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Analysis of Collaborative Brain Computer Interface (BCI) based Personalized GUI for Differently Abled

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ABSTRACT
Brain-Computer Interfaces (BCI) use Electroencephalography (EEG) signals recorded from the brain scalp, which enable a communication between the human and the outside world. The present study helps the patients who are people locked-in to manage their needs such as accessing of web url's, sending/receiving sms to/from mobile device, personalized music player, personalized movie player, wheelchair control and home appliances control. In the proposed system, the user needs are designed as a button in the form of a matrix, in which the main panel of rows and columns button is flashed in 3 sec intervals. Subjects were asked to choose the desired task/need from the main panel of the GUI by blinking their eyes twice. The double eye blink signals extracted by using the bio-sensor of NeuroSky's mind wave device with portable EEG sensors are used as the command signal. Each task is designed and implemented using a Matlab tool. The developed Personalized GUI application collaborated with the EEG device accesses the user's need. Once the system identifies the desired option through the input control signal, the appropriate algorithm is called and performed. The users can also locate the next required option within the matrix. Therefore, users can easily navigate through the GUI Model. A list of personalized music, movies, books and web URL's are preloaded in the database. Hence, it could be suitable to assist disabled people to improve their quality of life. Analysis of variance (ANOVA) is also carried out to find out the significant signals influencing a user's need in order to improve the motion characteristics of the brain computer interface based system.

KEYWORDS
Brain computer interface; locked-in patient; graphical user interface; personalized music player; personalized video player; robot and electroencephalography

1. Introduction

The severe motor loss leads due to a brain stroke, cerebral palsy and other neurological problems. People who cannot speak and cannot use their hands to operate a traditional input device such as a mouse, and key boards find it very difficult to communicate with outside environments. Invasive and non-invasive type BCI techniques are available for observing brain activity. The p300 is one of the components in the EEG, which is used to transfer the user's intent into input command (Lenhardt, Kaper, & Ritter, 2008). There are 6 different types of frequency band data that are measured from the scalp. A non-invasive type technique is proposed in this paper to measure the electrical activity of neurons; this technique is also termed as electroencephalography (EEG). NeuroSky's Mind wave EEG device is used to record the electrical activity of the brain, Electromyogram (EMG) and Electrooculogram (EOG) signals are related to muscle movement and eyeball movement. Bacivarov, Ionita, and Corcoran (2008) developed a statistical active appearance model to track blinking of the eyes and the location of the eyes in various expression or poses. Khushaba, Kodagoda, and Lal (2011) developed an algorithm to extract various physiological signals to detect driver drowsiness/fatigue. Cecotti and Graser (2011) used neural network classification for detecting the p300 responses to make decision-making. The weakness of the P300 was a low transfer rate. Improving the transfer rate is also possible by using Bayesian approach with threshold for taking adaptive decision about input signals (Karjalainen, Kaipio, Koistinen, & Vauhkonen, 1999; Postelnicu & Talaba, 2013; Throckmorton, Colwell, Ryan, Sellers, & Collins, 2013).

The source for the EOG signal is Cornea-retinal potential and is generated due to the movements of eyeballs within the conductive environment of the skull. While recording the EOG signal, it will be contaminated by the Electromyography (EMG) signal. As the EOG is a non-stationary signal, the multi resolution analysis using wavelet decomposition offers the best solution to the noise and feature extraction of EOG signals (Sammaiah, Narsimha, Suresh, & Sanjeeva Reddy, 2011). The model is designed to be robust to variations of a head pose or gaze. The model parameters, which encode the variations caused by blinking, are analyzed and determined. This paper presents a machine learning approach to detect eye movements and blinks from EEG data and maps them as intents to control external devices like a computer desktop or a wheel chair (Gupta, Soman, & Govind Raj, 2012). The objective is to control the direction (left or right) of an electric wheelchair by using a recursive training algorithm to generate recognition patterns from EEG signals (Gentiletti, Gebhart, Acevedo, & Yanez-Suárez, 2009; Tanaka, Matsunaga, & Wang, 2005). Long, Li, Tianyou, & Zhenghui, 2012 developed a cursor control on a monitor screen. To move the cursor to a target on the monitor screen the target selection or rejection functionality is implemented using a hybrid feature from motor imagery and the P300 potential. To select the target of interest, the user must

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focus his or her attention on a flashing button to evoke the P300 potential.

Gandhi and Prasad (2014) proposed a real-time implementation of a novel iAUI design for a mobile robot control task. The major advantage with the iAUI is the user-centric graphical user interface design that presents all the control options to the BCI user at all times. A new modality-independent interface can be used to command a robotic wheelchair. The wheelchair can be controlled by eye blinks, eye movements, head movements, brain waves and can also navigate in an autonomous mode, taking the user from the current location to a desired one, and it can also operate like an auto-guided vehicle by following metallic tapes. RFID was used to calibrate the odometer and to provide location feedback to the user. This was introduced by Bastos-Filho & Cheein, 2014.

Yom-Tov and Inbar (2003) proposed that Brain-Computer Interface is a device for enabling patients with severe motor disorders to communicate with the world. One method for operating such devices is to use movement-related potentials that are generated in the brain when the patient moves or imagines a movement of, one of his limbs. The mental motor imagery movement provides the enhanced alpha band desynchronization. It might be a useful aid in the identification and training of BCI signals (Boord, Craig, Tran, & Nguyen, 2010). Jin et al. (2011) presents a P300 BCI based on a 12 x 7 matrix and new paradigmatic approaches to flashing characters designed to decrease the number of flashes needed to identify a target character. The results indicate that 16-flash pattern is better than other patterns. RC approach and performance of an online P300 BCI can be significantly improved by selecting the best presentation paradigm for each subject. Mahmoudi and Erfanian (2006) examined the role of mental practice and concentration skills on the EEG control during the imaginative hand movements. The results show that the mental practice and concentration can generally improve the classification accuracy of the EEG patterns. It is found that mental training has a significant effect on the classification accuracy over the primary motor cortex and frontal area. Lugger, Flotzinger, Schlgl, Pregenzer, and Furtscheller (1998) focused on the problems of dimensionality reduction by means of Principal Component Analysis (PCA) in the context of single-trial EEG data classification. The principal components with the highest variance, however, do not necessarily carry the greatest information to enable discrimination between the classes. An EEG data-set is presented where the principal components with high variance cannot be used for discrimination. In addition, a method based on linear discriminant analysis, is introduced that detects principal components which can be used for discrimination, leading to data sets of reduced dimensionality but similar classification accuracy.

In this paper, the real time Raw EEG sensing is carried out by using a bio-sensor head set, also called NeuroSky's mind wave mobile. It is a device with portable EEG sensors. The personalized GUI contains different task such as Wheelchair control, personalized music player, personalized movie player, Home appliances control, Help and Personalized web browser. The user can access any task from the personalized GUI by blinking their eyes. Analysis of variance is done to find the significant signals influencing the subject to improve the motion characteristics of brain computer interface based system. ANOVA gives clearly how the parameters affect the response of the particular subject signal generation and the level of significance of the factor considered.

2. Methodology

The NeuroSky Mind Wave is a wearable device for observing the electrical signals generated by neural activity in the brain. The device is comprised of eight main parts; flexible ear arm, ear clip, battery area, power switch, adjustable head band, sensor tip, sensor arm and inside think gear chipset depicted in Figure 1(b). It contains one dry sensor that can be located on the forehead, and 3 other dry sensors on the left ear, for reference. It also contains of a microchip, which pre-processes the EEG signal, and transfers that data via blue tooth. The processing algorithms are not an open protocol, but it does a FFT on the signal, which gives the band powers. However, these powers are scaled and filtered and therefore only relative to each other, which can be used for several tasks. The developed Personalized GUI application collaborated with the EEG device to extract the subject's eye blink signal as input command to access all of the user's need. Experiments have been conducted with 3 males and 2 female students with different task on different sessions. The subjects were asked to wear the EEG device and sit comfortably in front of the laptop fixed in the wheelchair. Necessary instructions were given to the subjects clearly before conducting the experiment. Some tasks were assigned to them and their activities measured based on the number of flashes and time taken by the user. The subjects were asked to repeat 5 sessions with five different tasks. Finally the average data was taken for ANOVA analysis.

The proposed system utilizes the subject's biofeedback, EEG and EOG, for selecting the target of interest from the 3×2 main panel GUI. The main panel GUI contains Wheelchair movement control, Personalized music player, Personalized movie player, Home appliances control, Help and Personalized web browser. The user can access any of the above sub GUI panels from the main panel GUI window by blinking their eye twice, which intensifies the required flash box. The calibration of EOG is required to track the user's blinking of the eyes. The selection of target item assumes a continuous flashing process of symbols or coloured boxes contained in the GUI and the classified recorded EEG signal. This method is chosen in order to identify the accurate target location. Figure 1 shows the architecture of the collaborative based personalized GUI system.

2.1. Signal Acquisition and Pre-processing

The NeuroSky device is used for observing the raw EEG signals generated by neural activity in the brain. It is a device with portable EEG sensors depicted in Figure 1(a).The headset can be easily placed on the head and a dry sensor is used to read brainwave impulses. This allows interactions with Apps and digitized brainwave signals from the forehead. FP1 is used to transfer the control signals. NeuroSky devices have the ability to measure multiple mental states simultaneously. NeuroSky think gear technology generates the raw brainwaves and also the eSense Meter square measures computed on the thinkgear chip.

Filtering protocols eliminate the known noise frequencies such as those from muscle, heart beat and electrical devices. Frequency ranges between 3–100 Hz. A sampling rate of 512 Hz is used for the interpretation of sensory information, as depicted in Figure 2(a). A notch filter is used at frequency ranges between 50–60 Hz to eliminate interference from supply lines. The acquired EEG signals are transferred wirelessly to the PC by using Bluetooth interface. MindRec is the research

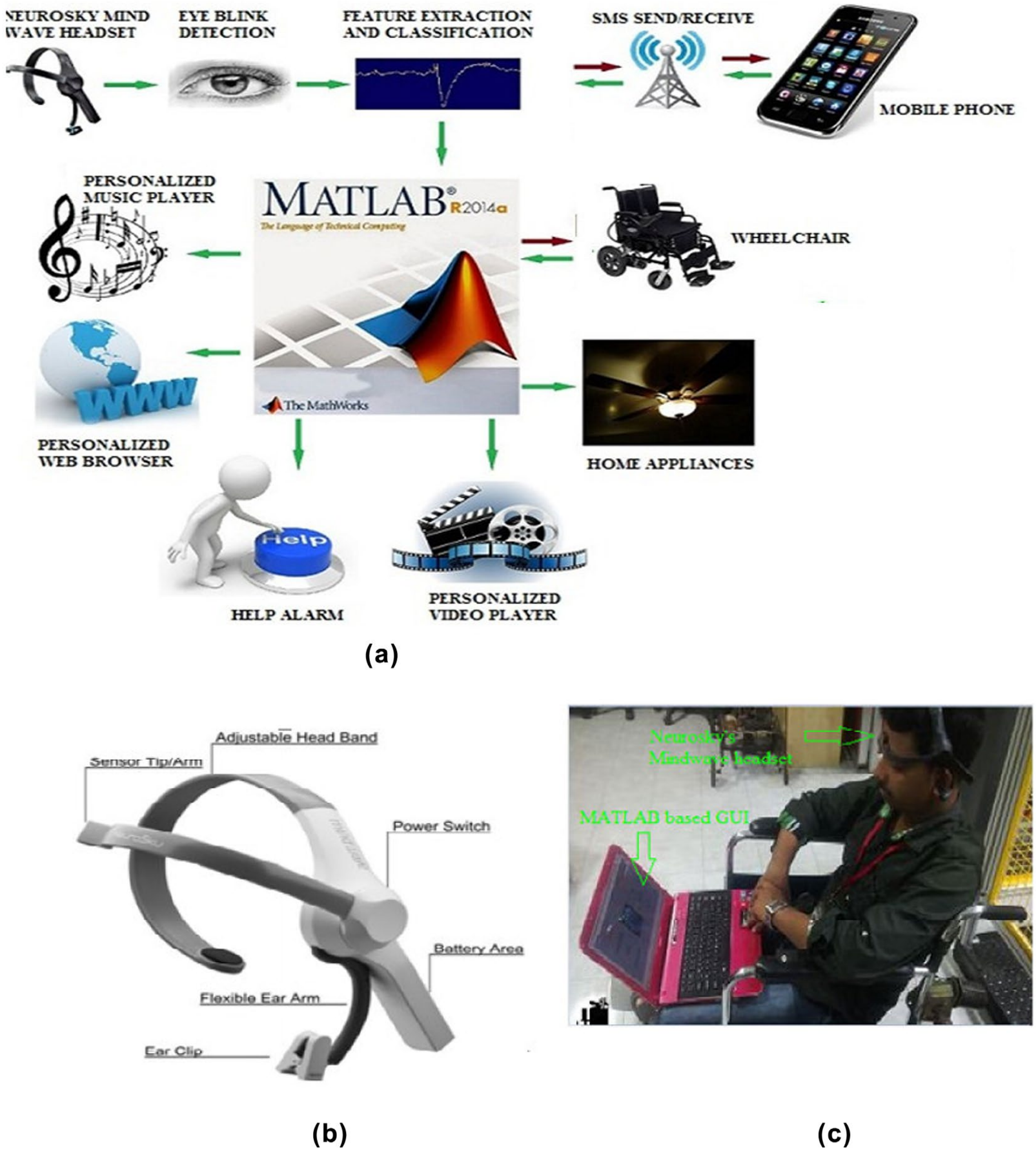

Figure 1. (a) Personalized GUI Controlled by Double Eye-blink, (b) Single Electrode Headset (Neurosky), (c) The Real Time Mode of Personalized GUI.

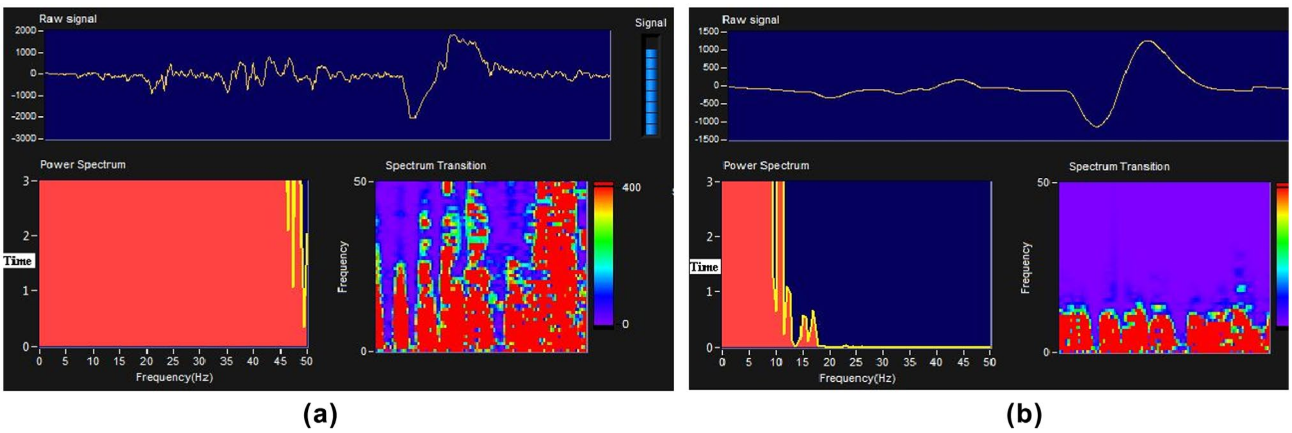

Figure 2. Power Spectrum Filtered EEG Signal.

tool, which is used to filter out eye blink signals from the EEG data. Araw EEG signal is allowed to pass through a 6th order Butterworth band pass filter with lower cut-off frequency 0.01 Hz and higher cut-off frequency 3 Hz with ripple of 1 dB, as depicted in Figure 2(b).

The power spectrum plot of EEG signals measured from the brain activity is observed. Figure 2(a) and (b) shows the signal power distribution along the range of frequencies. From Figure 2(a), it can be easily observed that power spectrums of all channels are closely concentrated and overlapping. On

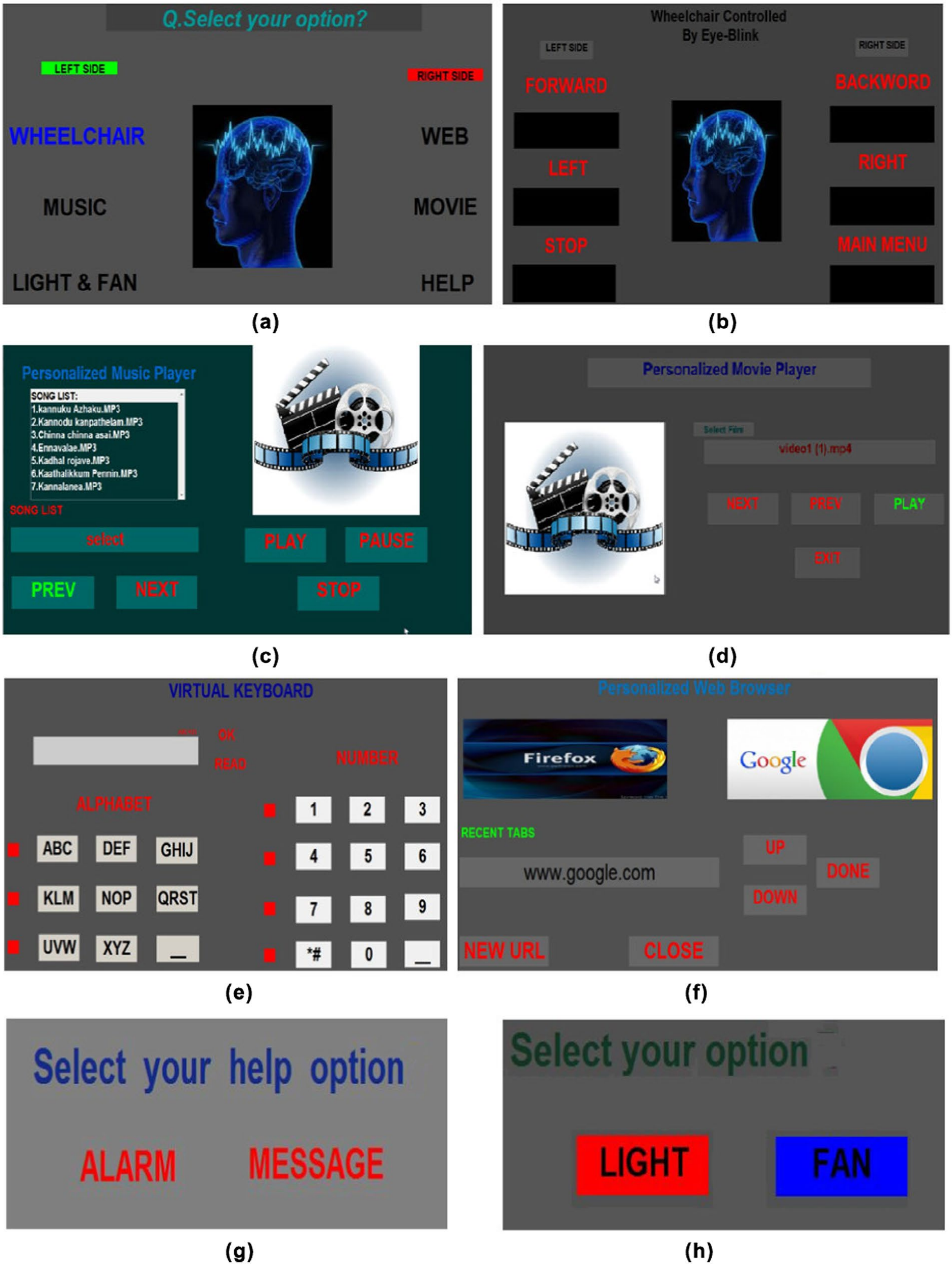

Figure 3. Personalized Graphical User Interface Models for; (a) Main Panel, (b) Wheelchair Control, (c) Personalized Music Player, (d) Personalized Movie Player, (e) Virtual Keyboard, (f) Personalized Web Browser, (g) Emergency, (h) Home Appliances.

analyzing these graphs, it is really difficult to comment on the power levels of different frequency bands. After filtration of raw EEG, commendable changes in the power spectrum plot are observed, which are depicted in Figure 2(b). Recorded EEG patterns are investigated and the relevant eye blink information is extracted. A feature extraction process is used to reduce the complexity of recorded raw EEG data from various trails and grouped according to the type of their feature. Neural network based classification algorithms are used to classify the target and non-targets in the stimuli with 2 N hidden layers to train the system for identifying them. The input of the classification algorithm is the output of the feature vector. It helps the expert system to take an accurate decision.

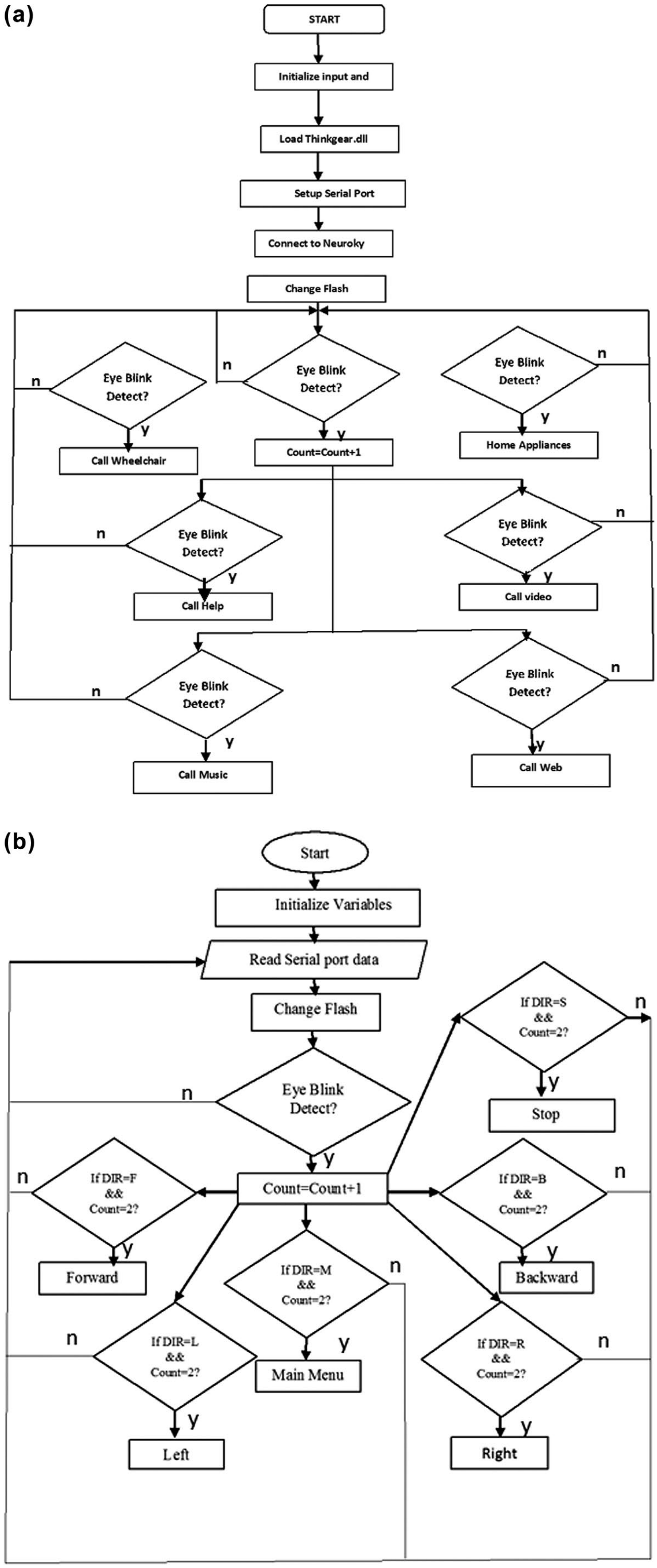

Figure 4. (a) Working Flow Chart of Personalized GUI, (b) Working Flowchart of Wheelchair Control GUI.

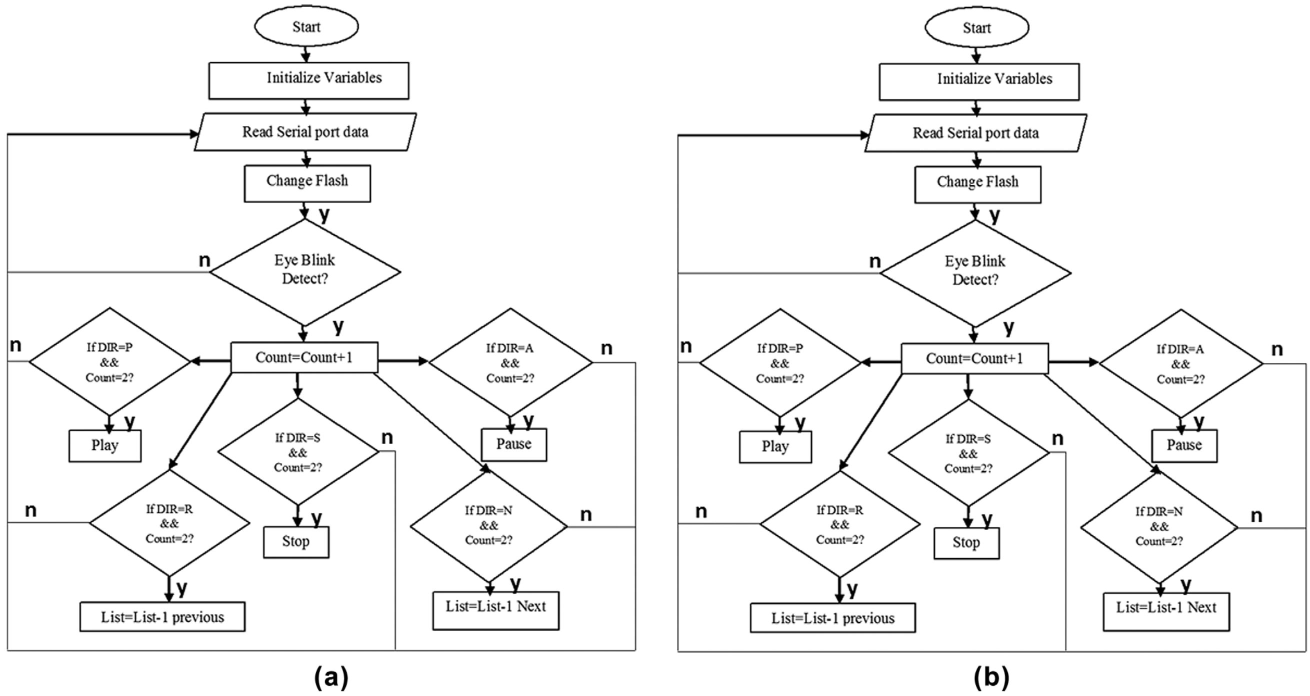

Figure 5. (a) Working Flow Chart of the PMP GUI, (b) Working Flow Chart of PVP GUI.

2.2. Collaborative Personalized Graphical User Interface (GUI)

Collaborative personalized GUI contains mainly seven panels; one main panel and six subpanels. The Main panel GUI depicted in Figure 3(a), has 3 rows and 2 columns. The flash boxes are represented by a Wheelchair movement control, personalized music player, personalized movie player, Home appliances control, and Help and personalized web browser. When a particular option is available to the user the corresponding flash box color will change from red/black to blue. Each option is available for a time period of 3s according to the flash queue.

The user can access the required target by blinking the eye twice when the particular flash box intensifies; when one option is chosen the blue color will change to green. Once a selection is made from any of the 6 options, the main panel GUI window is redirected to the selected sub GUI window. More number of commands is used to provide better accuracy. The advantage of the adaptive method is that it dynamically stops the flash to present another flash when the system is unable to take an unswerving decision about the target. This mechanism increases the communication speed and bit rate. This decreases the time of selection of the target element. Working flow chart of Main panel GUI is depicted in Figure 4(a).

2.3. Robot Wheelchair Movement Control

The sub GUI panel of the wheelchair movement control is depicted in Figure 3(b), it has 3 rows and 2 columns and they are grouped by two. The first column is denoted as the right side and the second column is denoted as the left side. Initially, the user needs to select the side, which contains the targeted direction of motion and then select the direction of motion from the 3 options. Initially, all options will be in red/black colour and it turns to blue when the particular option is made available to the user. When the user selects one option, the flash box colour turns to green while the others remain the same. A counter is used for counting the number of blinks; when the counter value exceeds two in a particular period of interval the system selects the available command option to do the action according to the user's intention.

2.4. Personalized Music Player (PMP)

The working of the Personalized Music Player (PMP) as depicted in Figure 3(c) is the same as the above and the only difference is in the GUI model. The GUI contains Pause, Next, Previous, Play and Stop options. The Next and Previous options are used for selecting particular songs from the preloaded list of songs, according to a user's interest. When the user wants to play a particular song, the user needs to select the Play button when the flash is available. If the user needs to change the song he must select the Pause button and he/she can change the song by selecting either the Next or the previous button. Once the user selected the Stop button the control will return to the Main panel GUI. Working flow chart of PMP GUI is depicted in Figure 5(a).

2.5. Personalized Video Player (PVP)

The Personalized Video Player GUI depicted in Figure 3(d) is implemented by using DOS system commands in MATLAB, which have the capability to access any of the system's default video players such as GOM player. The proposed Personalized GUI provides accessibility to the preloaded personal interested movies from the database list by using the commands NEXT or PREVIOUS in the GUI menu. PLAY is selected, and then the MATLAB calls the default system's media player through the DOS commands. The selected movie from the data storage is loaded for Play and it plays from the start. Once the media started to play, the MATLAB waits for the STOP command to return back to the main panel. Figure 5(b) shows the working flow chart of PVP GUI.

2.6. Personalized Web Browser

The personalized GUI for the web browser is depicted in Figure 3(f). The GUI model allows the user to access the

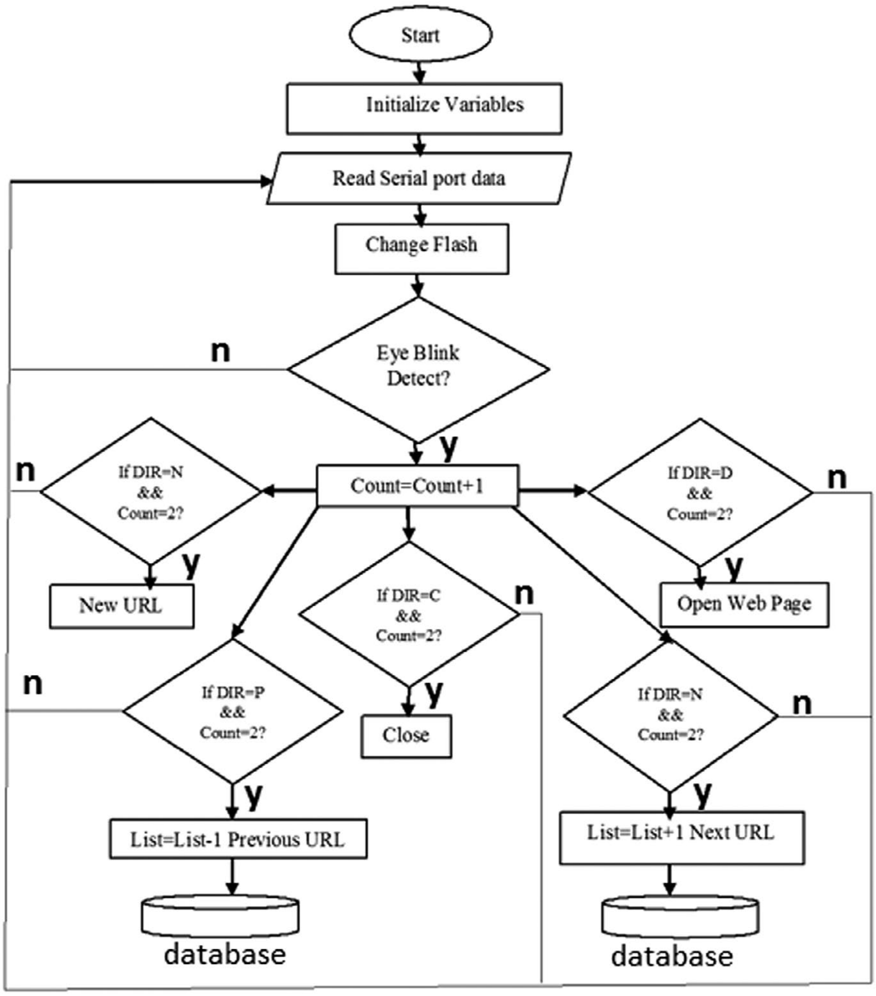

Figure 6. Working Flow Chart of the Personalized Web Browser.

system's default browser. By default, a recent tab option provided to access recently used web URL sites. The user can choose the sites from the list of recently accessed by using UP or DOWN commands and for confirming the selection, the user needs to choose the done button. On doing this he will then be redirected to the Chrome/Mozilla browser from where he can open the corresponding web URL. Additional virtual keyboard options are provided for typing the new web address. Figure 6 shows the working flow chart of the Personalized Web Browser.

2.7. Emergency Button

The emergency Graphical User Interface is portrayed in Figure 3(g), it provides two options to the user, namely HELP alarm and SMS. When the user chooses the alarm option it will ring for 2 min. A GSM SIM 300 modem is an interface with Arduino Atmega 2560 for sending a message to other people. A virtual keyboard depicted in Figure 3(e) is provided to the user to type out the new message. The keyboard provides access to numbers and alphabets for composing their own messages. The numbers are presented in the form of a 4×3 matrix and alphabets are presented in the form of a 3×3 matrix. The user can select from the available alphabets or numbers by blinking their eye twice. Figure 7(a) shows the working flow chart of the Emergency menu.

2.8. Home Appliances

The home appliances GUI model is depicted in Figure 3(h) including a light and fan control. If a user needs to turn on/off the fan he/she must choose the Fan flash button by blinking the eye twice. The count values are used for managing the on/off mode Figure 7(b) shows the working flow chart of Home appliances.

3. Result and Discussions

3.1. Experimental Setup and ANOVA Analysis

The purpose of the analysis of variance is to find the précised significant signals influencing the subject to improve the motion characteristics of a brain computer interfaced based knowledge system. ANOVA clearly shows how the system parameters affect the response of the particular subject's signal generation and the level of significance of the factor considered. The ANOVA table (Table 1) for five different subjects signal parameters of knowledge system is calculated. The ANOVA Tables 2-6 shows the effects of maximum and minimum values of signals that are statistically significant in confidence level for subject 3 compared to other four subjects. Value of R^2 is 0.295 for subject 3 motion, which signifies that the model can reasonably explain 29.5% of the variability in the expert system. It can be stated that no non-significant terms are included during empirical model

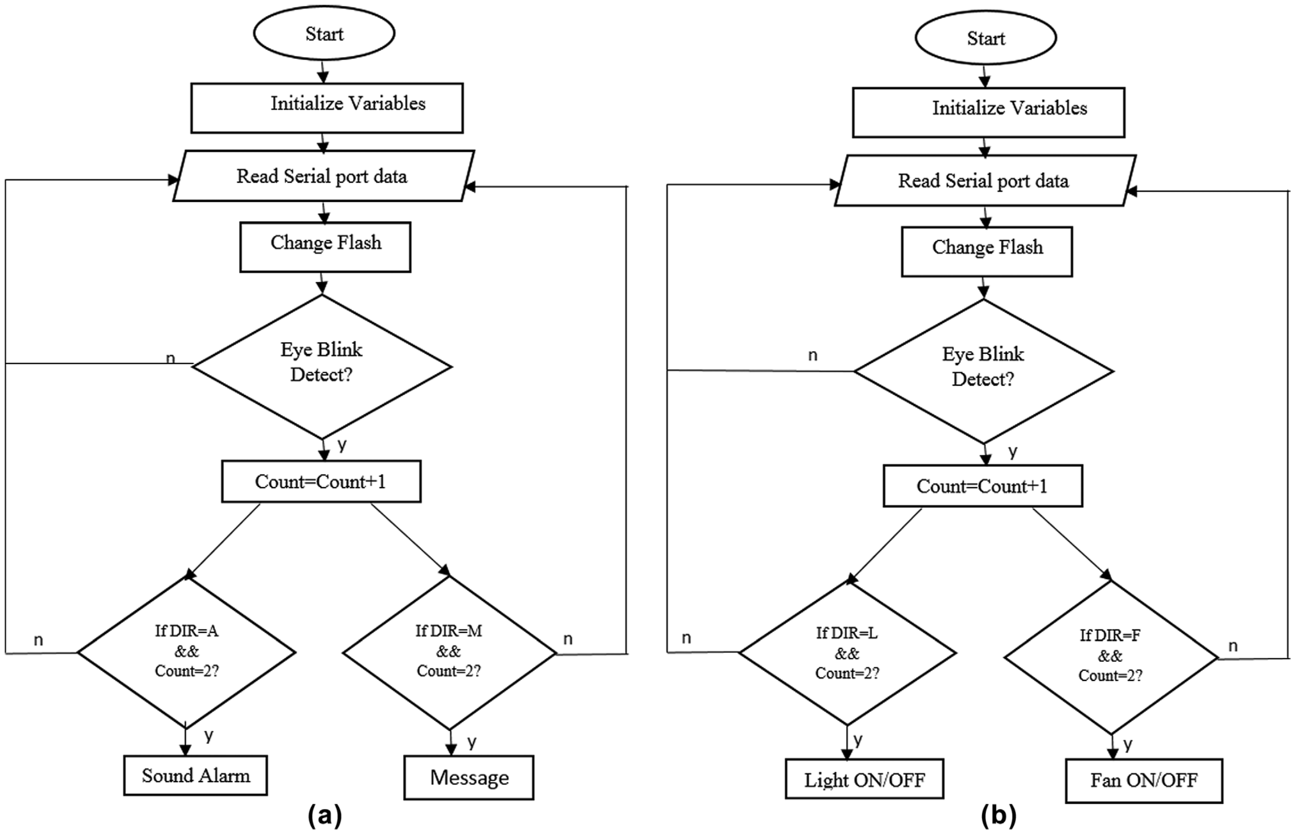

Figure 7. (a) Working Flow Chart of the Emergency Button (b) Working Flow Chart of Home Appliances.

Table 1. Brain Computer Interface Signal Data for Robot Motion.

	Subject 1		Subject 2		Subject 3		Subject 4		Subject 5	
Exp. No.	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
1	−2048	1417	−1662	598	−2048	2047	−2049	1845	−2005	1970
2	−2048	2047	−2048	978	−2048	2047	−2038	2087	−2148	2136
3	−2048	1522	−2048	1280	−2048	2009	−2058	2522	−2258	2279
4	−2045	2047	−2048	1130	−2048	1303	−2145	2347	−2284	2130
5	−2048	1522	−2048	1104	−1861	1616	−2248	1922	−2123	2104
6	−2045	2047	−2048	919	−1737	1443	−2047	2027	−2142	2059
7	−2048	2047	−2048	2047	−1969	1510	−2049	2183	−2098	2118
8	−2048	2047	−2048	2047	−2048	2047	−2048	1989	−2138	2137

Table 2. ANOVA Analysis for Subject 1 Signal for Robot Motion.

Parameters	Degree of Freedom (f)	Sum of Squares (SSA)	Variance (VA)	FAo	*P*	Contribution (%)
Signal	1	117600	117600	1.48	0.270	19.75
Error	6	477750	79625			80.25
Total	7	595350				100

S = 282.2, R^2 = 19.75%, R^2 (adj) = 6.38%.

Table 3. ANOVA Analysis for Subject 2 Signal for Robot Motion.

Parameters	Degree of Freedom (f)	Sum of Squares (SSA)	Variance (VA)	FAo	*P*	Contribution (%)
Signal	1	505210	505210	2.15	0.193	26.4
Error	6	1409147	234858			73.6
Total	7	1914357				100

*Significant.; S = 484.6, R^2 = 26.39%, R^2 (adj) = 14.12%.

building for expert system analysis. Degree of contribution developed by using ANOVA reveals that subject 1, subject 2, subject 3, subject 4 and subject 5 having 19.75, 26.39, 29.5, 21.56 and 20.74% contribution respectively showing that different people have different signals and thus leading to the accuracy of the expert system. Large FAo value 2.51 of subject 3 signals is accurate and this variation of the expert system parameter makes a big change on the accuracy of robot movement.

Table 4. ANOVA Analysis for Subject 3 Signal for Robot Motion.

Parameters	Degree of Freedom (f)	Sum of Squares (SSA)	Variance (V_A)	FAo	*P*	Contribution (%)
Signal	1	206656	103328	2.51	0.164*	29.5
Error	6	494605	82434			70.5
Total	7	701262				100

*Significant.; S = 287.114, R^2 = 29.5%, R^2 (adj) = 17.7%.

Table 5. ANOVA Analysis for Subject 4 Signal for Robot Motion.

Parameters	Degree of Freedom (f)	Sum of Squares (SSA)	Variance (VA)	FAo	*P*	Contribution (%)
Signal	1	76163	57901	1.52	0.448	17.9
Error	6	347407	38081			82.1
Total	7	423570				100

*Significant.; S = 195.14, R^2 = 21.56%, R^2 (adj) = 4.23%.

Table 6. ANOVA Analysis for Subject 5 Signal for Robot Motion.

Parameters	Degree of Freedom (f)	Sum of Squares (SSA)	Variance (VA)	FAo	*P*	Contribution (%)
Signal	1	85656	6509	1.37	0.467	15.7
Error	6	449694	341767			84.3
Total	7	535350				100

*Significant.; S = 232.8 R^2 = 20.74% R^2 (adj) = 4.02%.

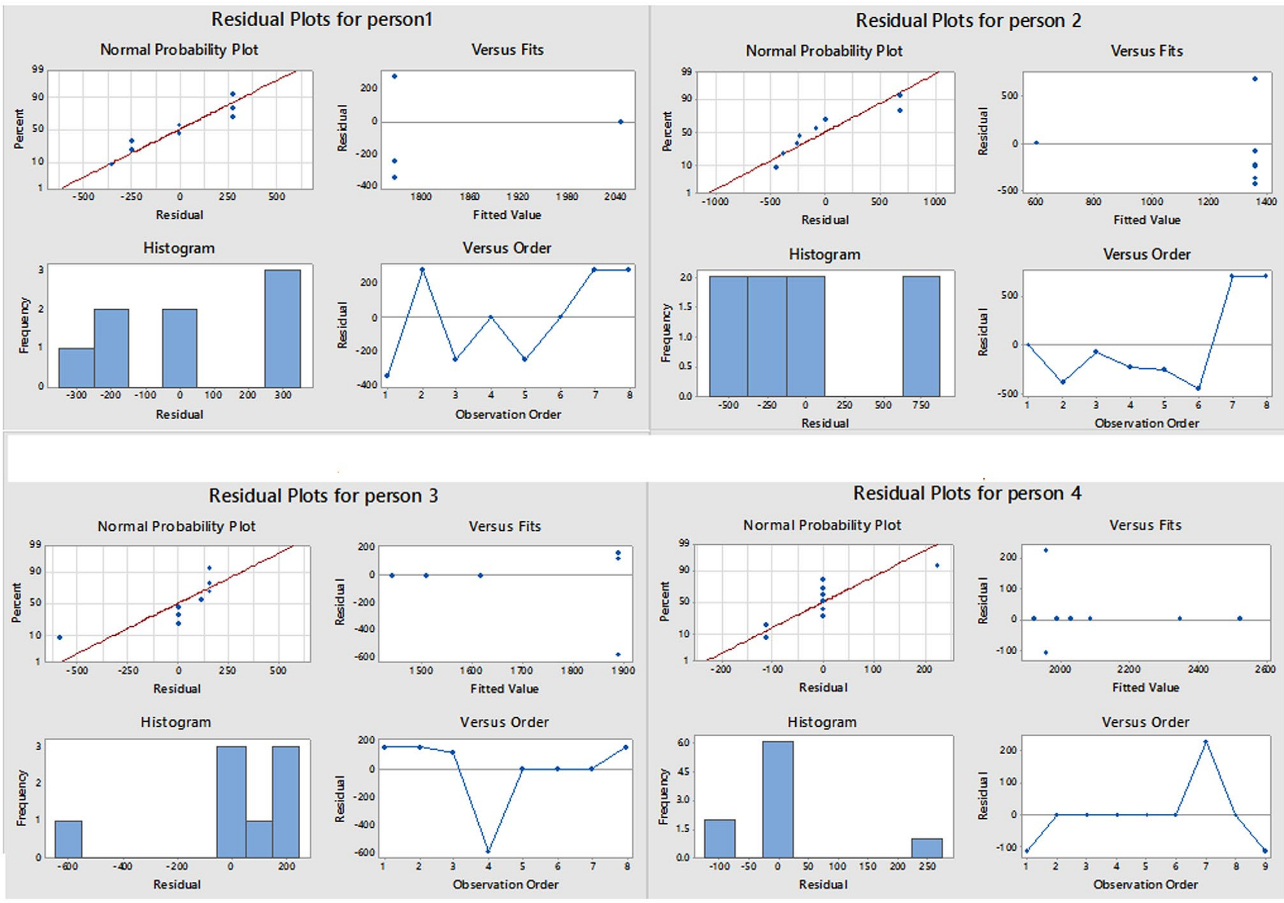

Figure 8. Plot of Residuals for Different Subject Signal Responses (Subject 1–5).

Additionally, the developed response of expert system models for a brain computer signal was checked using residual plot analysis. The residual plots for the response parameters of subject 1–5 with maximum and minimum signals of expert system are depicted in Figure 8. In normal probability plots, the data are spread approximately in a straight line, which indicates a good correlation between experimental and predicted values. The responses as depicted in Figure 8 indicates the residual versus predicted values, which shows only a minimal variation between observed and fitted values. The statistics about the residuals are depicted in histogram plots in Figure 8, (histogram plot). As a whole analysis of residual plots for

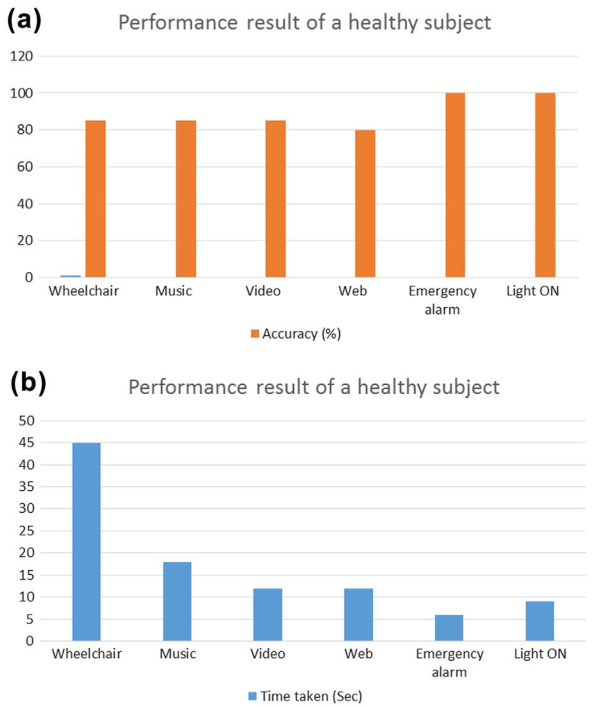

Figure 9. Performance Results of a Healthy Subject with Different Task (a) Accuracy Level (b) Time taken (sec).

both responses, the models do not reveal inadequacy of brain computer interface signal. Figure 8, (residual order plot) shows the residuals calculated against the order of experimentation received from a subject. It is asserted that a tendency to have runs of positive and negative residuals indicate the existence of certain correlation. As a whole analysis of residual plots for Subject 3 responses, the models do not reveal any inadequacy.

3.2. Results

A healthy subject has operated the newly developed Personalized GUI. After a few training sessions the subject achieved 90% average accuracy control over the system. Help options achieved 100% accuracy and time taken also very less than other task, because this option does not have additional number of choices depicted in Figure 9(a) and (b).

4. Conclusions

The newly developed personalized GUI helps the people who cannot move or communicate verbally due to complete paralysis. It provides a better quality of life in people's daily activities. The subject's needs are customized; hence changes can be made easily. The real time experiment is carried out by allowing healthy subjects to use the system. The results show that they can easily access the system without any misselection, within a good time and achieved 90% average accuracy control over the system after little training. Music and video players are developed based on the user's interest and preferences. The subject can access the entire task individually. By comparing the action time and selection time of the target of interest, it is found that the newly developed personalized GUI system gives a better performance, needing only little mental exertion to select the target. Due to ethical issues, healthy people are only used for the experimentation and not the patient. In a nutshell, this can be utilized for a better result among disabled people.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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Uma Mohan received an M.Tech in Computer Science from SRM University, Chennai, India, an MCA from Bharathidasan University, Trichy and is currently doing a Ph.D. in the area of Brain Computer Interface at Bharathiyar University, Coimbatore, India. She has software industrial experience of 2 years as a programmer and 14 years of teaching and research experience. Currently, she is an assistant professor (Senior Grade) in Software Engineering Department at SRM University, India. She is the author of 11 international journal papers and 10 conference papers. Her research interests include brain computer interface, personalization, robot control, P300, java and net.

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