Designing a Hierarchical Keyboard Layout for Brain Computer Interface Based Text Entry

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***Abstract*—Human beings are naturally blessed with sensory and motor functionalities. These abilities help us understand our surroundings and respond accordingly. However, sometimes, due to innate reasons or trauma, some people are deprived of these functionalities. In order to restore the natural motor functionalities to people with such disabilities, Brain Computer Interface (BCI) has been widely employed with other Human Computer Interaction (HCI) measures to find an optimum solution that ensures a high speed system with reasonable accuracy. In this paper, we have explored one of such systems for Text Entry mechanism using BCI. We have addressed the following three challenges for a BCI based Text Entry system- i)Four motor imagery signal based interaction ii)Processing and classification of noisy EEG data using the available methods iii) Language prediction model to increase input speed. We have tried to contribute in designing the Keyboard Layout for the Text Entry. Existing soft keyboard layouts for BCI systems have either a flat layout or a hierarchical static layout with very few functionalities in more than 2 layers. We propose to improve the hierarchical layout using a 2 layer multi-functional approach. We have prepared a prototype solution to substantiate our hypothesis. With a cognitive walkthrough based evaluation we have validated our hierarchical layout's performance to be accurate and more functional.**

Keywords—Brain Computer Interface (BCI), Text Entry, Electroencephalogram (EEG), Hierarchical Keyboard Layout

I. INTRODUCTION

The number of people afflicted with disabilities are gradually growing. About 15% of the global population have been suffering from mental and physical disabilities, according to a report prepared by the World Health Organization and the World Bank [1]. Moreover, according to [2], total Amyotrophic Lateral Sclerosis (ALS) cases is projected to increase up to 69% from 2015 to 2040. It is therefore empirically evident that there will be more people with disabled motor functionalities. Adding to these facts, the effects of primitive disability is prevalent amongst the regular computer users in the form of Carpal Tunnel Syndrome which is caused by overuse of keyboard typing [3].

In order to restore computer usage ability of these disabled people, the prospects of alternative Text Entry Mechanisms have already been explored in [4]. The potential of Brain Computer Interface as an alternative text entry mechanism has been explained in [5]. The popular brain imaging methods available now are Electroencephalogram (EEG), Magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), functional near-infrared spectroscopy (fNIRS) [6]. Among these possible methods, EEG has been proven to be the least expensive and noninvasive means of obtaining brain signals.

In this paper, we have worked with four types of motor signals such as – left hand raise, right hand raise, nodding up, nodding down movements. We have adopted the proven methods of preprocessing, feature extraction and classification of EEG signals stated in [5], since we propose to contribute in improving the hierarchical keyboard layout. A recent work in [7] shows the benefit of using a hierarchical approach to designing a soft keyboard layout. The benefits of a hierarchical keyboard layout are error reduction and a decrease in the number of actions to perform a task [7]. However, a three layer hierarchy has been proposed in [7]. We propose to contribute by reducing the layer to 2 and achieve the benefits of a reduced error rate with a flexible and more functional layout. We have found such a layout to perform better with respect to input accuracy and ease of use.

II. RELATED WORK

There have been numerous work done on BCI based text entry systems. A few short review of the most impactful and relevant systems are given below.

A. P300 based Speller

One of the most well-known BCI based typing system is the P300 based speller described in [8]. It assists motor disabled users in typing with EEG signals using P300 impulses. P300 works on the basis of the 'oddball paradigm' stated in [8]. In an oddball paradigm, an odd visual cue is presented suddenly within a regular series of visual cues. The irregular visual cue generates a signal from the viewer's brain. This is the P300 signal. In the case of a P300 speller, flashing rows and columns of alphabets help create the P300 signal. Using this signal attained from the EEG acquisition the user can type his/her intended letter. In [8], the data rate of a P300 based speller has been stated as 0.20 bits/second.

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B. Steady State Visually Evoked Potentials (SSVEP)

Steady state visually evoked potentials are signals that occur as the brain's response to visual stimulations. These stimulations are evoked within a specific range of frequencies. The visual stimulus is needed to be within a range between 3.5 Hz to 75 Hz for exciting the retina of the user [9]. Stimulus of different frequencies generate different electrical responses from the brain. Spellers using this method of EEG evocation use different flashing frequencies of alphabets to differentiate between user choices [9]. SSVEPs are useful in research because of the excellent signal-to-noise ratio within the frequency range 25 Hz and 45 Hz [10] and relative immunity to artifacts [11].

C. BCI Keyboard Layouts

Numerous experiments have been carried out with different types of BCI keyboard layouts. P300 speller was first introduced in 1988 [8]. This speller has a two-dimensional matrix of alphabets. The rows and columns keep on flashing. The user focuses on the desired letter from the cell. This focus generates a P300 signal with respect to the time of the focus. The time-locked P300 signal determines the selected letter [8]. In [12], a 3D layout of the P300 speller has been also used for an improved accuracy.

Another type of layout was presented by the Berlin BCI group in [13]. The layout is called "Hex-o-spell". It is based on motor imagery of imaginary hand and foot movement. The rotating motion of an arrow is controlled by these imaginary motor imagery. The arrow is used to select a desired letter. "Hex-o-spell" demonstrated a speed between 2.3 and 7.6 characters per minute during CeBIT 2006 [13].

D. Predictive Spelling Program

The importance of a predictive model in text entry is realized with the limitations of the text entry interface. For example, QWERTY keyboard layout requires minimal to no prediction at all because of the speed of touch typing possible with this layout. However, in mobile phones the interface is very limited because of the form factor. The screen presents a few buttons spaced very close to each other. So, the typing speed decreases in these devices. In such cases, word predictions help to increase the typing speed. And, for BCI keyboards, the input modality is even more limited with only binary decisions. Predictive models have been very useful for increasing the word entry rate with BCI keyboards as shown in [14].

III. PROPOSED SYSTEM

Our proposed system will contain two sub-systems such as BCI subsystem and HCI subsystem. The BCI subsystem will be dedicated to classify the motor signals from EEG data. The HCI subsystem will provide a hierarchical keyboard with a predictive model to the user.

A. BCI Subsystem

The BCI sub system involves all the steps of a typical components of BCI system. The BCI sub system is developed in two steps, by first creating a model for the application, that is, off-line analysis, second real-time processing of captured signals, that is online analysis. The BCI subsystem consists of data acquisition, preprocessing, feature extraction, classification and evaluation.

1) Preprocessing: EEG Signals are usually full of noise and artifacts. These noises are mostly generated from AC

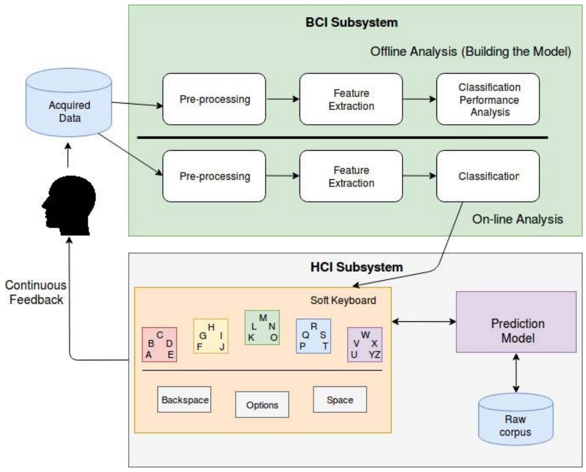

Fig. 1. Proposed System

power line, electronic equipment, lightning etc. The artifacts due to power line interference have been found to be above 50Hz. Some biological reasons such as sweating and experimental reasons such as misplacement of electrodes lead to slow changes in the measured voltage. Such a change can cause noise with frequencies below 0.01 Hz [15]. In order to remove such noises, band-pass filter that allowed only signals in the range of 8-30Hz is used [5].

Some artifacts cannot entirely be removed with the filtering. So, further preprocessing is usually required to remove noise from EEG signals. Independent Component Analysis (ICA) [16], Common Spatial Pattern (CSP) [17], are mostly used in preprocessing EEG signals [5].

Since the EEG signal from Emotiv consists of multiple channels, each channel is composed of signal that is a linearly mixed signal from the different channels. However, for better classification accuracy, each channel should have linearly independent signals. In order to reduce such linear dependencies, ICA is popularly used to reduce correlation among different channels. ICA is theoretically most suitable for preprocessing linearly mixed signals. But, it is memory intensive [5].

Another efficient method for reducing correlation between signals is CSP which performs spatial filtering with respect to only two classes of signals [17]. Since, CSP has been claimed to perform better than ICA in [5], we have used CSP to preprocess the data using the following procedure:

At first, we have considered two different types of signals such as: i) hand movement (X_1) and ii) nodding (X_2). Let X_1 of size (n, t_1) and X_2 of size (n, t_2) be two windows of a multivariate signal, wh ere n is the number of signals and t_1 and t_2 are the respective number of samples. The CSP algorithm determines the component w^T (transpose of weight vector w) such that the ratio of variance (or second-order moment) is maximized between the two windows [18]

$$w = \arg\max_{w} \frac{\|wX_1\|}{\|wX_2\|} \quad (1)$$

2) Feature Extraction: The accuracy and speed of a BCI system depends on an efficient set of features. If the best features are extracted from the preprocessed signal and then input into the classifier, the resulting output will have better accuracy. Moreover, with an optimized set of features, the speed of classification can be reduced. According to [5], the best features were found to be the following:

a) Signal Power: At first, the time-limited energy of the signal from channel k is calculated using the equation (2) [19]. Then, from the energy of the signal, we can compute the average power of the signal of channel k using equation (3) [19]. Here, P_k represents the signal power of channel k, over a range of n samples and x_i represents the i^{th} signal sample of channel k.

$$E_{k_{n_1,n_2}} = \sum_{i=n_1}^{n_2} |x_i|^2 \tag{2}$$

$$P_k = \frac{E_{k_{n_1,n_2}}}{n_2 - n_1 + 1} \tag{3}$$

b) Hilbert Transform: The discrete Hilbert transform of a function f(x) is defined in [20]. Here, Hilbert transform of the k^{th} sample is being calculated; n is the different odd/even samples.

$$DHT\{f(nT)\} = \begin{cases} \frac{2}{\pi} \sum_{n\ \ odd} \frac{f(nT)}{k-n}; k \quad even \\ \frac{2}{\pi} \sum_{n\ \ even} \frac{f(nT)}{k-n}; k \quad odd \end{cases} \tag{4}$$

In equation (4), F(t) is the Hilbert transform of the signal for the sample k. Discrete Hilbert transform can also be computed using the efficient circular convolution stated in [21]. Here h(k) is the impulse response of the Hilbert filter for sample k.

$$h(k) = \frac{2}{N} \sin^2\left(\frac{\pi k}{2}\right) \cot\left(\frac{\pi k}{N}\right); N \quad even \tag{5}$$

$$h(k) = \frac{1}{N}\left[1 - \frac{\cos(\pi k)}{\cos\left(\frac{\pi k}{N}\right)} \cot\left(\frac{\pi k}{N}\right)\right]; N \quad odd \tag{6}$$

$$DHT(f(k)) = -f(k) \otimes h(k) \tag{7}$$

As a result of Hilbert transform, we can convert the original signal into an analytic signal. Analytic signals have the important property of filtering out the negative frequency component and doubling the positive frequency component [22].

c) Fast Fourier Transform: The preprocessed signal, when passed through a Fast Fourier Transformation, will produce signal values in the frequency domain. These frequency domain signal values can be used as the FFT coefficients.

The outputs from the Signal Power, Hilbert Transform and Fast Fourier Transform are considered as the features of the signal. These three features are combined for a signal window to form the feature vector and passed on to the classifier.

3) Classification: After extracting the feature vector, we can use either Support Vector Machines (SVM) or Linear Discriminant Analysis (LDA) as supervised classifiers. Since, SVM was found to perform better than LDA in [5], we have chosen to use SVM as our classifier. The goal of SVM is to find the optimal separation hyperplane which maximizes the margin between different classes of the training data.

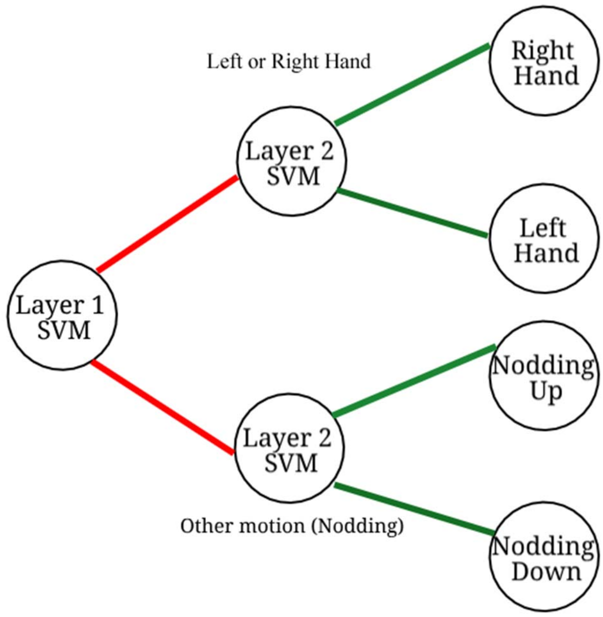

Fig. 2. Two layer SVM classifier

We have used Weka API [23] for Java as our data analysis tool. The SMO function of Weka was used to perform the classification. SMO classifier is a variant of SVM. The data tuples were not linearly separable in the original dimension. So, a kernel function had to be used to take the data to a higher dimension where they are linearly separable. Two types of kernel functions were experimented with. They are the RBF (Radial Basis Function) kernel and the Polynomial kernel. However, the RBF kernel worked better than Polynomial kernel. The parameters used to tune the SVM was the Gamma value and the Complexity value. The more complex the model was, the better it performed for the training set and worse for the test set because it could not generalize the dataset good enough to classify test data.

Since CSP is a two-class preprocessing tool, the classifier has to be binary so that it can recognize the stages of hierarchy. We intend to extend our classifier so that at first it classifies hand (left or right) or other (feet, tongue or nodding) signal, as in Fig. 2.

B. HCI Subsystem

In our study, we propose a keyboard with primary clusters such as prediction (at the top), letters (in the middle) and control clusters (at the bottom). This virtual keyboard is designed to have big selection boxes, each box containing letters or words that can be selected for typing. Each box consists of five letters. Five such boxes are arranged at the top with optimum design aspects in mind. Control buttons (Space, Backspace, Options etc.) are arranged at the bottom layer.

The keyboard coupled with a language prediction model produces contextual word prediction to aid a user with spelling. Whenever a user locks into a selected letter, above that letter box, a horizontal prediction cluster consisting of a list of words will appear. The user can then execute Up/Down/Left/Right nod movement thoughts to traverse the

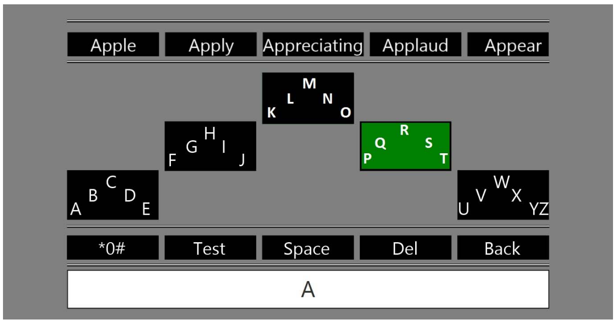

Fig. 3. Layer 1 of the hierarchical layout

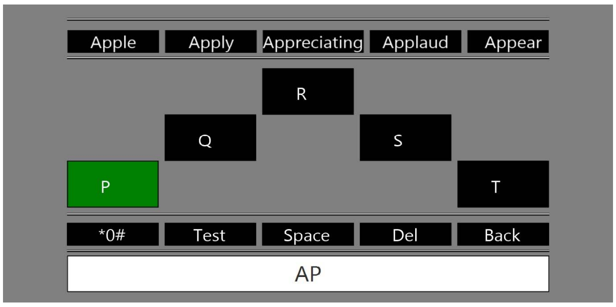

Fig. 4. Layer 2 of the hierarchical layout

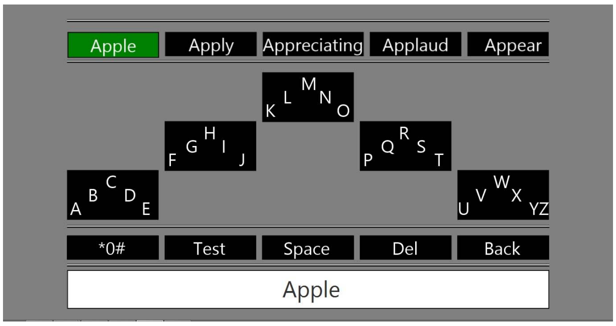

Fig. 5. Selecting the word 'Apple' from the prediction cluster

prediction cluster. The HCI subsystem will consist of a hierarchical soft keyboard and a language prediction model.

1) Hierarchical Prototype Design: The keyboard application has been developed using Java. The keyboard has been designed for our prototype. It is a hierarchical keyboard with three different types of clusters. The prediction cluster is at the top, the letter cluster is in the middle and the control cluster is at the bottom.

The user of the system will begin with an empty input. The user can navigate to the left and right clusters in the letter cluster group, by thinking about raising his/her left and right hand respectively. After reaching the target cluster by thought induced left/right hand motor signal, the user will dwell on the target cluster for 1.5s and it will be selected. Then, five letters from the target cluster will appear as the layer 2 of the keyboard. Then, from those five letters the user can once again use his/her thought induced left/right hand motor signals to select a letter. Once, the user dwells on a letter for 1.5s, that letter is selected. When a letter is selected, the control is shifted to the layer 1 of the keyboard. Eventually, the top prediction cluster will show at least 5 prediction of probable words from a user specific corpus also containing general textual data. The user can either use one of these new 5 letters or use thought induced nod up/down signals to navigate to the prediction cluster and then select the desired word.

2) Language Prediction Model: We have used an n-gram language prediction model following the Markov Chain property [24]. If w_1, w_2, w_3 … and w_{m-1} are the words of a sentence, then the probability of having w_m as the next word is as follows:

$$P(w_1,...,w_m) = \prod_{i=1}^{m} P(w_i | w_1,...,w_{i-1}) \quad (8)$$

We can use the context information of the previous consecutive n words. If we only want to perform an n-gram prediction, then we can get an approximate to $P(w_1, …, w_m)$ as follows [24]:

$$P(w_1,...,w_m) \approx \prod_{i=1}^{m} P(w_i | w_{i-(n-1),...,} w_{i-1}) \quad (9)$$

IV. Experimentation

We have conducted an experiment to collect EEG data sample from the participants. We collected EEG data for 4 different motor functionality. These motor functionalities were performed as thought processes only. They are as follows:

- Left hand movement
- Right hand movement
- Nod up movement
- Nod down movement

A. Hardware

We have used the Emotiv EPOC+ headset [25]. It is a research grade device capable of acquiring EEG signals from 14 channels. It has 16 electrodes - 14 of these electrodes measure the EEG signal and 2 of these are reference electrodes. The 14 measuring EEG sensors are named as the following: AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1, and O2. P3 (Common Mode Sense - CMS) and P4 (Driven Right Leg - DRL) sensors are the reference sensors. With a sampling rate of 128 samples per second, low pass filter of cut-off frequency 45 Hz, a resolution of 14 bits, and wireless transfer of EEG signal, Emotiv EPOC+ stands out as one of the most accepted EEG devices.

B. Participants

We chose two subjects for collecting the EEG data. They were first informed about the type of data that we would collect from them. We received their consent to use the collected EEG signal for our research purposes. Then, they were provided information regarding the experimental procedure. One was male and the other was female. The subjects were between the ages 18 to 25.

Fig. 6. Emotiv EPOC+

C. *Experimental Procedure*

- All the surrounding pieces of equipment running on alternate current were switched off to reduce the effect of noise
- The subject was seated in a relaxing position with as less distractions as possible
- For each class of the data, the subject was shown a corresponding cue while having been thinking of the representing orientation
- The data was recorded according to the duration specified for session one and two
- Data tuple:

TABLE I. RAW BCI DATA WITH CLASS LABEL

Ch1	Ch2	Ch3	…	Ch12	Ch13	Ch14	Class [a]

a. Left/Right hand and Node Up/Down

D. *Data Acquisition*

The subjects were requested to seat on a chair. They were asked to sit in a relaxing position. They placed their arms on the arm rest and sat comfortably. The surroundings were made as much noise proof as possible by switching off all the electronic devices and minimizing interference. The Emotiv EPOC+ device was put on the scalp of one of the subjects according to the international 10/20 system.

The international 10/20 system is an internationally recognized method of electrode placement for EEG data acquisition. The electrode positions are determined with respect to the cerebral cortex points of significance. The numbers '10' and '20' in 10/20, refers to the fact that the distances between adjacent electrodes are either 10% or 20% of the total front-back or right-left distance of the skull [26]. The Emotiv EPOC+ electrodes are integrated together in a housing that supports the International 10/20 method.

After placing the EPOC+ headset on the scalp of the subject, she was shown visual stimulus using our custom Java GUI and the integrated Emotiv SDK. She was asked to perform imaginary hand movements according to the left/right arrow on the screen. The visual stimulus was present on the screen for 5 s. We have recorded the EEG signal for the hand movement during the first session. In the second session we have recorded the nodding up/down signals from the subjects. The visual stimulus for the up/down signals were up and down arrows. The signal acquisition was performed for both of the subjects in the same way with no interactions during the signal collection. Both the left/right hand signals and the nod up/down signals were collected for 5 trials each.

E. *Data Labeling*

The subjects were shown left, right, up, down arrows in random order on the screen and subjects had to think about lifting/moving the corresponding arm. Subjects were instructed to focus on the cues to reduce noise. To minimize the artifacts in the recordings, subjects were asked to minimize eye blinks, jaw and head movements during recording. The duration of the gap between trials was random for each trial. The data is recorded into a multiple files. Afterwards, a script is used to merge the signals from the different trials into a single file for preprocessing according to table 1.

V. EVALUATION

We have evaluated our system from two aspects. Firstly, we have got the EEG classification rate from Weka. Secondly, we have performed a usability study of our hierarchical keyboard layout on 3 users. The results are given below.

A. *BCI Subsystem*

The system has shown 88% accuracy with CSP as the preprocessor, Signal Power, Hilbert Transform and FFT coefficients as the features and SVM as the classifier. The accuracy can be increased by reducing the noise around the signal acquisition setup, experimenting with signals from different motor functionalities (leg, tongue movement).

B. *HCI Subsystem*

For any User Interface system, the primary requirement is for it to be easily understood so that users can themselves explore and learn to use the interface. Therefore, learning by exploration is a good way to evaluate a User Interface system. Cognitive Walkthrough has been shown to be effective in evaluating such a learning [27], [28]. Therefore, we have evaluated our BCI Text Entry prototype with the Cognitive Walkthrough method. Since, this method requires expert analysis, we have chosen three relevant experts for evaluating our prototype system. The details of the Cognitive Walkthrough setup with the feedback from different users are tabulated below:

TABLE II. COGNITIVE WALKTHROUGH OF BCI TEXT ENTRY SYSTEM

Task	Type “Hello World” with BCI
List of Actions	
i.	Navigate to the cluster having “H”, by a thought induced left hand movement from initial central cluster.
ii.	Dwell on the “H” cluster for 1.5s
iii.	After going in the “H” cluster navigate to the letter “H” by thought induced left hand movement.
iv.	Dwell on the letter “H” for 1.5s
v.	Find the desired word from the prediction cluster.
vi.	If desired word is in the prediction cluster, navigate to the prediction cluster and select the desired word by thought induced nod up and hand movements.
vii.	Dwell on the desired word for 1.5s
viii.	If desired word is not in the prediction cluster, navigate to the desired next letter from the new set of letters by thought induced left/right hand movements.
ix.	Dwell on the desired letter for 1.5s
x.	If neither desired word nor the desired next letter is found then navigate to the back button in the control cluster by thought induced nod down and hand movements.
xi.	Repeat steps i – x for the remaining letters in “Hello World”.
Questions	
a.	Is the effect of the action the same as the user’s goal at that point?
b.	Will users see that the action is available?
c.	Once users have found the correct action, will they know it is the one they need?
d.	After the action is taken, will users understand the feedback they get?

Responses		
User 1 *UI/UX Expert*	a. b. c. d.	Yes. The user achieves the goal of typing. No. More visible cues need to be present. Partially. The dwelling action to select, needs a UI feedback. Yes. The intended letter is typed on the screen.
User 2 *HCI Expert Academician*	a. b. c. d.	Yes. The user can type letters as required. Partially. More visual guidelines are required. Yes. Explanation helped to identify the correct selection by dwelling. Yes. The color combination helps to identify and understand feedback.
User 3 *Motor disabled person*	a. b. c. d.	Yes. The user can type the intended letters. Yes. Explanation helped the user understand. Yes. Yes. The typed letter appears on the screen with highlight on the right cluster.

The cognitive walkthrough sessions have given us a view from the actual users' usability criteria. We have understood that a few aspects of the keyboard layout need to be improved e.g. a better guidance system to help users understand how the keyboard works.

VI. CONCLUSION

BCI based text entry systems provide a feasible alternative to input text for the disabled people. Much work has been done on developing user friendly hardware and software that can bridge the human mind with the computer. EEG signal has been proven to be the least expensive and more commercially viable method for a BCI system. We have explored a BCI based text entry system using EEG signals and a hierarchical keyboard layout. We have conducted a usability study on our 2 layer multi-functional hierarchical keyboard layout and have found it to be user friendly, accurate and easy to use.

As our future work, we plan to build on this system and add a probabilistically dynamic clustering to improve the navigation speed within the different hierarchies. We will improve the layout following the cognitive walkthrough suggestions of the current system. We also plan to conduct more quantitative and qualitative usability studies on more users.

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