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Brain Computer Interface for Neurodegenerative Person Using Electroencephalogram

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ABSTRACT Brain–computer interface (BCI) connects the outside world, in real time and in a natural way, like biological communication system. It facilitates the communication link from the brain to the external world by converting brain thoughts in to control commands to control the external devices, such as wheelchair, keyboard mouse, and other home appliances. Measuring the electrical brain activity by placing electrodes over scalp is called electroencephalogram (EEG). By combining these two techniques, we are able to create EEG-based BCI. In this paper, we use band power and radial basis function to analyze the signal for four mentally composed tasks to design four states BCI for a neurodegenerative person using EEG. Online study was conducted to analyze the performance of the wheelchair for a neurodegenerative person. The result shows that an overall average classification accuracy of 92.50% and individual tasks with an average classification of 95%, 87.50%, 92.50%, and 95.00% were achieved for the four tasks. The result proves that control commands generated from the EEG signal have the bcapacity to control the intelligent systems.

INDEX TERMS Brain computer interface, band power, radial basis function, FRDM-KL25Z.

I. INTRODUCTION

In India total population was crossed over 121 Crore. Among that total population 2.68 Crore (2.21%) individuals were disabled. From the total disabledpercentage 56% (1.5 Cr) were males and 44% (1.18 Cr) were females. In the total disabled population Amongst 1.86 Crore (69%) and 81Crore (31%) of persons were resided in the rural and urban areas. Disable persons were varied due to various age groups and disease. The total number of handicapped persons is highest in the age group between 10-19 years (46.2 lakhs). 17% of the disabled population is in the age group 10-19 years and 16% of them are in the age group 20-29 years. Elderly above 60% immobilize constituted 21% of the total incapacitate at all India level [1], [2] which was shown in Table.1.

Different types of disability shown in Table.2. Interprets that 20%, 19%, 19% and 10% of individuals affected by the movement, Vision, Hearing and multiple disabilities. From the Table.2 We analyzed that most of the disabled individuals were affected by movement. So there is a need of assistive device for the individuals with motor impairment. Brain Computer Interface is one of technique to overcome such problem with help of mental thoughts [1], [2].

People with disabilities due to spinal cord injuries, cerebral palsy, locked in Syndrome or Amyotrophic Lateral Sclerosis, Multiple Sclerosis are unable to use the biological channels for communication. These disorders affect the muscles and cause weakness or reduced the motor neurons in both upper and lower limps and stop the message communication from brain to muscles. Finally the individual person loses the voluntary movement and controls.

Humanoid robots are playing important role in our daily life. By converting motor imagery thoughts to neural activity to control the external devices called BCI. In the earlier days assistive robots are widely used in industry, nowadays need of assistive device are gradually increased and there is lot of demand for such product. So the researcher's turn their attention towards EEG based BCI. BCI receives electrical signals and converts it into control commands like

TABLE 1. Total disabled in India.

Range	Total number of Disabled Individuals	No. of Male Individuals	No. of Female Individuals
0-4	1291332	690351	600981
5-9	1955539	1081598	873941
10-19	4616050	2610174	2005876
20-29	4189839	2418974	1770865
30-39	3635722	2112791	1522931
40-49	3115651	1851640	1264011
50-59	2492429	1430762	1061667
60-69	2657679	1394306	1263373
70-79	1769370	884872	884498
80-89	723585	337170	386415
Above 90	225571	97409	128162
Age not Mentioned	137790	76155	61635
Total	**26810557**	**14986202**	**11824355**

TABLE 2. Types of disabilities.

Type of Disability	No. of Male Individuals	No. of Female Individuals	Total number of Disabled Individuals
Movement	3370501	2066325	5436826
Speech	1122987	875705	1998692
Mental retardation	870898	635066	1505964
Hearing	2678584	2394330	5072914
Mental Illness	415758	307122	722880
Vision	2639028	2394403	5033431
Others	2728125	2199464	4927589
Multiple Disability	1162712	953986	2116698

biological communication channel without compromising the natural way. With the help of assistive device neurodegenerative individuals are fulfill their needs without others assist. EEG is one of most important research area for developing the assistive device for disabled, so most of the researcher focuses to develop the BCI for inactive [3], [4]. Some of the important BCI developed for immobilized users were virtual Keyboard [5]–[8], Home Appliances [9], Mouse Controller [10], Music Player [11], [12], Remote Control System [13], Wheelchair [14]–[18]. In this study we discuss the online performance of the wheelchair in real time by executing four mental tasks by three trained users and one untrained user.

II. LITERATURE SURVEY

Some of the EEG based BCI studies related to this paper work were explained below. Han and Im [19] developed real time communication using EEG-based brain control interface system for the patients in completely locked-in state and obtain classification accuracy of 87.5 % for online and yes or no communication using five second EEG record. Pinheiro *et al.* [20] patterned EEG based BCI for patients with ALS, Spine lesions or Cerebrovascular accident. Signals collected for four movements from 106 subjects to validate the result. The classification accuracy obtained from this was 74.96% for the movement related to the imagination. Choi *et al.* [21] created visual and auditory stimuli-based BCI system to detect the drowsiness using common spatial pattern and frequency-band optimization algorithms and obtained the classification accuracy of 71.8% and 68.07%. Nguyen *et al.* [22] designed EEG based speller by collected signals from two tasks. The obtained signals applied with support vector classifiers to identify the chance and stability of executing a real-world BCI speller and obtained the accuracy of 93.8%. Dehzangi and Farooq [23] (2018) developed wearable Brain Computer Interface to assist patients in the critical condition by using Android tablet. The signals obtained from ten subjects were applied to Canonical Correlation Analysis (CCA), Power Spectral Density Analysis (PSDA). Steady State Visually Evoked potential was used to identify the tasks and attained an average maximum classification accuracy of 98.7%.

Pelayo *et al.* [24] developed Brain-Computer Interface Controlled robotic arm for disabled individual to improve the lifestyle of the immobilized individuals. State Visual Evoked Potential method was used to identify the tasks to control the servo motors and obtained the classification accuracy of 85.56%. Mohammadi and Mosavi [25] developed BCI to convert the human movement thoughts in to control signal for four movement class using Filter Bank Common Spatial Pattern to extract the features and trained with Mutual Information (MI) algorithm and Naive Bayesian classifier and got improved result compare to previous study. Liu *et al.* [26] created BCI to control limp using Power Spectral Density and linear discriminate analysis by collecting the signals from five able-bodied individuals. The new system developed for online shows an average classification accuracy of 0.67±0.07. Rajesh and Mantur [27] modeled wheelchair for patients suffering from quadriplegia and locked in state. Convolutional neural network method was used as classifier to categories the eye movements and blinks. The modeled system shows an average accuracy of 99% for upward movement alone.

Huang *et al.* [28] designed EEG based BCI for the persons with physically disabled using wheelchair to progress patient's quality of life by using LABVIEW. The classification accuracy of 70% and 60% for imagination of left and right tasks were obtained. AlQattan and Sepulveda [29] designed sign language recognizing system using EEG methods for speech disabled. Entropy method was used to select the features and preferred features were applied to SVM and LDA to analyze the accuracy of the designed system. Finally the study shows an average classification accuracy of 75% and proves that sign language recognizing system was possible with the help of brain signals [48], [49]. Smitha *et al.* [30] designed a BCI to classify the familiar and unfamiliar voice signals using EEG samples collected from eight subjects. The system demonstrates the classification accuracy of 72.2% to identify the familiar and unfamiliar voices. Pan *et al.* [31] Proposed BCI based on EEG to recognize the emotion by collecting the signals from six subjects. Signals were applied to specific frequency bands instead of using fixed frequency bands to extract the features. SVM and Common Spatial pattern were used to identify the emotion. The proposed method shows an average accuracy of 74.17% in online test for happiness and sadness [32]. Smitha et al., (2015) demonstrate the BCI to convert human thought with the help of showing familiar and non-familiar images samples collected from seven subjects. Discriminative EEG features were extracted from samples. The obtained feature shows a classification accuracy of 70.71% for familiar and non-familiar images [32], [46].

Fan *et al.* [33] designed BCI to identify the Autism Spectrum Disorder by collecting signals from a 14-channel EEG neuro-headset. From this signal spectral features were extracted and classified with seven classifiers. The classifier shows 80% accuracy for mental tasks and 75% accuracy for classifying emotional states. Aydemir [34] proposed BCI using different feature extraction techniques under different time segment to interface the system. By this proposed system average accuracy of 65.35% was increased to 69.08% compared to the previous study [50]. Sarmiento *et al.* [35] developed EEG based Brain computer interface by using twenty one electrode system to assist amputated individuals. Power Spectral Density (PSD) and SVM were used to identify brain signal. The obtained signals achieved an average classification accuracy of 84% to 94%. Aznan and Yang [36] designed EEG-Based Brain Computer to classify to classify the motor imagery tasks by using eye movements. Hidden Markov Model was used to categorize the eye movement tasks for motor imagery classification and achieved 90% detection rate without training.

Kim *et al.* [37] modeled alternative approaches to design EEG controlled wheelchair to overcome the limitations in earlier works and needless stop by replacing the new techniques. This method allows the user to navigate in multi directional pathway like left, right, right-diagonal, left-diagonal and forward. Reshmi and Amal [38] designed EEG based wheelchair to control five different states using wavelet coefficients and Support Vector Machine [47]. Pascual *et al.* [39] modeled non-invasive BCI using Motor Imagery tasks to controlled neuroprosthesis with the help of neuromuscular electrical stimulation and obtained 80% accuracy for two imagery classes using single trail analysis. From these surveys we concluded that Brain computer Interface using Electroencephalogram is possible. So in this study we planned to conduct online study for mobile robot to analyze its performance in real time.

III. METHODOLOGY OF THE RESEARCH

EEG signals acquired from the human subjects for four different tasks are converted to digital signal by AD Power Lab instrument (T26) bio amplifier. Digital signals were further pre-processed to remove the tainted signals present in the collected signals. The obtained signals were applied to feature extraction techniques to capture out the prominent features from all bands. The feature sets obtained from feature extraction method was applied to neural networks as input to categorize the signals into four different patterns. Different pattern signals from the graphical user interface were applied as a control signals to control the hardware. A complete methodology of this research is illustrated in fig.1.

IV. EEG EXPERIMENTAL PARADIGM

Subjects are seated in a comfortable chair and requested to read the sentence mentally without vocalizing according to the instructions and are asked not to make any other muscle movements during data collection. The room used for the experiments does not have any sound proof control. The subjects were particularly initiated to execute four different mental tasks without vocalizing according to the direction of the mobile robot. Protocol design for four mental tasks executed by each individual subject during the signal acquirement has been explained below.

Forward: The subjects are requested to mentally compose a letter FORWARD continuously for five seconds without vocalization and overt movements during measure of EEG.

Right: The subjects are requested to mentally compose a letter RIGHT continuously for five seconds without vocalization and overt movements during EEG signal acquisition.

Left: The subjects are requested to mentally compose a letter LEFT continuously for five seconds without vocalization and overt movements to acquire EEG signal.

Stop: The subjects are requested to mentally compose a letter STOP continuously for five seconds without vocalization and overt movements during measure of EEG.

A. EEG SIGNAL ACQUISITION

EEG signals of four mentally composed tasks are acquire by a single channel AD Instrument T26 Bio amplifier. Three non invasive cup shaped gold plated, electrodes are placed right and left side of the head namely T3 and T4 position and ground electrode FP1 are placed above on left eyebrow. A Notch filter (0.1 Hz to 50 Hz) is applied to the raw signal. The EEG signals were amplified and sampled at 200 Hz. Subjects are given the four mentally tasks to be executed by mentally composed a letter as per the protocol given for each task. EEG is recorded for 5 seconds for each task per trial. Four subjects are participated in the experiment are aged between 20 to 25 years and confirms that all subjects were healthy during data collection. 40 EEG signals collected from T3 and T4 electrodes for the four mentally composed tasks are considered for classification. Ten trials are records for each task. All trials for a single subject are conducted on the same day. EEG is recorded for 5 seconds for each task per trial. For each subject, a data set consisting of 40 sets of EEG signals are formulated. For this experiment artifacts such as eye blinks are not removed.

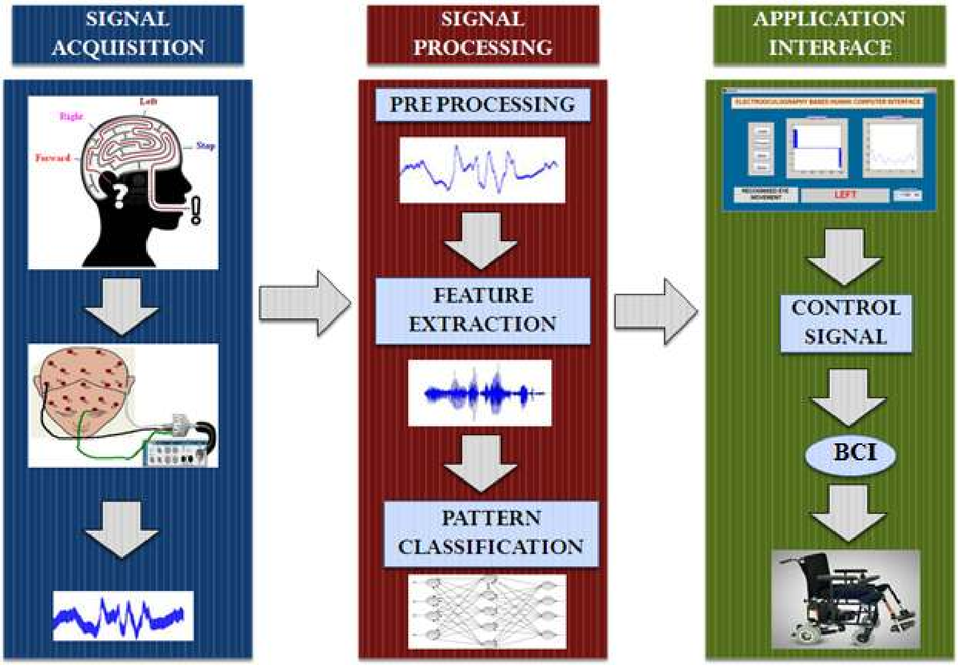

FIGURE 1. Methodology of the research.

V. REAL TIME STUDIES

A. ONLINE FEATURE EXTRACTION

Subjects are seated comfortably in a wheelchair and asked to execute four different mental tasks to drive the wheelchair on the path by reading the sentences without vocalizing as per the procedure given for each task. Online analog signals collected from four different mental tasks are converted to digital signal by AD Power Lab Instrument (T26) bio amplifier. Digital signals are additionally amplified to increase the strength of the signal using amplifier circuit shown in fig.2.

Each recording trial lasts for five seconds and sampled at 200 Hz. During data compilation a notch filter is applied to take away the 50 Hz power line artifacts. The amplified audio signals are feature extracted based on the band power techniques.

The feature extraction technique applied in this study consists of three steps:

Step1→Chebyshev filters are applied to extract the 22 frequency band signals.

Step2→Sum of the power values are extracted

Step3→Logarithmic transform is performed on the summed power value.

Twenty two features are gathered using a Chebyshev2 band pass filters by segregate the signal in the limits of four Hz to clean the noisy data. The twenty-two frequency ranges are (13-16) Hz, (16-20) Hz, (20-24) Hz, (24-28) Hz, (28-32) Hz, (32-36) Hz, (36-40) Hz, (40-44) Hz, (44-48) Hz, (48-52) Hz, (52-56) Hz, (56-60) Hz, (60-64) Hz, (64-68) Hz, (68-72) Hz, (72-76) Hz, (76-80) Hz, (80-84) Hz, (84-88) Hz, (88-92) Hz, (92-96) Hz and (96-100)Hz. Twenty two features are modeled with Radial Basis Function to identify the pattern analyzed from the mental tasks to generate the control signal with the help of FRDM-KL25Z based controller illustrated in the fig.3 and its control logics are shown in the Table.3.

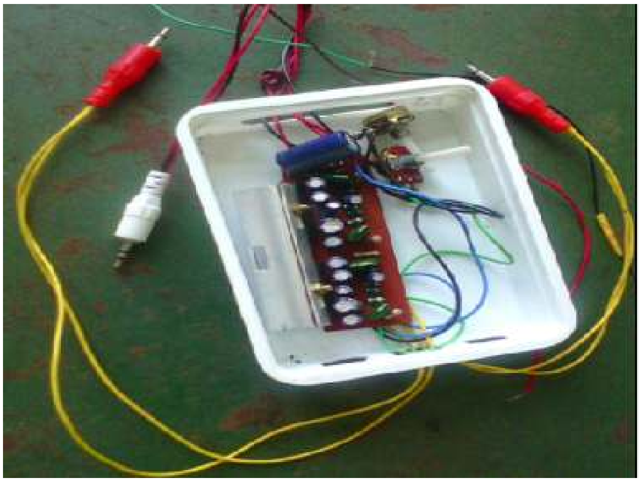

FIGURE 2. Amplifier circuit.

TABLE 3. Control logic of FRDM-KL25Z based control drive.

Mental Thought	Wheelchair Movement
Mentally compose a letter RIGHT	Right
Mentally compose a letter LEFT	Left
Mentally compose a letter FORWARD	Forward
Mentally compose a letter STOP	Stop

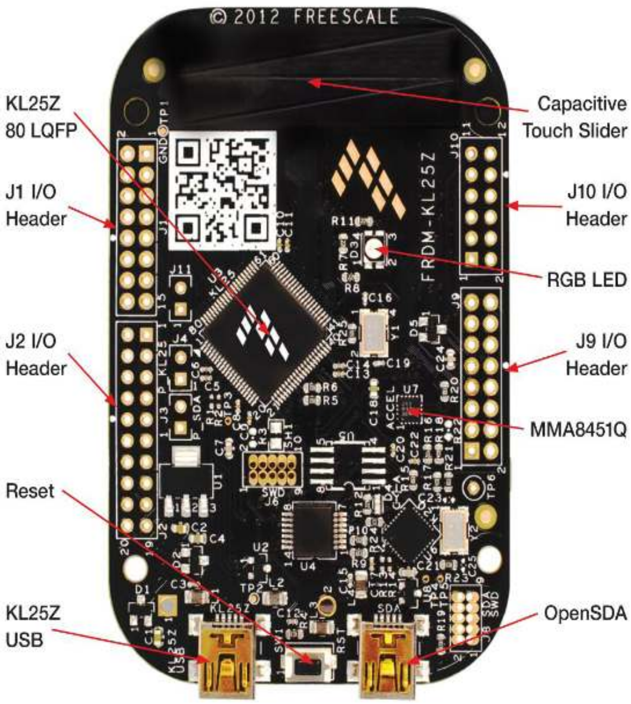

FIGURE 3. FRDM-KL25Z based control drive.

B. CLASSIFICATION TECHNIQUE

The RBF has a feed forward structure consisting of a single hidden layer of locally tuned units which are fully interconnected to an output layer of linear units. All the hidden units concurrently receive n dimensional real valued input vector. Output from each hidden unit is acquired by calculating the closeness of the input vector. Each hidden unit output is obtained by calculating the proximity of the input to an n-dimensional parameter vector associated with the hidden units. The most important features that distinguish the RBF network are its adaptive nature, which generally allows it to make use of a comparatively smaller number of locally tuned units [40], [45].

C. IMPLEMENTATION IN CONTROL

After sufficient training the resulting trained network is ready to classify unlabeled test data into appropriate classes called control signals. The input can be fed into the trained neural network resulting in an output which signifies the class in to control signal. This phenomenon can be made use of to classify the input data obtained from the EEG, during online operation, into class corresponding to the direction mentally composed letter. The aim of this classification is to generate correct control signals to turn a wheelchair in the appropriate direction corresponding to the mentally composed tasks of the subject. Control signals from the neural network classifier is connected through serial port interface to communicate to Free scale Freedom development platform board for sending the values to generate the required square wave for driving the servo motors to control the movements of the motor wheelchair. The servo motors present in BCI controls,

FIGURE 4. Developed BCI controls.

FIGURE 5. A prototype wheelchair integrated with BCI during Online Testing.

the joystick of the wheelchair according to the subject mental thought which is illustrated in fig.4.A prototype wheelchair is designed and integrated with the developed BCI for online analysis is shown in fig.5

VI. REAL-TIME EXPERIMENTS

The experiment is modeled with RBF to check the applicability of BCI in real–time environment to control the wheelchair. The output from classifier is decoded into control commands through a Free scale Freedom development platform board to operate a powered wheelchair. BCI is controlled manually to stop and back when obstacles are detected. Control is passed again to the subject for further navigation. Control signals are given to the interface every 5s by the subject with a delay of two second. In real-time experiments four of the three subjects are participated. One naive subject who

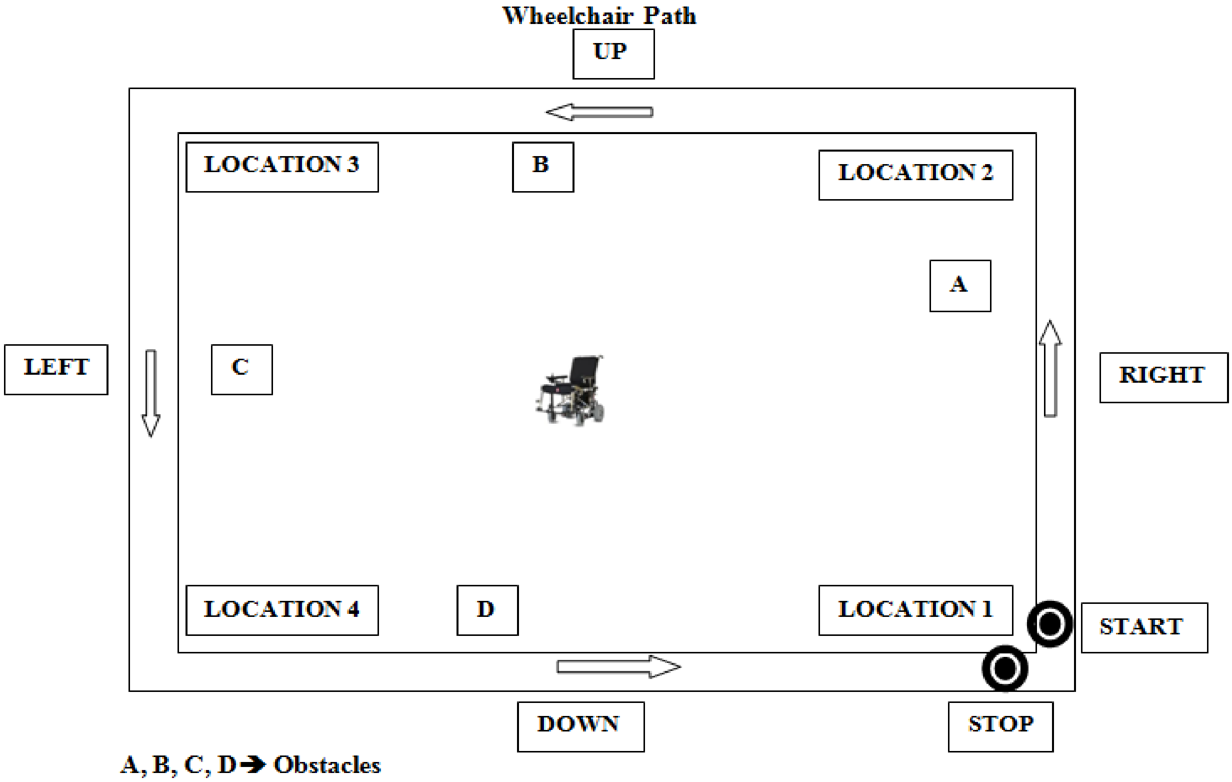

FIGURE 6. Real-time navigation path.

TABLE 4. Overall online signal classification using RBF with band power.

Subject	Online Signal Classification for RBF using Band Power Technique				
	Forward	Right	Left	Stop	Wrongly Classified Trials
S1	10	9	9	10	2
S2	9	9	8	9	5
S3	10	10	9	10	1
S4	9	9	9	9	4
Total	38	37	35	38	12
Individual Tasks classification Average	95.00	92.50	87.50	95.00	7.50

TABLE 5. Overall performance of BCI in online signal classification using RBF with band power.

Subject	Overall performance of BCI in Online Signal					
	Total no of Trials	Correctly classified	Wrongly Classified	Recognizing Accuracy in (%)	Bit Transfer Rate (bits/sec)	Error rate in (%)
S1	40	38	2	95.00	19.63	5.00
S2	40	35	5	87.50	15.10	12.50
S3	40	39	1	97.50	21.50	2.50
S4	40	36	4	90.00	16.47	10.00

did not participate in any of the experiments also participated. Experiments are carried out in an indoor environment, the room dimensions are 5m by 3m. Four mentally composed tasks namely forward, right, left and stop are performed by each individual subject during the signal acquisition for real time study. The subjects are requested to follow a protocol continuously to navigate on a path is shown in Fig.6. A simple navigational protocols are given to the subjects are

Step1: Subjects are needed to operate the wheelchair from location 1 to location 2 (5 m) following an anti-clockwise sequence.

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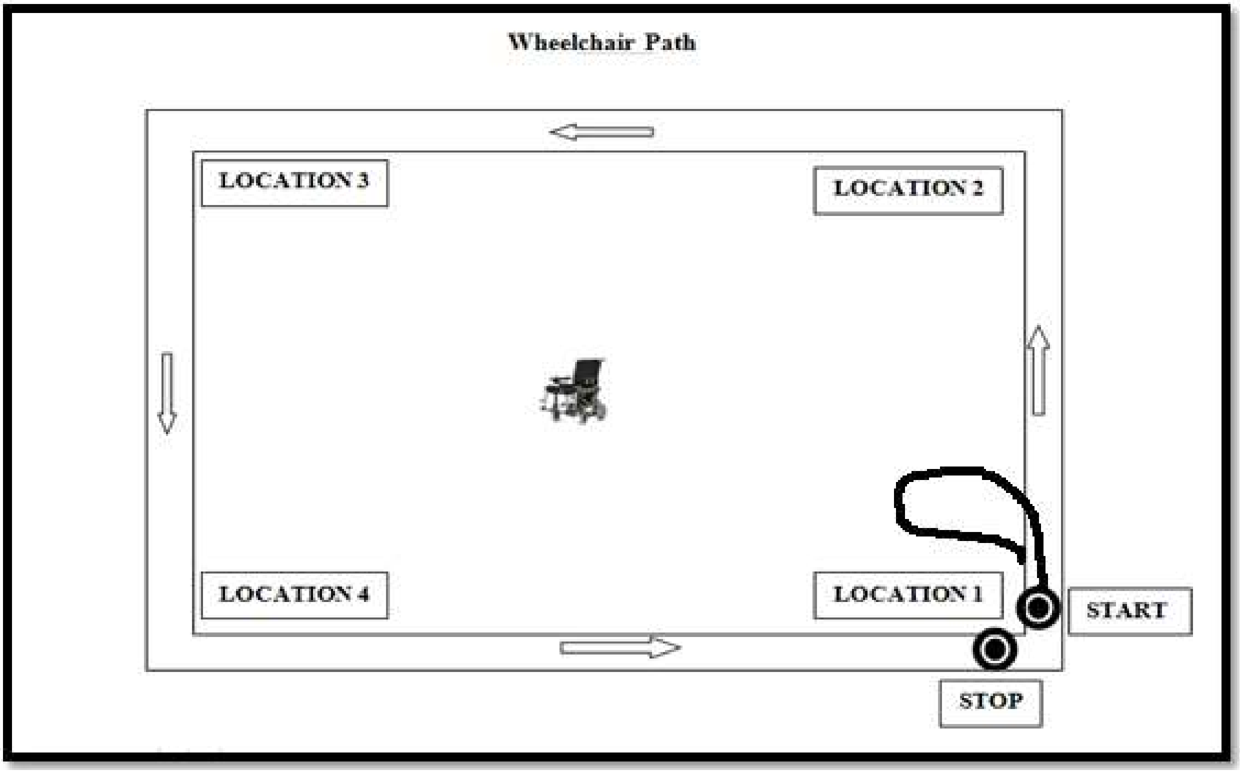

FIGURE 7. Online navigation of subject S1 in Day1.

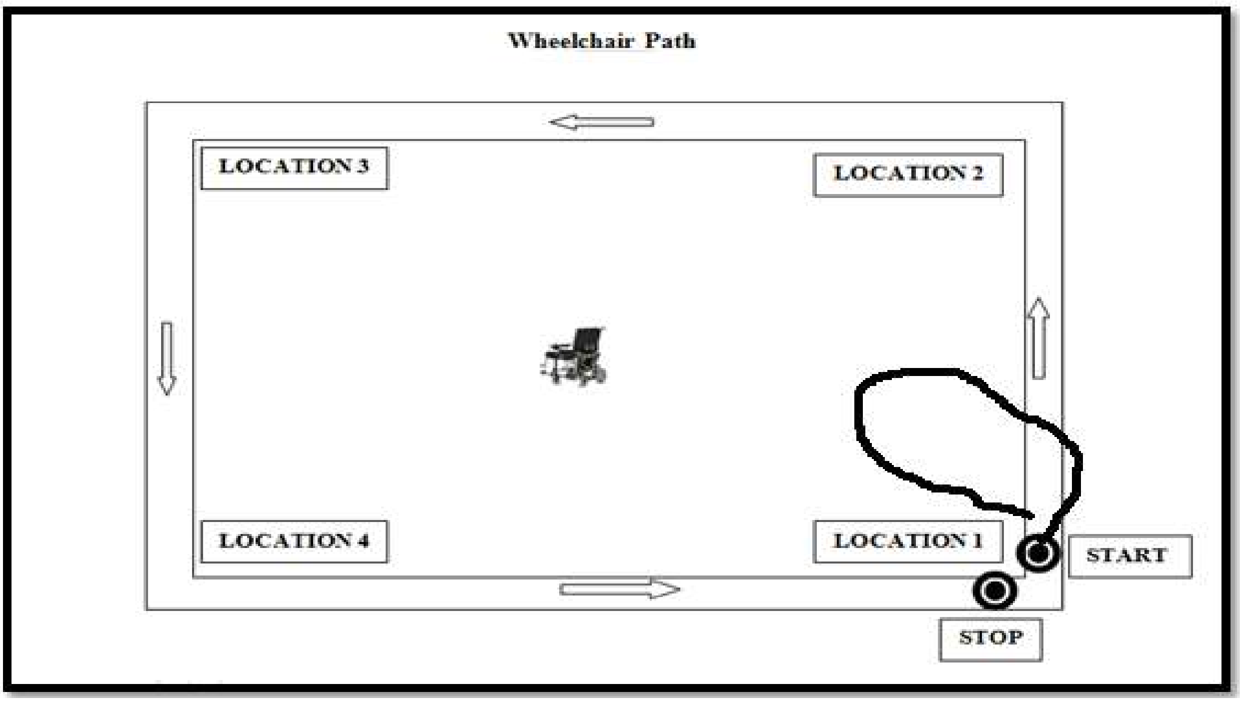

FIGURE 8. Online navigation of subject S1 in Day3.

Step2: Subjects are needed to operate the wheelchair from location 2 to location 3 (3 m)

Step3: Subjects are needed to operate the wheelchair from location 3 to location 4 (5 m)

Step4: Subjects are needed to operate the wheelchair from location 3 to location 4 (3 m).

The task given to the subjects was to drive the wheelchair in an indoor environment using the protocol. Each subject

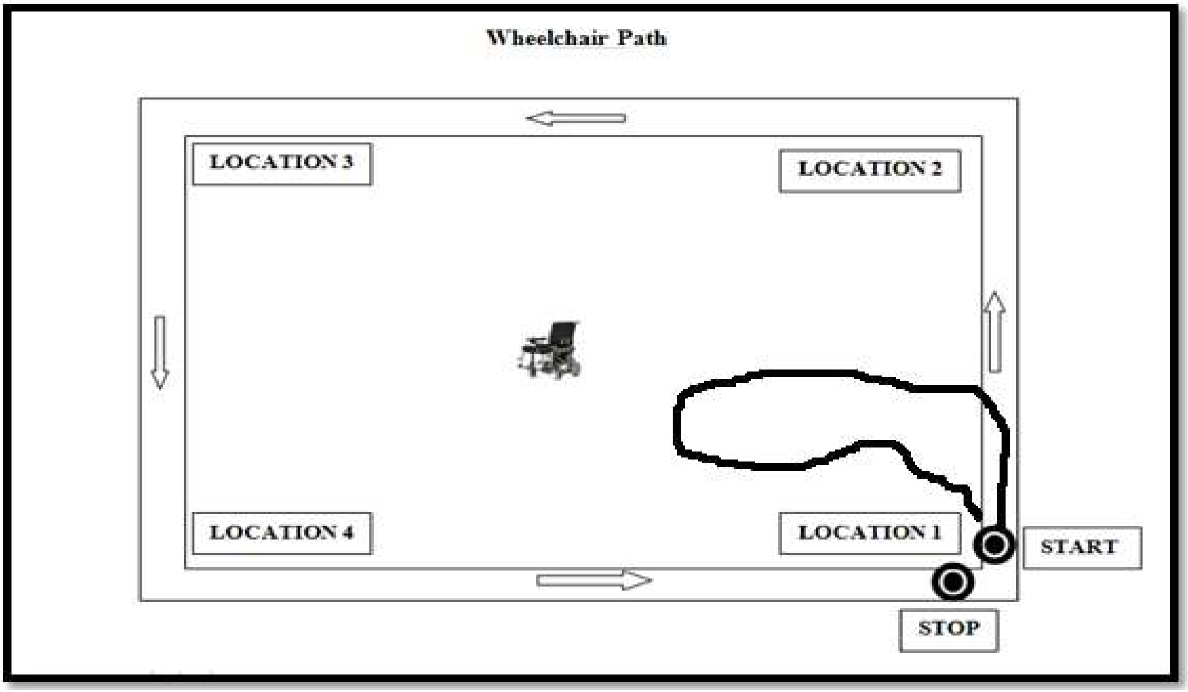

FIGURE 9. Online navigation of subject S1 in Day4.

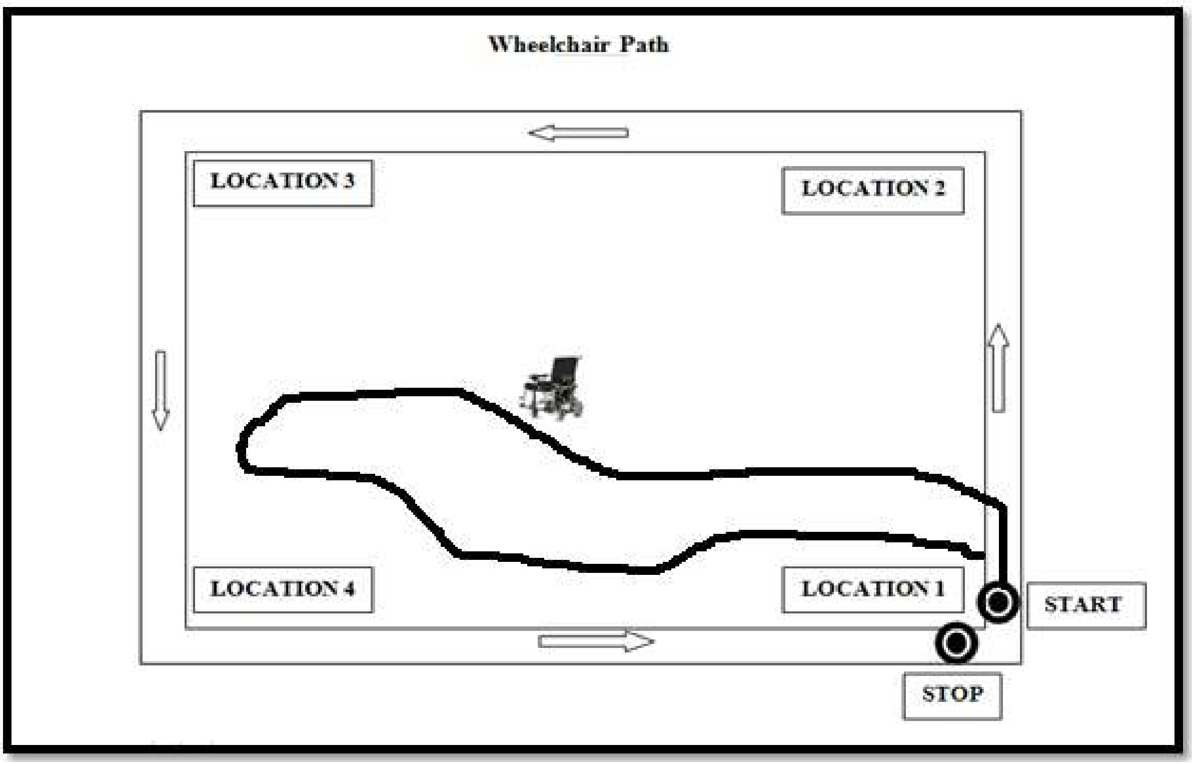

FIGURE 10. Online navigation of subject S1 in Day5.

navigated the wheelchair only once in a 30 minute session. Our study validate that all the participated subjects are able to successfully navigate the wheelchair by generating all the four states, forward, left, right and stop. From the online study we found that some subjects are not able to switch between states immediately. Subjects S3is able to complete all the protocols, with an average of thirty seconds navigational time per protocol and its performance is high compared with other

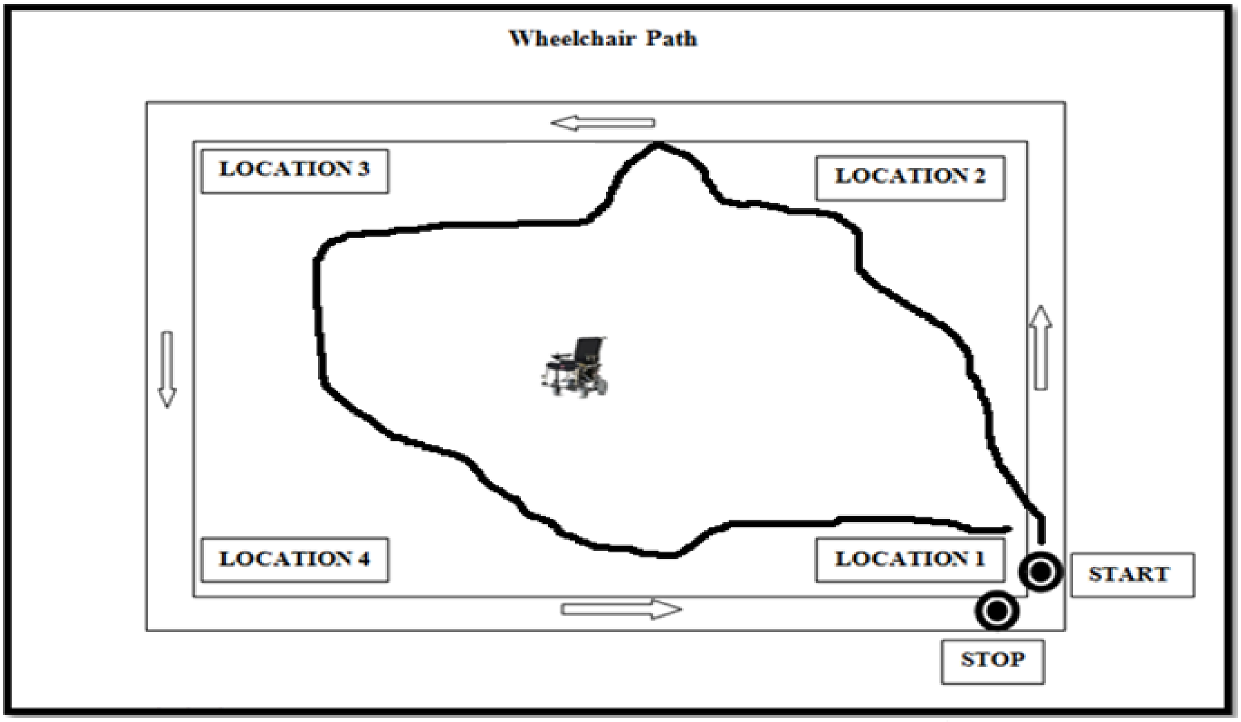

FIGURE 11. Online navigation of subject S1 in Day7.

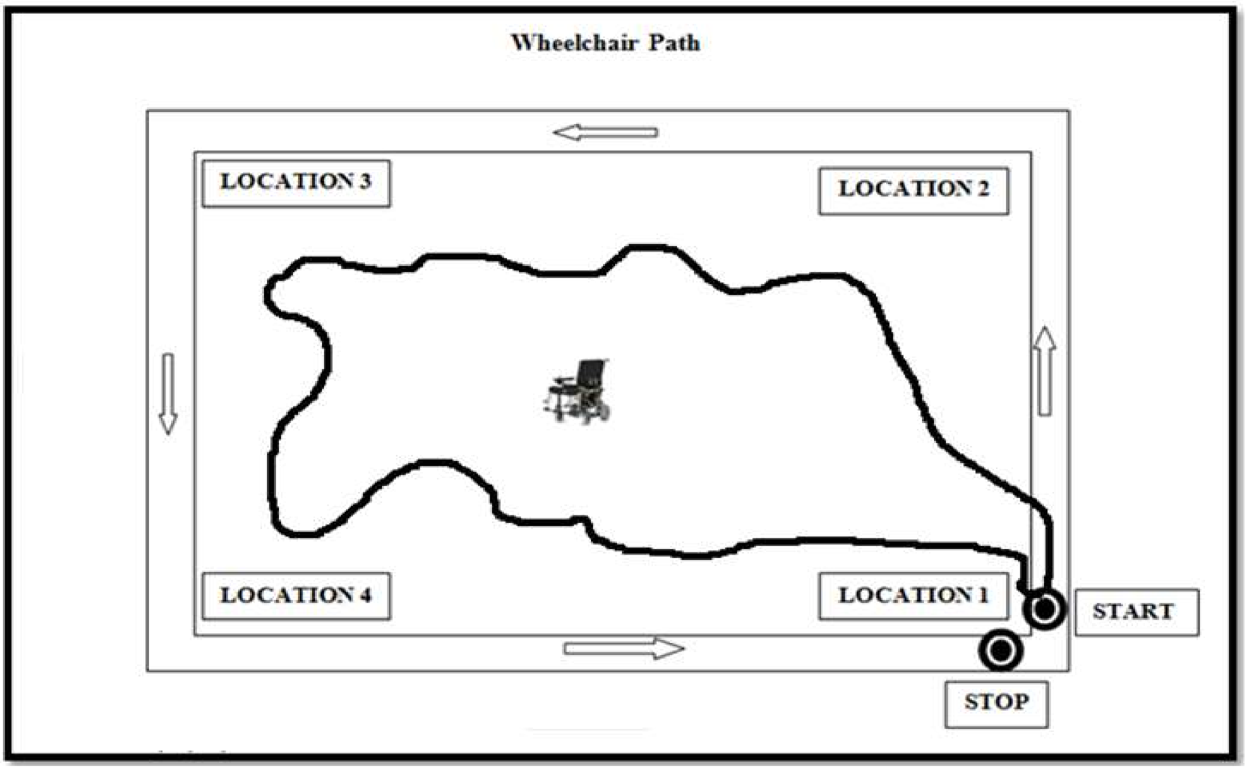

FIGURE 12. Online navigation of subject S1 in Day10.

subjects take part in this study which is shown in fig.15. Second highest online recognition is achieved by subject S1. Minimum online recognition is achieved for naive subject S2.Subject S1, S3 and S4 easily controlled the navigation of the BCI controller, their performance is comparatively better than all the subjects who participated in the real time

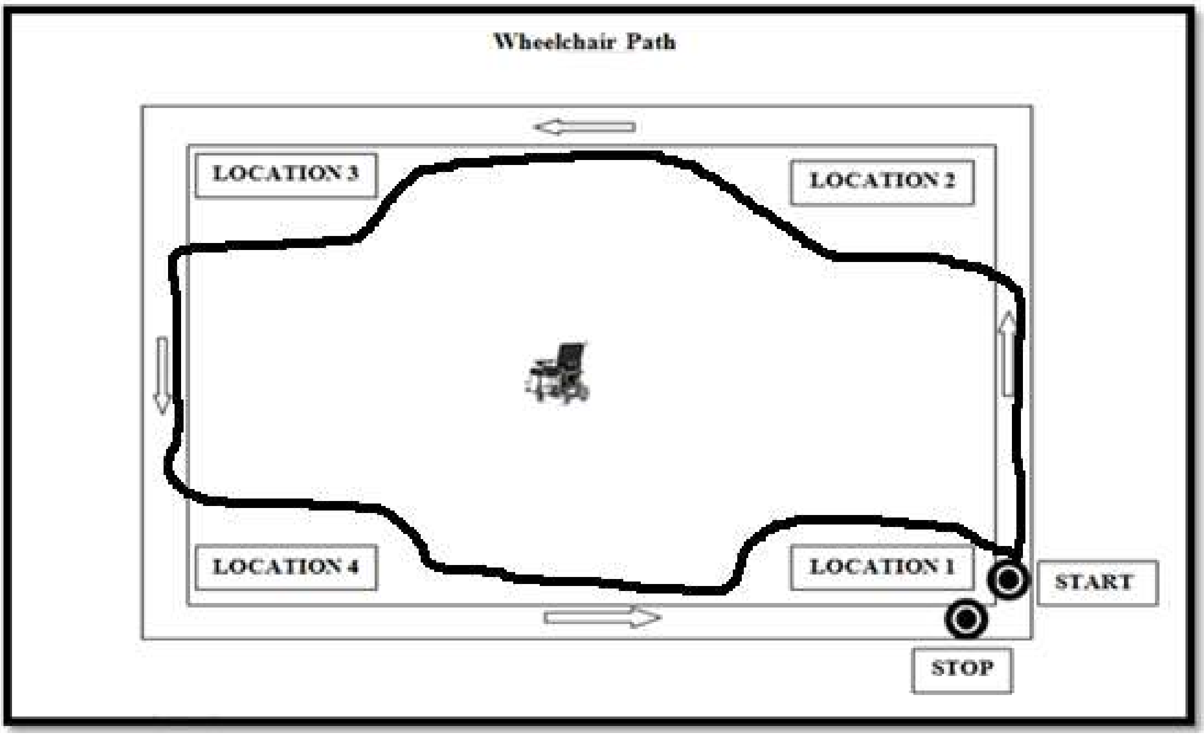

FIGURE 13. Online navigation of subject S1 in Day14.

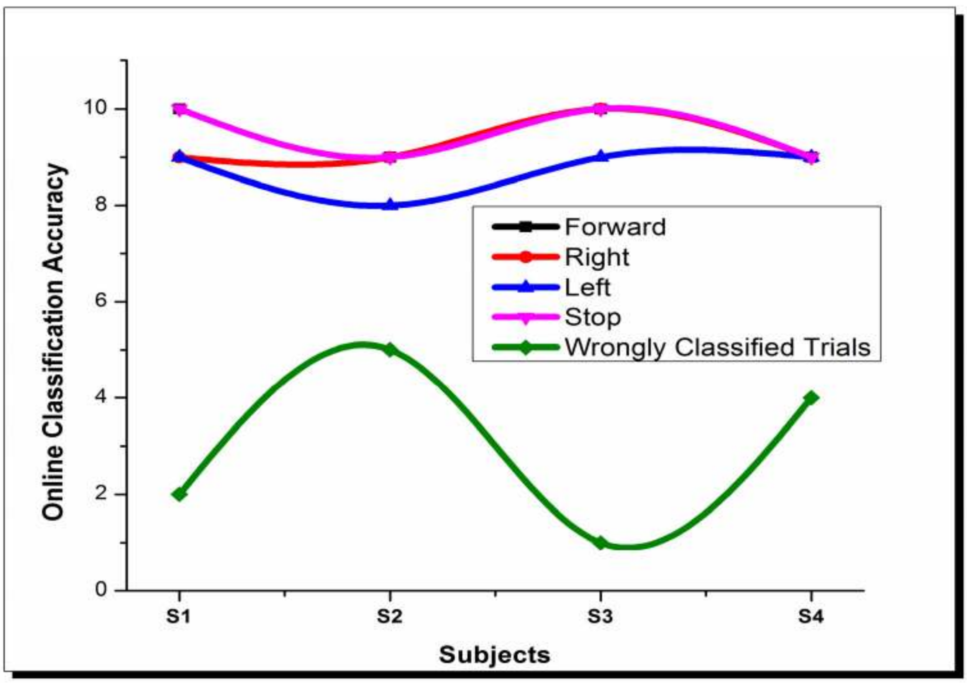

FIGURE 14. Overall online signal classification.

experiments in day 14 is shown in Fig.13. Training from day1 to day10 is shown in the fig.7 to fig.12.

From the Table.4 we analyze that naive user performance is minimum compare with trained user. Online study shows an average classification accuracy of 92.50% for overall tasks and individual tasks with average classification of 95%, 87.50%, 92.50%, 95% are achieved for four tasks which is shown in Table.4, Table.5 and fig.14,

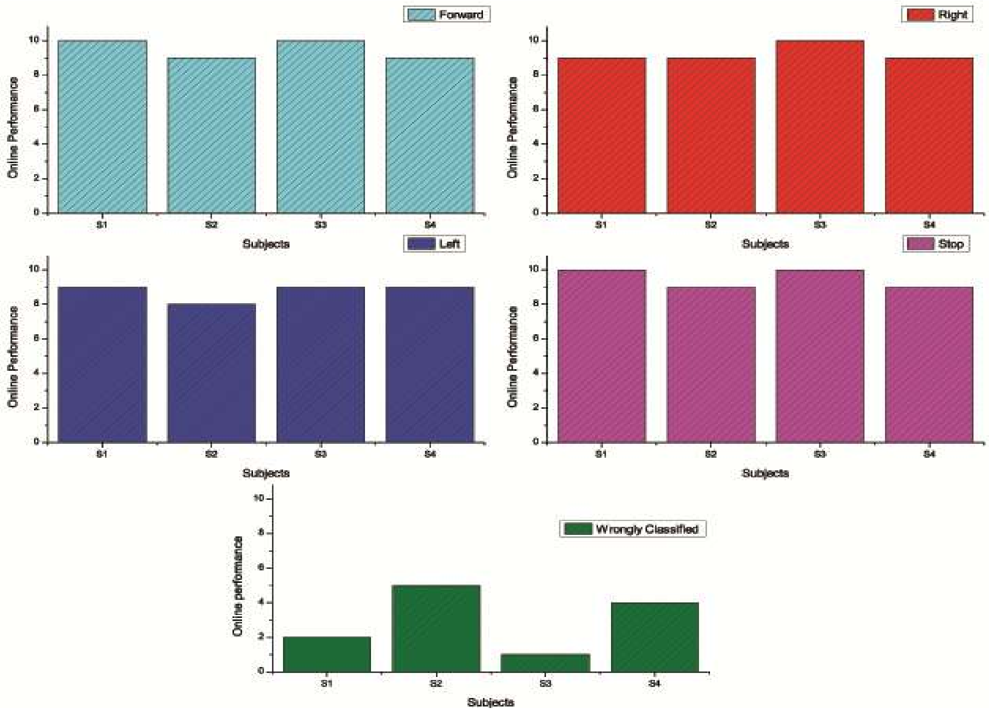

FIGURE 15. Task wise classification accuracy for individual subject.

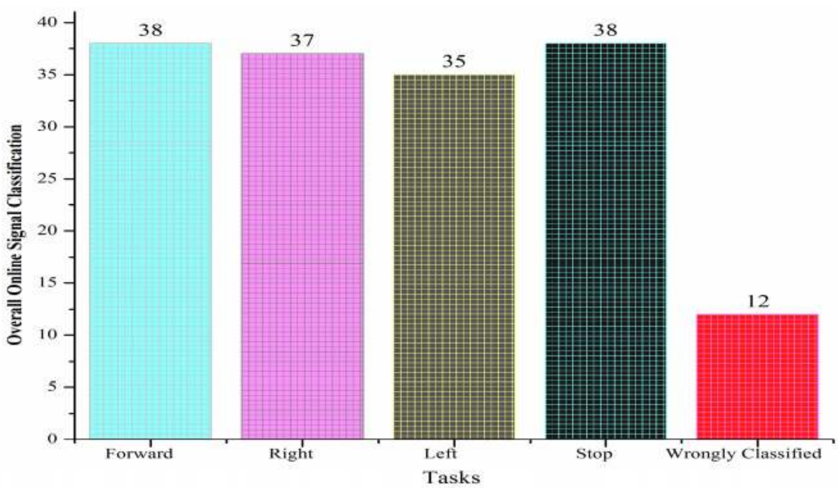

FIGURE 16. Overall individual task classification.

fig.15 and fig.16. Real time studies proves that performance of the method obtain major statistical improvement to control wheelchair in more natural way. From the Table.4 and Table.5 we interpret that compared to previous study [14]–[20], [26]–[28], [35]–[37], [39], [41]–[44] our system outperformance in terms of accuracy, user friendly and less training with sophisticated design. From the online analysis, Subject S1, S3 and S4 performance was appreciated compared with S2. Finally the study concluded that subjects need training sessions to complete the given protocols and also experiment proves that experience user performance is marginally appreciated in compared with naive users participated in the experimentation.

VII. CONCLUSION

Through this study we evaluate the online recognizing accuracy of wheelchair by using RBF and Band power features for four tasks. Three trained user as well as one new user without any training is also participated in the study and present overall classification accuracy of 92.50% and individual tasks with average classification of 95%, 87.50%, 92.50%, 95% and 95.00%, 87.50%, 97.50, 90% are achieved for four tasks in task wise classification as well as individual classification. The result shows that trained subject performance is high compared with new subject. From this study we analyzed that Subject S2 is not able to switch from one state to another state. The study shows that our methodology and design outperforms some of the other techniques used in the literature survey. This experiment proves that person with disability can able to drive the motor wheelchair by converting mental thoughts to control signal. In future we planned to conduct the online study with more number of naive users to progress the execution of the BCI in terms of accuracy and reliable.

Training Video Link is Given Below for Your Kind Notice: https://www.youtube.com/watch?v=5nb048fnqTY

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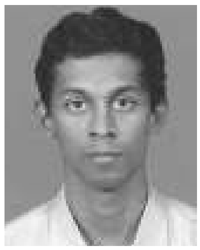

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