THINK AND TYPE: DECODING EEG SIGNALS FOR A BRAIN-COMPUTER INTERFACE VIRTUAL SPELLER

Joanne Tan Si Ying, Liu Jiani Sherry, Yap Lin Hui

INTRODUCTION

Amyotrophic lateral sclerosis (ALS) or locked-in syndrome prevents voluntary muscle movement, resulting in paralysis in patients suffering from this condition.[1] These patients are unable to communicate with their loved ones and rely greatly on others to help them in their activities of daily living. Due to problems in physical functioning and communication, studies have shown that depression occurs in ALS patients [2]. To alleviate these issues, an immediate goal is to provide these patients with basic communication capabilities so that they can independently express themselves or even operate word processing programs [3].Towards this goal, studies have investigated the use of non-invasive scalp brain signal activity or EEG, which may provide a non-muscular channel for sending messages to the external world. Such studies have led to the development of the Brain-Computer Interface (BCI), shown in Appendix II. The BCI empowers the subject to use his brain signals and control external devices such as a computer, wheelchair or a virtual speller [3]. Virtual spellers, such as those in Figure 1, hold promise for these patients to communicate with their loved ones by allowing the typing of words on the computer. This is possible when different states in the EEG are elicited during different types of mental activities (MA), such as the P300 [4], mental arithmetic (AR) and motor imagery (MI) [5] [6]. For example, in Mental Arithmetic (AR), distinct brain signals are elicited when the user is solving mental sums [7] During MI, the subject imagines motor movement from a first-person perspective without executing the movement [8]. Different types of MI result in discernible spatial changes in the EEG, as different body parts have a spatially ordered layout in the primary motor cortex [9] as shown in Appendix II. Hence, different types of MI could be detected non-invasively from the EEG by an electrode cap. These different states are recognized by the system and translated into commands for a virtual speller.

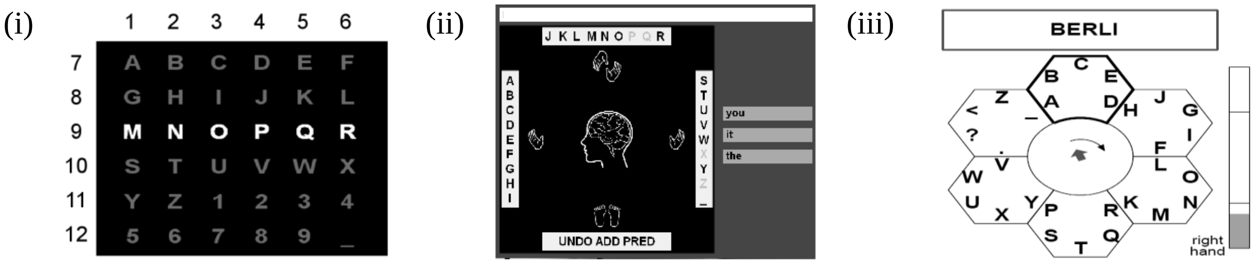


Figure 1: Designs of virtual spellers using BCI, (i) Classical P300 [4] (ii) AIRLab-BCI [5] and (iii) Hex-o-spell [6]

To process and interpret the EEG data, different signal processing and machine learning approaches have been developed to classify different types of EEG data during MA to serve as different commands for a BCI. One such approach is the Filter Bank Common Spatial Pattern (FBCSP) algorithm which has proven to be effective on offline EEG classification by performing relatively the best on multi-class MI data of the Left-hand, Right-hand, Foot and Tongue during the international BCI Competition IV [12] . The validation of this algorithm motivates development of BCI applications which employs it to decipher changes in the EEG as commands. Hence, this paper seeks to investigate the following: propose the design and development of a virtual speller which could employ multiple classes of mental activities as commands. To reduce the amount of effort on typing words, additional features are included. This paper also investigates the type of mental activities which could be classified accurately by the FBCSP algorithm, so that they could be employed into the proposed virtual speller.

METHODOLOGY

A. Filter Bank Common Spatial Pattern (FBCSP)

The FBCSP algorithm was developed for two-class single-trial motor imagery (MI) [13], and is employed in this study to process and interpret EEG signals during mental activities (MA). Its architecture is shown below in Figure 2.

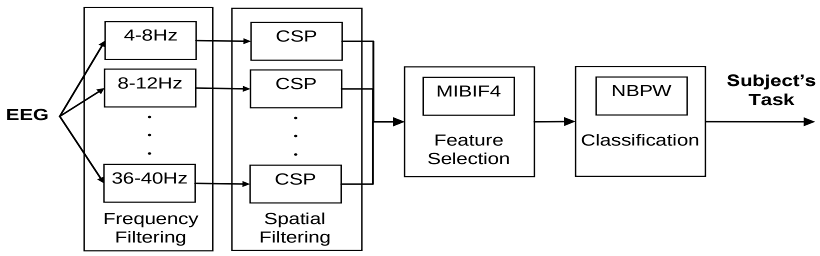


Figure 2: Filter Bank Common Spatial Pattern Algorithm which performs 4 stages of signal processing and machine learning to decipher the subject's action from the EEG

The FBCSP algorithm comprises of four main stages of signal processing and machine learning to decipher the MI from raw EEG data. The 1st stage performs frequency filtering with Chebyshev Type II filters, which decomposes the EEG measurements into various frequency ranges, with nine bandpass filters from 4-8Hz, … and 36-40Hz. The 2nd stage employs Common Spatial Pattern (CSP) filters on the band-passed EEG data and linearly transforms the EEG data into a feature vector for quantization. The 3rd stage performs feature selection using the Mutual Information Best Individual Feature (MIBIF) algorithm to select relevant features for classification. Finally, the 4th stage performs classification of the feature vector using a Naïve Bayes Parzen Window (NBPW) classifier.

The Brain-Computer Interface (BCI) decides on the most probable mental activity ω, undertaken by the subject, given the random trial represented by a feature vector **x.** For a multi-class BCI, the One-Versus-the-Rest (OVR) extension of the FBCSP algorithm could be employed. Component classifiers which classify one class versus all other classes are constructed. In a 5-class BCI, the posterior probability outputs from the five component classifiers are then compared; and the most probable MA action is decided based on the following equation, where $p_{\mathrm{OVR}} \quad \omega \,|\, \mathbf{x}$ denotes the probability of classifying x between ω= 1,2,3,4,5 and ω'={1,2,3,4,5}\ ω, where \ denotes the set theoretic difference operation:

$$\omega = \underset{\omega=1,2,3,4,5}{\arg\max}\ p_{\mathrm{OVR}} \quad \omega \,|\, \mathbf{x}$$

B. Speller Device

The graphical interface of the proposed virtual speller is shown in Figure 2. The virtual speller is single-trial based i.e. in each trial which lasts 10s and requires four classes of MA from the subject to convey commands. A cue prompts the subject to send a command through his scalp brain signals during the performance of specific MA. An example of typing the word 'hello' using the virtual speller is shown in Appendix I.

Figure 3: Interface Layout of the Proposed Virtual Speller

The proposed virtual speller has the following features:

- Types a letter: The subject must select and confirm the appropriate column and row of the desired letter. Column selection takes place first. Using either MA1 or MA2 in each trial, the subject shifts the highlighted column to the column where the intended letter is located. When the desired column is highlighted, MA3 is performed to confirm the column selected. Row selection takes place in a similar way. The button which the highlighted row and column intersects will be shown as text output. This process is repeated to form words.
- Predicts words: Considering the time taken for each single trial, a word prediction function is proposed to increase efficiency. Whenever letters are typed, the speller will search an XML file containing common words. Words that begin with the typed letter(s) are displayed in the last row on screen, to be selected by the user, reducing the time needed to type every letter.
- Undo function: This feature rectifies a misinterpretation of EEG signals or human error. If the user types a wrong letter, MA4 is used to delete the letter. The speller is also designed to maintain a history of the rows and columns so that if the wrong column or row is confirmed, MA4 undoes the confirmation. A flowchart illustrating the use of the speller is summarized in Appendix III.

EXPERIMENT

The experiment is conducted on one healthy subject, with the setup as shown in Figure 4. EEG signals were recorded from 25 electrodes placed around the sensorimotor cortex area as also shown in Appendix II. There were 3 experiment sessions: Initial Training Session, Training Session with Visual Feedback and Testing Session with the Virtual Speller.

A. Initial Training Session

The purpose of this session is to evaluate which mental activities (MA) could be employed in virtual speller. The subject performs five types of MA to train mathematical models in the FBCSP algorithm to classify EEG data into different MA states during the second experiment session.

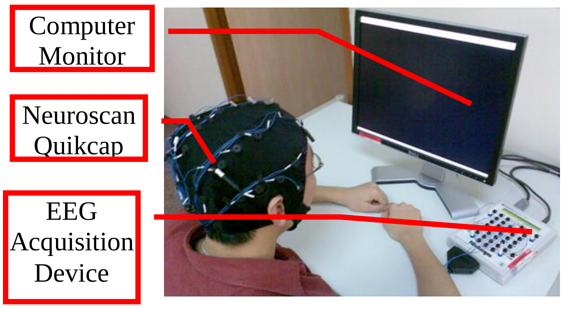


Figure 4: Illustration of subject using the MA-BCI.

In this study, motor imagery (MI) of the Left-hand (L), Right-hand (R), Foot (F), Tongue (T) and Mental Arithmetic (AR) were investigated. The protocol for one single-trial MA is shown in Figure 5. A trial starts with a fixation cross at the center of the screen. 1s later, a cue will be shown, representing a specific MA that the subject is instructed to perform. The subject will perform MA for 3s, followed by a break (4s). Based on the existing studies conducted on MI [12], the EEG data collected from the time segment 0.5s – 2.5s from the start of the visual cue is used to train the FBCSP algorithm.

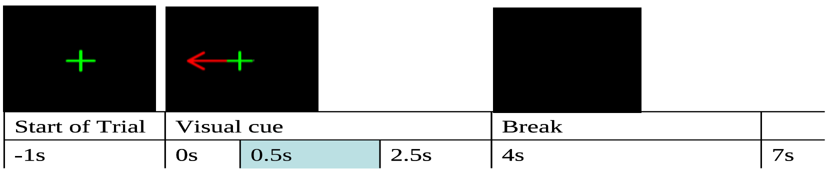


Figure 5: Timeline of training session for a single-trial

B. Training Session With BCI Visual Feedback

Once the Brain Computer Interface (BCI) has been trained using the EEG data in the initial training session, the BCI could be used for online testing sessions. To familiarize the subject with the online BCI, a training session with visual feedback is provided. The data in this session will not be used to train the FBCSP algorithm. Instead, the trained computational models perform classification of EEG data collected in each trial. The single-trial data is classified to the class with the highest posterior probability. If the MA-BCI has performed a correct classification i.e. the predicted class of MA matches the cued class of MA, visual feedback is shown in the form of a smiley face at the end of the trial. The subject performs 400 trials of MA (80 L, 80 R, 80 F, 80 T MI and 80 AR).

C. Testing Session With Virtual Speller

This session was conducted on a separate day after results on the first two sessions were evaluated. Four MAs were selected from the choice of five MAs in this session. To train the BCI, the subject is first instructed to perform 320 trials of MA (80 trials of 4 different actions each). After the BCI is trained, the subject proceeds to use the virtual speller. The subject is instructed to type the word "hello", once without the text prediction function and once with the text prediction function. At the start of a trial, the user may perform any type of MA from the 4-classes. EEG data will be recorded for the next 4s. This data is then sent to the BCI which classifies the data to predict the MA.

RESULTS

In the following section, left hand motor imagery (MI), right hand MI, foot MI, tongue MI and mental arithmetic mental activity is denoted by L, R, F, T and AR respectively.

A. Classification accuracy on training session and training session with BCI visual feedback

10 run x 10 fold cross validation (denoted as 10 x 10CV) is performed on training data to estimate the accuracy of the FBSCP algorithm on five class data. In each run, the 400 trials of EEG data randomly split into 10 equal folds. Using 9 out of 10 folds as training set to train the algorithm, which is then employed on the remaining one fold to evaluate classification performance.This repeats for each of the 10 folds in this run and the classification accuracy is recorded. This process is repeated for a total of 10 runs by randomly dividing the data into 10 equal folds for each run. The performance is computed from the average accuracy of all runs, obtaining mean accuracy of 66.62±1.8785%. With the FBCSP algorithm trained on the training session, the classification accuracy on the training session with BCI visual feedback was 59.50%.

B. Selection of Mental Activities for the Proposed Virtual Speller

To select the mental activities (MA) for the proposed speller, the breakdown in the performance of the algorithm on each of the five classes is presented in the confusion matrices, shown in Table 1 based on the 10x10CV on the initial training session and the classification accuracy on the Brain Computer Interface (BCI) visual feedback session. The confusion matrices show the relationship between the output classes the user intended (the true class) versus the actual output of the classifier (the predict class). In both cases, the confusion matrices suggest the FBCSP algorithm achieves the highest accuracy on R, followed by L, AR, F and T respectively.

Table 1: Confusion matrix of the training session (left) from the 10x10CV and the training session with BCI Visual Feedback (right), using the training session data, with L, R, T, F and AR respectively.

		10x10 CV on initial training session Predicted Class					Training session with visual feedback Predicted Class				
		L	R	T	F	AR	L	R	T	F	AR
True Class	L	77.50%	13.75%	1.250%	5.000%	2.500%	75.0%	20.0%	2.50%	2.50%	0.00%
	R	11.25%	86.25%	0.000%	1.250%	1.250%	10.0%	87.5%	0.00%	2.50%	0.00%
	T	6.330%	6.330%	39.24%	21.52%	26.58%	7.50%	10.0%	35.0%	15.0%	32.5%
	F	2.500%	1.250%	16.25%	62.50%	7.500%	7.50%	10.0%	32.5%	42.5%	7.50%
	AR	11.25%	1.250%	15.00%	3.750%	68.75%	15.0%	0.00%	22.5%	5.00%	57.5%

The choice of the four MA was narrowed down to either L, R, F, T or L, R, F, AR with the fourth MA being either T or AR. 10x10CV was performed on the initial training session with these four classes, and the confusion matrices are shown in Table 2. The confusion matrix (left) above shows that L, R, F, T and L, R, F, AR has an average accuracy of 73.86±1.8762% and 79.41±1.1918% respectively. These 4 optimal classes of MA involving L, R, F and AR gave a higher total average CV training testing accuracy of 79.41% that of L, R, F and T. The deviation for the former is also smaller by 0.8608 than the latter, meaning the results for the former are more consistent. In the training session with BCI Visual Feedback using L, R, F, T and L, R, F, AR respectively, the mean accuracy for the 2 combinations is similar, with the former being 72.50% and the latter, 71.88%. From the results, there is a significant increase in 10x10CV accuracies when L, R, F, AR were used compared to L, R, F, T. AR is preferred to T and was employed with L, R and F.

Table 2: 10x10 CV confusion matrices of the initial training session for L, R, F, T (left) and L,R, F, AR (right) respectively based on the FBCSP algorithm trained using the initial training session data

		10x10 CV					10x10 CV			
		L	R	T	F		L	R	F	AR
True Class	L	77.50%	17.50%	2.500%	2.500%	L	81.25%	13.75%	3.750%	1.250%
	R	7.500%	88.75%	2.500%	1.250%	R	15.00%	80.00%	3.750%	1.250%
	T	7.590%	3.800%	74.68%	13.92%	F	7.500%	10.00%	71.25%	11.25%
	F	7.500%	10.00%	27.50%	55.00%	AR	11.25%	3.750%	3.750%	81.25%

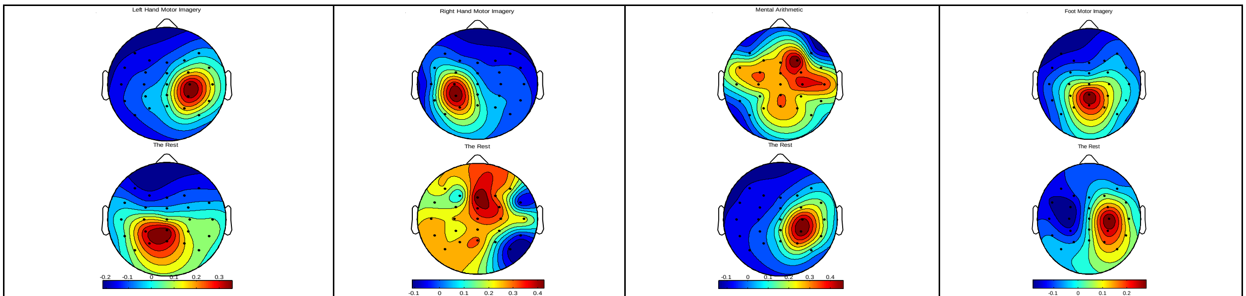
C. *Testing Session with Virtual Speller*

The number of trials taken to type "hello" was noted, with and without text prediction (Table 3). With the text prediction function, time taken to type the word significantly reduced from 267s to 115s, with a 56.93% decrease, effectively doubling the number of letters typed per minute.

Table 3: comparing the speed of speller with/without text prediction when typing the word "hello"

Text Prediction	theoretical no. of trials	actual no. of trials	time taken/s	Characters per min/ min^{-1}
With	13	16	115	2.61
Without	23	40	267	1.12

D. *Analysis of Common Spatial Pattern plots*



L versus the Rest | R versus the Rest | AR versus the Rest | F versus the Rest

Figure 6: Selected spatial patterns of the features for each of the 4 component classifiers: L, R, F and AR

The selected Common Spatial Pattern (CSP) features are plotted as spatial patterns in Figure 6. The spatial patterns arising from the 3 MI achieved a distinct, focused point of activation. The subject performing left hand MI resulted in contralateral activity in the region around the right side of the brain, particularly the C4 electrode (refer to Appendix II for electrode placement). Similarly, contralateral activity was seen in the region around the C3 electrode for right hand MI. The foot MI resulted in the activity of the region close to the middle. These results also tallied with the understanding of the human homunculus illustrated Appendix II. As AR is not a type of MI, the activation in the spatial pattern for this MA is not well-defined.

DISCUSSION

Five types of MA were investigated for use in the proposed virtual speller: Left-hand (L) motor imagery (MI), Right-hand (R) MI, Foot (F) MI, Tongue (T) MI and Mental Arithmetic (AR). During MI, the subject performs imagination of movement of the appropriate body part from a first-person perspective without actually performing it. During AR, the subject performs mental calculations. Experimental results show that L and R are consistently more accurate relative to the other classes. The FBCSP algorithm was originally designed for these two types of MI [1] which could explain why their performances are the best. The subject is also experienced with performing L and R, but is relatively naive with the other three MA. Furthermore, these two types of MI have been shown to activate distinct contralateral regions of the motor cortex i.e. L activates the right side of the motor cortex and vice versa as suggested by the Common Spatial Pattern (CSP) plots in Figure 6. F is more accurate when compared against T. This could be because F is represented in the top part of the motor cortex as exhibited in the human homunculus in Appendix II and the CSP plots show that the center of the motor cortex is activated as exhibited in Figure 6. The activation in the center of the motor cortex could have been more distinguishable compared to the tongue MI, whose CSP plot has been shown to be similar to the hand MI [12]. AR which is not a type of MI, and hence could be more differentiable compared to the foot or tongue MI. Results on the virtual speller show that the 4 MA: L, R, F and AR could be employed in the virtual speller to type words. The proposed undo function also allowed the subject to correct errors in the virtual speller, while the proposed text prediction function in the virtual speller improved the usability of the application as it decreased the time taken to type a five-letter word by 56.39%.

In summary, the performance of the system motivates future work to improve the virtual speller design. To reduce the time taken to type words, an area of investigation could include an auto-elimination feature, which eliminates the letters that cannot follow the previous letter and shorten the number of trials needed to choose the next desired letter. This is beneficial in typing long words or sentences and hence improves its usability for real-world applications.

REFERENCES

[1] H. Ramoser, J. Muller-Gerking, and G. Pfurtscheller, "Optimal spatial filtering of single trial EEG during imagined hand movement," *IEEE Trans Rehabil Eng.*, vol. 8, pp. 441-446, 2000.

[2] M. D. Horowitz, "Does Social Problem-solving Moderate the Relationship Between Physical Functioning and Depression in ALS Patients?," 2008.

[3] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, et al., "Brain Computer interfaces for communication and control," *Clin Neurophysiol.*, vol. 113, 2002.

[4] L. A. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials," *Electroencephalogr Clin Neurophysiol.*, vol. 70, pp. 510-523, 1988.

[5] T. D’Albis, "A predictive speller for a brain-computer interface based on motor-imagery," 2009.

[6] K.-R. Müller, M. Tangermann, G. Dornhege, et al., "Machine learning for real-time single-trial EEG-analysis: From brain-computer interfacing to mental state monitoring," *Journal of Neuroscience Methods,* vol. 167, pp. 82-90, 2008.

[7] C. W. Anderson and Z. Sijercic, "Classification of EEG Signals from Four Subjects During Five Mental Tasks," in *Proc*. *Proceedings of the Conference on Engineering Applications in Neural Networks* 1996, pp. 407-414.

[8] H. H. Ehrsson, S. Geyer, and E. Naito, "Imagery of Voluntary Movement of Fingers, Toes, and Tongue Activates Corresponding Body-Part-Specific Motor Representations," *J. Neurophysiol.,* vol. 90, pp. 3304-3316, 2003.

[9] W. Penfield and T. Rasmussen, *The Cerebral Cortex of Man*. New York, N.Y: The Macmillan Company, 1950.

[10] B. Blankertz, R. Tomioka, S. Lemm, et al., "Optimizing Spatial filters for Robust EEG Single-Trial Analysis," *IEEE Signal Process. Mag.,* vol. 25, pp. 41-56, 2008.

[11] I. Volosyak, H. Cecotti, D. Valbuena, et al., "Evaluation of the Bremen SSVEP based BCI in real world conditions," in *Proc*. *IEEE International Conference on Rehabilitation Robotics*, 2009, pp. 322-331.

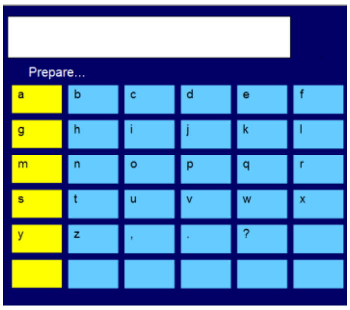
[12] Z. Y. Chin, K. K. Ang, C. Wang, et al., "Multi-class filter bank common spatial pattern for four-class motor imagery BCI," in *Proc*. *EMBC '09*, 2009, pp. 571-574.

[13] K. K. Ang, Z. Y. Chin, H. Zhang, et al., "Filter Bank Common Spatial Pattern (FBCSP) in Brain-Computer Interface," in *Proc*. *IJCNN'08*, 2008, pp. 2390-2397.

Appendix I

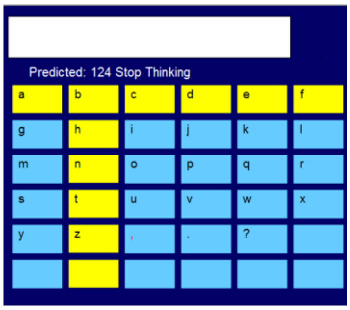
As an example, the process of typing the word "hello" is illustrated as follows:

(i)



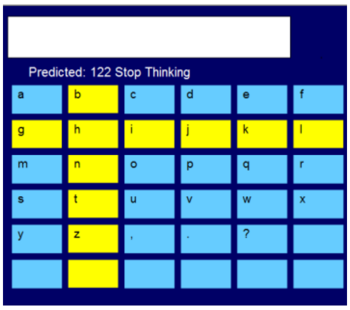
(ii)

(iii)

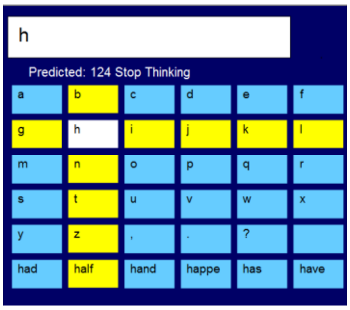


(i) Column 1 is highlighted indicating the start of the column selection phase. The target letter is 'h'
(ii) To shift right to Column 2, perform MA2 once the instruction "Start thinking" appears on screen,
(iii) To confirm the highlighted Column 2, perform MA3. Row 1 is highlighted indicating the start of the row selection phase.

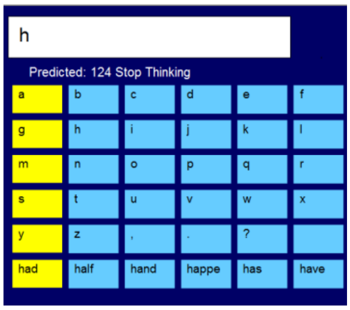
(iv)



(v)



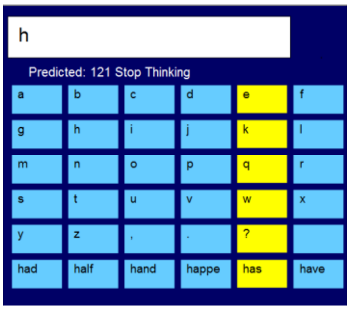
(vi)



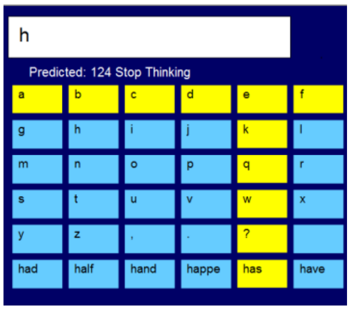
(iv) To shift down to Row 2, perform MA2 once the instruction "Start thinking" appears on screen.
(v) To confirm the highlighted Row 2, perform MA3. The character which the highlighted row and column intersects will be typed into the main textbox on screen. Six predicted words will be shown in the last column
(vi) After a second, Column 1 is highlighted indicating the start of the column selection phase again. The target letter is 'e'

(vii)

(viii)

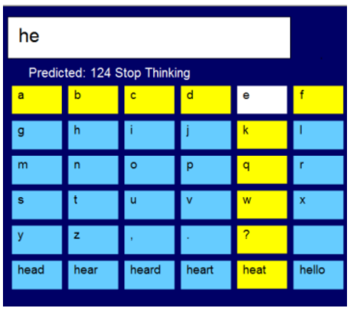


(ix)

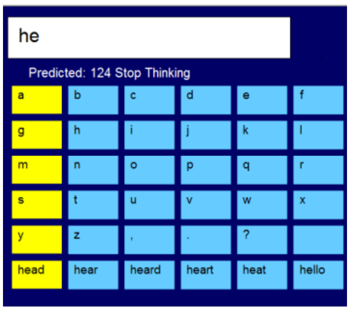


(vii) To shift left to Column 6, perform MA1 once the instruction "Start thinking" appears on screen
(viii) To shift left one more time to Column 5, perform MA1
(ix) To confirm the highlighted Column 5, perform MA3. Row 1 is highlighted indicating the start of the row selection phase.

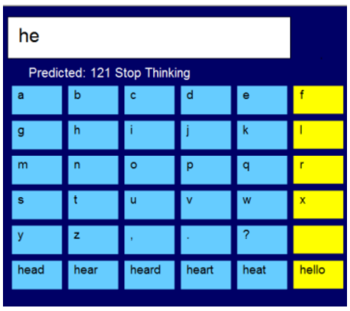
(x)



(xi)



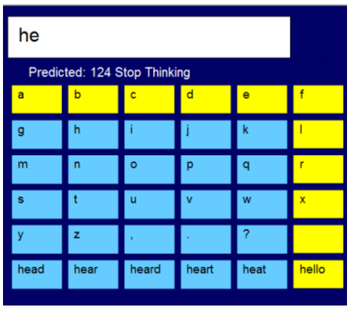
(xii)



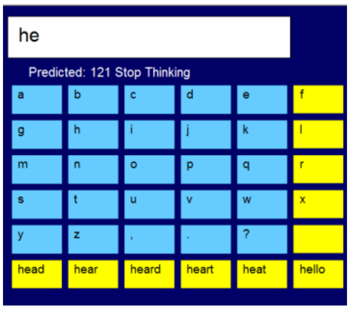
(x) To confirm the highlighted Row 1, perform MA3. The character which the highlighted row and column intersects will be typed into the main textbox on screen. The six predicted words will also update themselves
(xi) After 1s, Column 1 is highlighted indicating the start of column selection phase. The target letter is either 'l' or the

predicted word “hello”.
(xii) To shift left to Col 6, perform MA1 once the instruction “Start thinking” appears on screen again.

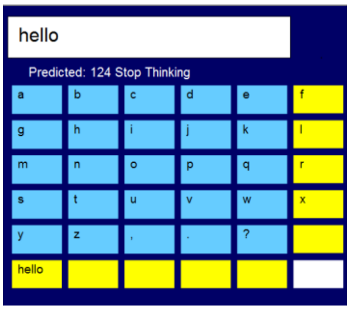
(xiii)



(xiv)

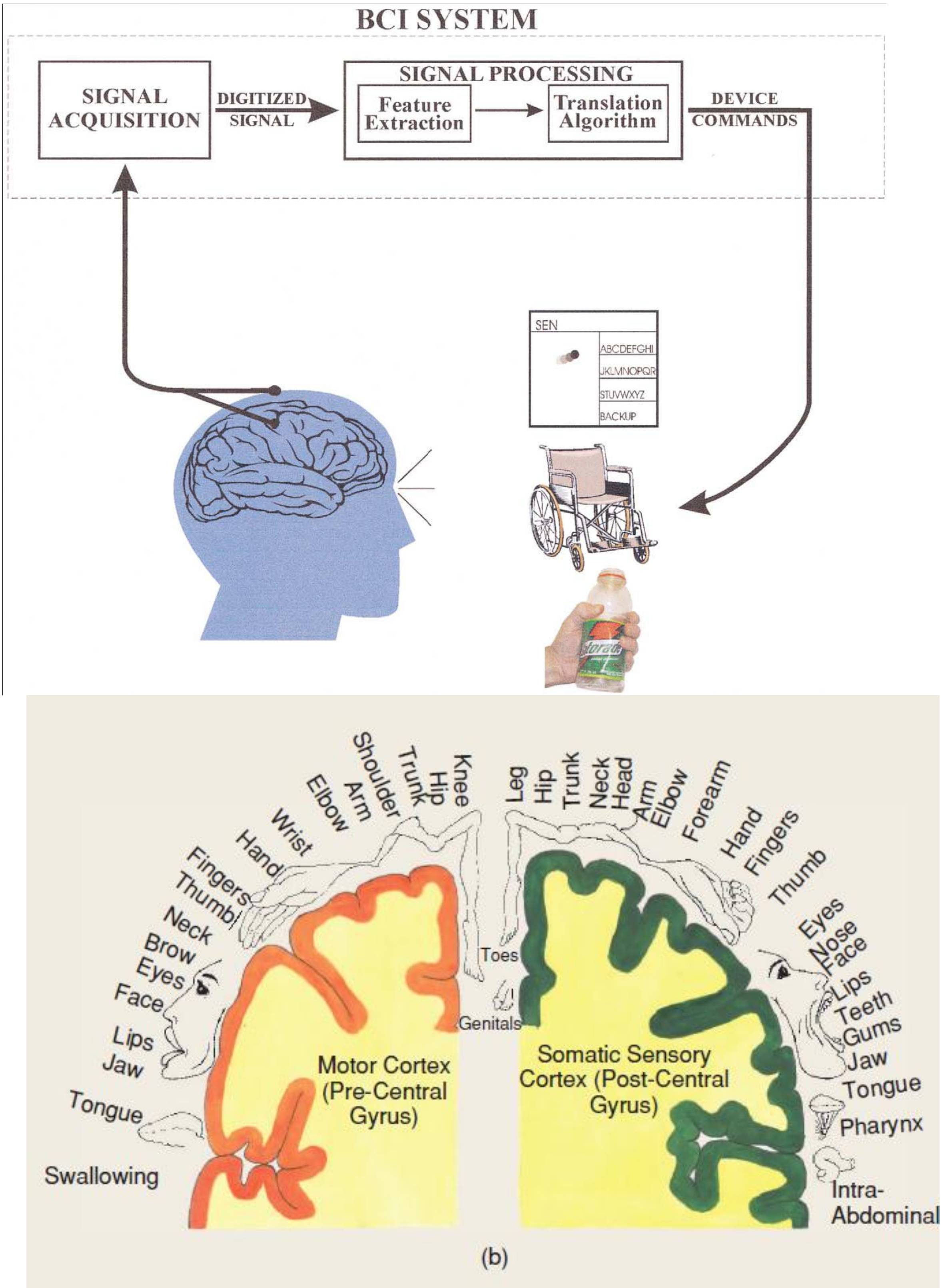


(xv)

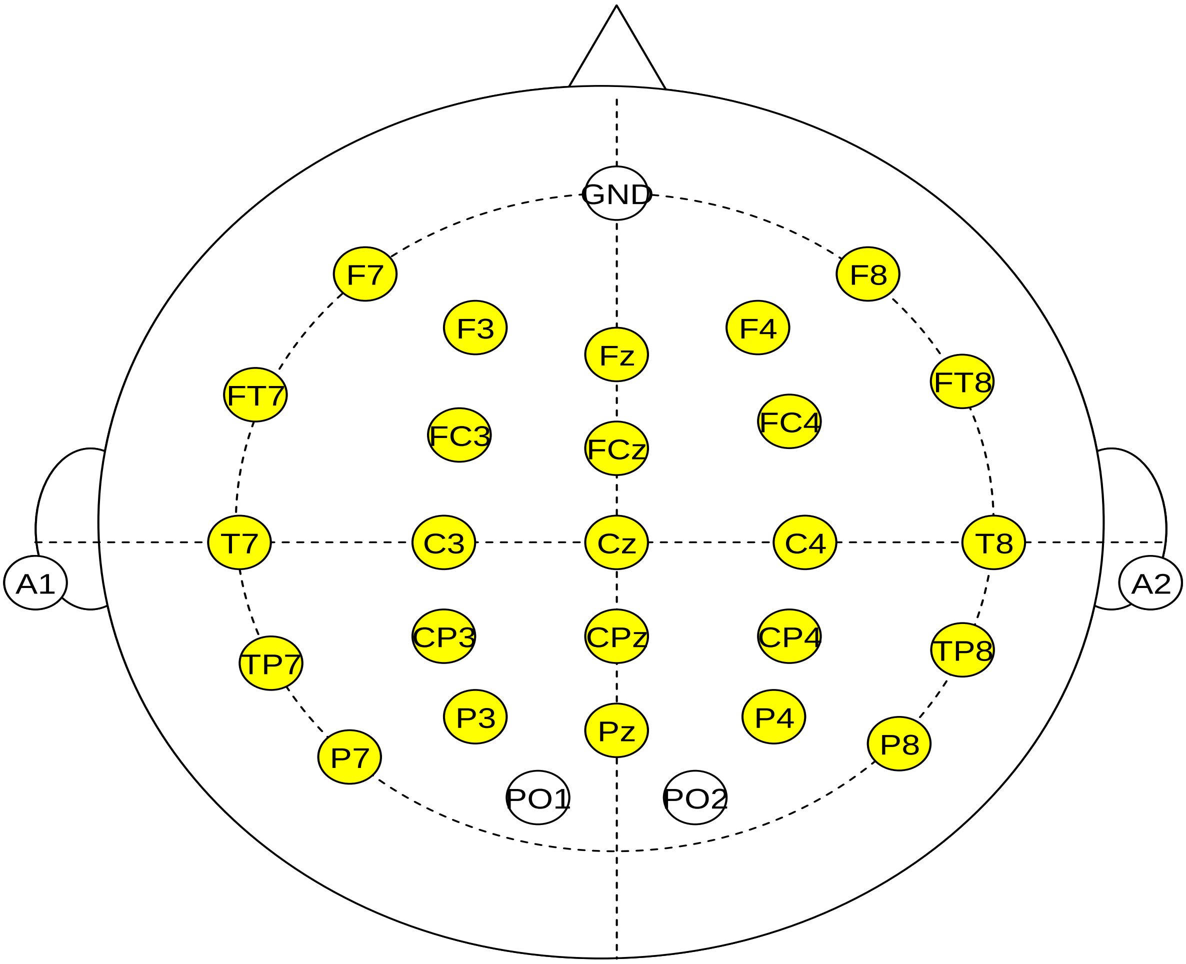


(xiii) To confirm the highlighted Column 6, perform MA3. Row 1 is highlighted indicating the start of row selection phase.
(xiv) To shift up to Row 6, perform MA1 once the instruction “Start thinking” appears on screen.
(xv) To confirm the highlighted Row 6, perform MA3. “hello” will then replace the ‘he’ typed previously on the screen.

APPENDIX II

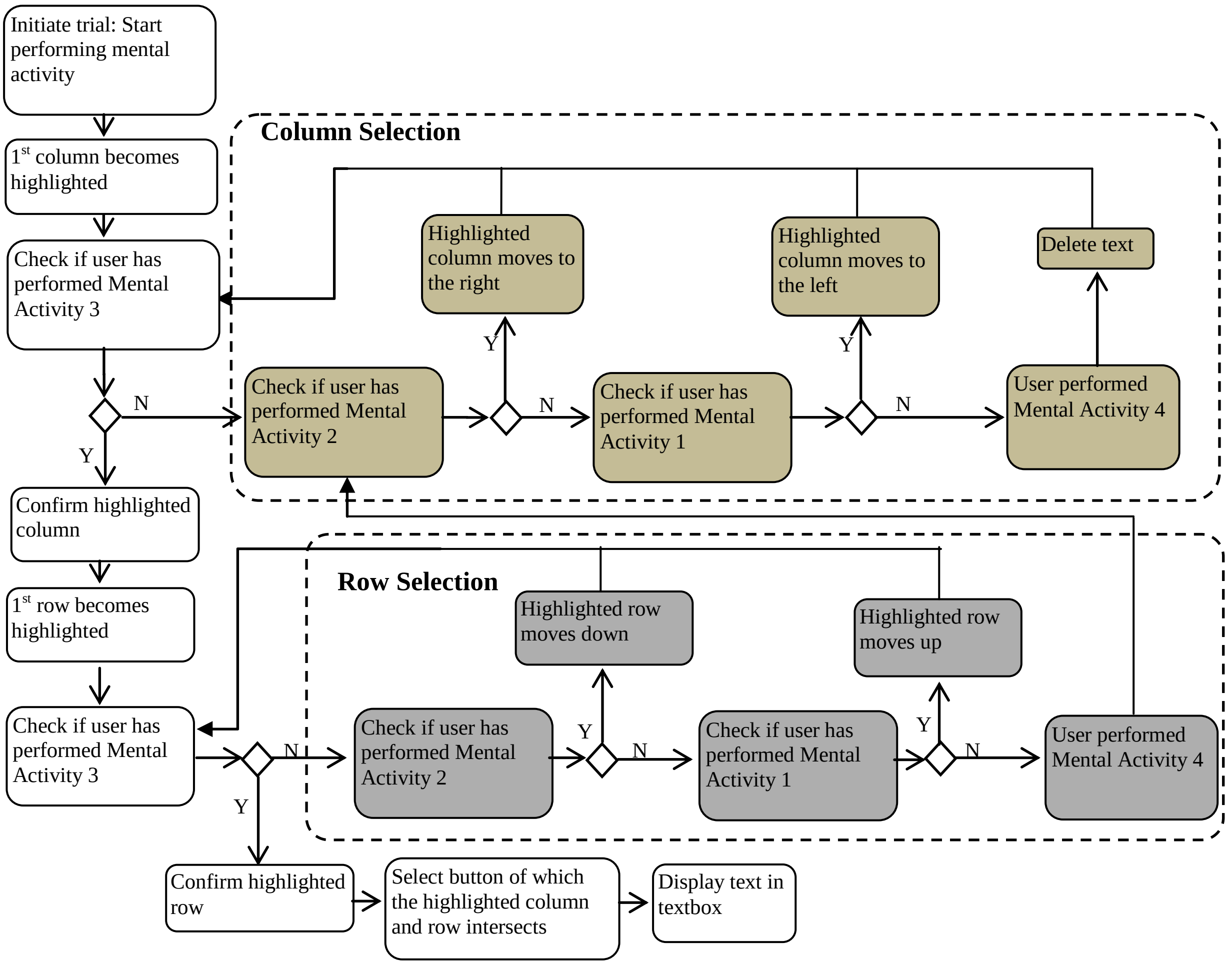


Basic workflow of a Brain-Computer Interface(Top) Geometric mapping between body parts and somatosensory cortex (Bottom) [12]



Locations of electrodes and labels of corresponding channels; the highlighted channels reflects the channels used in our investigation.

APPENDIX III



Flow chart illustrating the usage of the speller application