation rate and stop command in an average of 5.28s with 0.52 per min false activation rate. In [18] the author perform two experiment a simulated wheel chair test and test with a real wheel chair, in simulated wheel chair 5 subject is used and achieved 100% successful navigation in path length of average 2843.46 pixel with path length to the optimal path ration of 1.25, time taken in average by the 5 subject is 84.42 seconds and the time during which the simulated wheel chair travel in low speed is 26.67s, in experiment two with real wheel chair subjects were required to drive through 5 shaded parts in low speed and 5 shaded part in high speed, during low speed area region the result obtain in terms of mean path length, path length to optimal path ratio, time taken and wrong speed control time is 5.43 meters,1.14,45.38 seconds and 4.54 seconds with no collision respectively and during high speed area region the result obtain in terms of mean path length, path length to optimal path ratio, time taken and wrong speed control time is 5.21 meters,1.10,20.14 seconds,4.16 respectively with no collision. Different paper have different performance measure and there is a lack of standard performance measure so comparing this paper is really difficult, on the other hand BCI control wheelchair performance can be greatly affected by the environment they are exposed to some paper only uses simulated environment which can vary from real world environment, the measure of difficulty that an environment present in navigating needs consideration. Combining automatic navigation with only BCI control wheel chair can give less burden to the user for controlling and increases accuracy[1][5][10][13][16].

Table III
Result

Paper	***Pattern recognition Accuracy***	***Path Length***	***Path Length to optimal path ratio***	***Time Taken***	***Correct command executed***
[1]	Subject 1: 75%-80% Subject 2: 70%-80%	Different Path length	-	-	79.25%
[3]	Subject1: 59% Subject 2:61%	Complex random path length	-	-	80%-100%
[4]	82.56%	Not specified	-	-	``-

[6]	-	8 meters	-	120 second	-
[7]	81.81%	-	-	-	-
Paper	***Pattern recognition Accuracy***	***Path Length***	***Path Length to optimal path ratio***	***Time Taken***	***Correct command executed***
[10]	100%-90%	10.99,13.53,11.84 meters	-	1884, 2021, 2227 seconds	78%
[11]	65%	-	-		90%
[13]	94-95%	15.7 meter and 39.3 meter	1.20,1.6	571 and 659 seconds	-
[14]	93.61%	14*10 m^2 grid	-	-	-
[15]	-	-	-	-	90%
[17]	P300-65%-85% SSVEP-90%-100%	-	-	-	14.8 command is true positive per minute
[18]	Motor imagery 75.6% and Hybrid accuracy 75.4 %	5.43 meters	1.25	20.14 seconds	-

4. DISCUSSION AND CONCLUSION

Most of the research perform experiment with healthy subject, signal acquisition system used mostly are for lab and not for commercial use more over wet electrode are used mainly in this system, exploring the option of more sleek design commercial BCI which uses dry electrode which are more comfortable to wear will be a good research direction. Exploring the process of teaching robot about movement instead of just obstacle avoidance or path planning to provide ease in navigation will be a good research direction. A well known performance measurement metrics should be established to generalize the performance of such system.

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