Towards increasing the number of commands in a hybrid brain-computer interface with combination of gaze and motor imagery

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***Abstract*— Non-invasive brain-computer interface (BCI) provides a novel means of communication. This can be achieved by measuring electroencephalogram (EEG) signal over the sensory motor cortex of a person performing motor imagery (MI) tasks. However, the performance of BCI remains currently too low to be of wide practical use. A hybrid BCI system could improve the performance by combining two or more modalities such as eye tracking, and the detection of brain activity responses. In this paper, first, we propose a simultaneous hybrid BCI that combines an event-related de-synchronization (ERD) BCI and an eye tracker. Second, we aim to further improve performance by increasing the number of commands (i.e., the number of choices accessible to the user). In particular, we show a significant improvement in performance for a simultaneous gaze-MI system using a total of eight commands. The experimental task requires subjects to search for spatially located items using gaze, and select an item using MI signals. This experimental task studied visuomotor compatible and incompatible conditions. As incorporating incompatible conditions between gaze direction and MI can increase the number of choices in the hybrid BCI, our experimental task includes single-trial detection for average, compatible and incompatible conditions, using seven different classification methods. The mean accuracy for MI, and the information transfer rate (ITR) for the compatible condition is found to be higher than the average and the incompatible conditions. The results suggest that gaze-MI hybrid BCI systems can increase the number of commands, and the location of the items should be taken into account for designing the system.**

I. INTRODUCTION

Non-invasive brain-computer interface (BCI) provides a communication pathway for healthy as well as differently-abled people such as those with severe motor impairments. With the aid of analyzed EEG signals, BCI systems have the potential to be used in neuro-rehabilitation, controlling robots, virtual keyboard and other augmentative devices, and entertainment such as video games, switching control, and virtual automobile control [1],[2]. Current BCIs are mainly dependent on the cognitive functions associated with motor imagery (MI) [3]. A BCI system can be devised by measuring EEG signal over sensory-motor cortex, while a user is performing an MI task [4]. The vividness of MI is highly dependent on visual perception and imagery. However, current BCI systems' performance remains too low to allow users to fully exploit the advantages [5]. Although some research groups have claimed to achieve systems' accuracy of up to 96% [6],[7] they came along with limitations such as low information transfer rate (ITR), reliability, and user acceptability. By incorporating other modalities, i.e. hybrid BCIs, the performance can be improved.

To design a hybrid BCI system for clinical and rehabilitation purposes, the constraints of the patients have to be considered. For example, for patients who are not completely locked-in (e.g., quadriplegic), they may still be able to control their gaze and a hybrid BCI can exploit this ability [8],[9]. The recording of gaze position may be done using an eye-tracker system, which measures eye movements and positions with two major monitoring features. The first feature measures the position of the eye relative to the head, and the second feature measures the orientation of the eye in space (point of regard). The recorded eye position and movement data can be analyzed to determine the pattern, duration of eye fixations (dwell time), and the sequence of the scan paths on a screen [10],[11].

An eye-tracker can be used independently to search and select an item; the searching is done by gaze coordinates and the item selection may be done by the dwell time [3],[12]. Therefore, the dwell time should be sufficiently long enough for a correct selection of the intended item. Otherwise, high false selections may result, leading to high level of frustration in the user and thus delaying the overall process. A hybrid BCI may overcome such dwell time issue, by a combination of two or more different systems, often combining different neurophysiological (e.g., EEG) signals, or neurophysiological with other physiological input signal sources [13],[8]. For designing hybrid BCIs, the systems can be combined sequentially or simultaneously [13],[8],[14]. Furthermore, to enhance the effectiveness and use of hybrid BCIs, it is important to increase the number of commands for the user. This can be achieved through combining the gaze and the brain responses (i.e., MI, SSVEP, and P300) [8],[9],[15],[16].

In this work, we propose a novel simultaneous gaze-MI hybrid BCI (see Fig. 1) to increase the number of commands from two or four to eight. The system is based on the item search through gaze, and item selection by the EEG response detection during an MI task simultaneously on the computer screen. The novelty of the task stems from the inclusion of visuomotor compatible and incompatible task conditions to allow more potential choices to the user. However, as far as we know, there is no study in BCI that evaluates the performance of incompatible task conditions. In our incompatible condition, a word "Left" would appear on the right of the screen, or a word "Right" appearing on the left of

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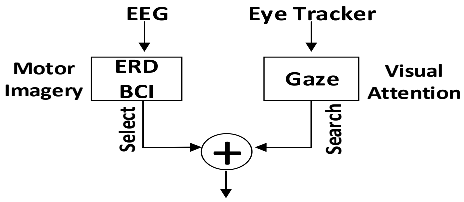

Fig 1: A simultaneous hybrid BCI that combines an ERD BCI and an eye tracker, wherein an item is searched through gaze and the item selection is made by motor imagery simultaneously.

the screen. Several signal processing techniques are tested on these data. Our results show that the accuracy for MI and the ITR of the compatible condition is higher than that of the average and the incompatible condition. This paper is organized as follows: Section II discusses the experimental protocol. Section III is dedicated to the methods used. Section IV presents the results. Finally, Section V provides a discussion and conclusion.

II. Experimental Protocol

A. Subjects

Seven consenting healthy male subjects participated in the study. They were in the age range 21-35 years, (mean age of 28.7 and standard deviation=4.2). All subjects had no prior experience with an eye tracker. None of the subjects had any visual or neurological conditions. Prior to experiments, every subject was advised about the nature and purpose of the study. No financial reward was received by the subjects for their participation in the study. The experiments were conducted with full consent of the subjects as per the revised Helsinki Declaration of 2000.

B. Design and Operational Procedure

Fig. 1 depicts the proposed model of simultaneous hybrid BCI system. The experiment consisted of a search and select task in a two dimensional environment. It is mainly divided into two categories. The recording is done simultaneously for both EEG and eye movement data from subjects. The eye tracker is used as a searching device, which has a direct mapping to the mouse cursor, providing a real-time feedback response. The BCI was used to provide an additional selection command to the user, using left or right hand MI. We have used a visual cue paradigm for stimulus representation on a computer screen. It consists of four visual stimuli, each containing a fixation cross to fixate the gaze. Two visual stimuli are located on each side of the screen, with an additional visual stimulus located at the center of the screen, representing an idle state (Fig. 2 (A)-(B)).

Subjects used the eye tracker controlled search command to direct the cursor to the target visual stimuli, whilst attempting the prompted select command by left or right hand MI. A rigid and stable eye tracker head lock was used for positioning the subjects' head at the center of the screen. Each subject was seated in a comfortable chair located in front of the eye tracker head lock and approximately 55 cm from a 22 inch LCD monitor. Lighting conditions were maintained constant during the experiments.

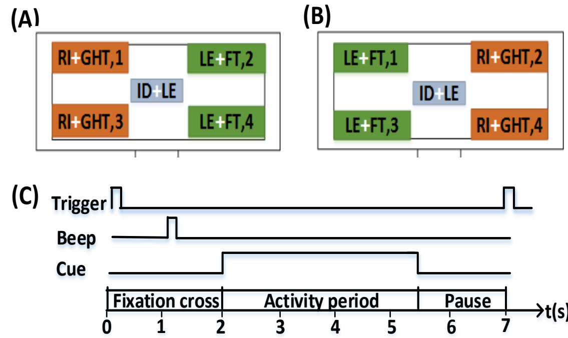

Fig 2: Proposed hybrid BCI and timing scheme of the paradigm. Computer screen in (A) represents an incompatible state of imagining right and left hand movements with four gaze coordinates (1, 2, 3, 4), Computer screen in (B) shows a compatible state of imagination of right and left hand movements with four gaze coordinates (1, 2, 3, 4). (C) Timing scheme of the single trial paradigm.

Prior to an experiment, the eye tracker was calibrated using a 16-point calibration scheme. This provides each subject with an accurate position of his/her gaze. Each experiment consists of one session, comprising of 40 trials each lasting about 7 s. In each trial, the target of interest appears in a pseudo-random order with equal probability but they are evenly distributed over a session, appearing 10 times each. During each trial, subjects were prompted to search for a single target of interest on the visual display using the eye tracker controlled mouse cursor, while attempting a left or right hand MI command. Fig. 2 (C) shows a timing scheme of the paradigm. A beep command is issued at 1 s to indicate a get ready signal, with a visual cue appearing at 2 s. The visual cue, a colored rectangle with a fixation cross, appears for a period of 3.5 s, and during this period subjects would perform the search and select assessment task. On/off-set times should not be deterministic to minimize anticipatory responses. Each session lasts about 5 minutes. For each subject, one session is provided.

C. Data Acquisition

The eye tracker signals were recorded from an Arrington Research Eye Tracker system comprising of a monocular high resolution infrared camera, which records gaze x, gaze y, trigger, and label indexes at 128Hz sampling rate. The EEG signal was recorded at a 128Hz sampling rate using the gUSBamp and g.SAHARA dry electrode system from g.Tec. It consisted of two bipolar recordings (C3 and C4), with the right mastoid serving as ground. A bandpass-filter between 0.5Hz and 60Hz, and a notch filter at 50Hz were enabled.

III. Methods

A. Gaze Detection

Eye tracker signals i.e., gaze x- and y-coordinates were distributed according to label indexes (1, 2, 3, and 4). The label indexes were used to identify one of the four classes and these indexes show the start activity in each trial. A median filter was applied to the eye tracker data to remove eye blinks and the mean gaze position in horizontal and vertical directions were recorded for each trial. The distance of x- and y-coordinates from each visual stimulus was calculated, and corresponding to the minimum distance from the gaze coordinates, the actual output was estimated according to label indexing. The confusion matrix was used to compute the accuracy.

B. Feature Extraction and classification

Band-power features for all the channels are extracted for mu (μ) (8-12Hz) and beta (β) (12-30Hz) rhythms. During each trial, the time over the imagery period is selected for extracting the band-power features. This information called event-related de-synchronization (ERD) and event-related synchronization (ERS) over μ and β frequency bands are used for classification. The ERD/ERS can be seen as a correlate of an activated cortical area, so as to effectively account for ERD and ERS phenomena observed during MI tasks. The performance of the proposed hybrid system was assessed by seven binary classifiers: support vector machines (SVM) with linear kernel, quadratic kernel, q-polynomial kernel, Gaussian kernel, k-nearest neighbors (kNN) with (K=1 and K=5), and linear discriminant analysis (LDA). The performance evaluation was performed with a ten-fold cross validation. In the next section, we report the accuracy (in %) and the ITR [9],[17] in bit per symbol (bps).

IV. RESULTS

A. Gaze Detection

The performance evaluation of gaze detection was based on 40 trials per subject. The minimum distance between the fixation point (i.e. the center), and the detected gaze location was used to assign the item selected by the user. The offline gaze detection (eye tracker only) results are presented in Table I. The mean accuracy for all subjects is 95.2 ± 6.3%.

B. Single-Trial Detection

To evaluate the performance of single-trial detection we considered two classes – left and right hand MI, with respect to the four events – left computer screen (1, 3) and right computer screen (2, 4). The single-trial detection results were computed in the form of visuomotor compatible and incompatible conditions for each subject. Accordingly, the single-trial detection results are divided into three classes: (L_M vs R_M); ($L_M \cap L_S$) vs ($R_M \cap R_S$); ($L_M \cap R_S$) vs ($R_M \cap L_S$). Here, the symbol L_M denotes the left MI and symbol R_M represents right MI whereas L_S and R_S represent left and right sides of the computer screen, respectively. The symbol ∩ denotes the combination of the two conditions. The class (L_M vs R_M) is a standard situation which considers the total number of trials for each subject, consisting of left and right hand MI with four gaze events for all trials. The ($L_M \cap L_S$) vs ($R_M \cap R_S$) is a compatible situation for each subject, and considers the total number of trials when left MI appears on left side of computer screen and right MI appears on right side of computer screen. ($L_M \cap R_S$) vs ($R_M \cap L_S$) is an incompatible situation for each subject wherein we considered only the situation when left MI appears on right side of computer screen and right MI appears on left side of computer screen for all trials.

Tables II, III, and IV present the accuracies of MI (EEG only) (in %) and Table V provide the ITR (hybrid BCI) in bps. The accuracies are obtained with motor imagery with two classes, N_{out}=2 (left and right). In the Table II, the achievable mean accuracy of standard condition for all

TABLE I. Gaze detection accuracy

Sub	Accuracy (%)					Level of expertise
	Total	1	2	3	4	
S01	100	100	100	100	100	Moderate
S02	97.5	100	95	100	93	Novice
S03	99.1	100	100	96	100	Experienced
S04	91.6	91	100	90	85.4	Moderate
S05	100	100	100	100	100	Experienced
S06	95.9	100	100	100	83.3	Novice
S07	82.5	82	100	75	73	Novice
Mean	**95.2**	**96.1**	**99.3**	**94.4**	**90.7**	
Std.	**6.3**	**7.1**	**1.9**	**9.3**	**10.5**	

TABLE II. Single trial detection performance for (L_M) Vs (R_M) in standard state.

Sub	SVM				kNN		LDA
	Linear	Quad.	Poly.	Gauss.	K=1	K=5	
S01	85.0	77.5	77.5	82.5	72.5	80.0	85.0
S02	62.5	50.0	50.0	52.5	65.0	55.0	62.5
S03	57.5	55.0	55.0	55.0	50.0	47.5	55.0
S04	55.0	50.0	55.0	55.0	62.5	60.0	52.5
S05	55.0	52.5	50.0	47.5	47.5	57.5	47.0
S06	57.5	60.0	50.0	55.0	60.0	52.5	55.0
S07	60.0	57.0	70.0	60.0	62.5	65.0	60.0
Mean	**61.8**	**57.4**	**58.2**	**58.2**	**60.0**	**59.6**	**59.6**
Std.	**10.6**	**9.6**	**11.1**	**11.3**	**8.7**	**10.6**	**12.3**

TABLE III. Single trial detection performance for ($L_M \cap$ Ls) Vs ($R_M \cap$ Rs) in compatible state.

Sub	SVM				kNN		LDA
	Linear	Quad.	Poly.	Gauss.	K=1	K=5	
S01	90.0	90.0	80.0	90.0	85.0	80.0	85.0
S02	55.0	55.0	40.0	55.0	70.0	45.0	65.0
S03	65.0	55.0	55.0	55.0	60.0	55.0	50.0
S04	54.3	56.7	61.7	55.0	61.7	66.7	53.3
S05	65.0	60.0	60.0	65.0	50.0	55.0	65.0
S06	65.0	60.0	50.0	60.0	70.0	65.0	65.0
S07	58.3	60.0	71.6	68.3	58.5	58.3	66.6
Mean	**64.7**	**62.4**	**62.3**	**64.1**	**65.0**	**60.7**	**64.3**
Std.	**12.1**	**12.4**	**13.3**	**12.6**	**11.2**	**11.1**	**11.3**

TABLE IV. Single trial detection performance for ($L_M \cap R_s$) Vs ($R_M \cap L_s$) in incompatible state.

Sub	SVM				kNN		LDA
	Linear	Quad.	Poly.	Gauss.	K=1	K=5	
S01	85.0	63.3	61.7	80.0	65.0	66.7	78.3
S02	60.0	45.0	50.0	50.0	40.0	45.0	60.0
S03	56.6	51.7	56.7	48.3	43.3	46.0	53.3
S04	55.0	40.0	45.0	40.0	60.0	45.0	50.0
S05	59.1	58.0	55.0	58.3	48.3	50.0	54.5
S06	61.0	60.0	50.0	58.3	60.0	60.0	56.6
S07	55.0	55.0	65.0	60.0	65.0	55.0	60.0
Mean	**61.7**	**53.3**	**54.8**	**56.4**	**54.5**	**52.5**	**59.0**
Std.	**10.6**	**8.4**	**7.0**	**12.6**	**10.5**	**8.4**	**9.3**

subjects is 61.8 ± 10.6% computed by SVM linear kernel whereas the mean accuracy of ($L_M \cap L_S$) vs ($R_M \cap R_S$) and ($L_M \cap R_S$) vs ($R_M \cap L_S$) conditions are 64.7 ± 12.1% and 61.7 ± 10.6% achieved, respectively with SVM linear kernel, shown in the Table III and IV. The highest mean accuracy was achieved in compatible condition using SVM linear kernel. However, the gain in performance achieved under the compatible condition is not statistically significant with the small number of novice subject group used in the trials.

In addition, in the Table V, we provide the ITR using linear SVM method for the combination of gaze and EEG when the system is used for 4 and 8 commands, by combining the selected item, and MI detection for all three conditions. The proposed hybrid BCI achieved the highest

TABLE V. ITR in bps by SVM linear for MI (EEG only (N_{out}=2)), gaze (eye tracker only (N_{out}=4)), and hybrid BCI (N_{out}=8) for all conditions.

Sub	(L_M) Vs (R_M)			($L_M \cap$ Ls) Vs (R_M $\cap$ Rs)			($L_M \cap R_s$) Vs (R_M $\cap L_s$)		
	2	4	8	2	4	8	2	4	8
S01	0.4	2.0	2.0	0.5	2.0	2.3	0.4	2.0	2.0
S02	0.1	1.8	0.9	0.0	1.8	0.7	0.0	1.8	0.9
S03	0.0	1.9	0.8	0.1	1.9	1.1	0.0	1.9	0.8
S04	0.0	1.5	0.6	0.0	1.5	0.6	0.0	1.5	0.6
S05	0.0	2.0	0.7	0.1	2.0	1.1	0.0	2.0	0.9
S06	0.0	1.7	0.8	0.1	1.7	1.0	0.0	1.7	0.9
S07	0.0	1.1	0.6	0.0	1.1	0.5	0.0	1.1	0.5
Mean	**0.1**	**1.7**	**0.9**	**0.1**	**1.7**	**1.0**	**0.1**	**1.7**	**0.9**
Std.	**0.1**	**0.3**	**0.5**	**0.2**	**0.3**	**0.6**	**0.1**	**0.3**	**0.5**

mean ITR of 1.0 ± 0.6 in compatible condition. With the current subset of subjects, only S01 in compatible condition would obtain a gain in performance from combining the BCI and eye tracker to increase the number of commands, as compared to the use of eye tracker only.

V. DISCUSSION & CONCLUSION

In this paper, a hybrid BCI has been proposed that combines motor imagery detection and eye tracking. Whereas eye-trackers can provide an efficient way to specify the location of an item on a screen, a more user-centered approach needs to be proposed to select the chosen items. In addition, inexpensive eye-trackers are often not reliable in term of the precision of the gaze location, hence limiting the number of items that can be selected at any given time. Selection can be achieved by gazing for a specified duration (i.e. dwell time) on an item, or the detection of an event such as eye-blinking. In this paper, we have investigated the performance that can be obtained with the detection of motor imagery, and how this detection can increase the number of commands. This solution may provide a more convenient alternative communication means especially for differently-abled people. The eye-tracker can be used for pointing to an item, and BCI can be used as a switch to select the item through brain activity responses. The presented results suggest that the drop of performance is due to the low accuracy of motor imagery detection as only two sensors were used with dry electrodes. Larger number and better quality of electrodes may provide better performance. The use of different modalities may however increase the difficulty in using the system as the user has to pay attention to the location of his gaze and to the movement imagery. Furthermore, naïve subjects have to get used to both the eye-tracker, and the motor imagery task [18],[19].

The performances have been evaluated for three different classification scenarios corresponding to the effect of the similarity between the gaze direction (left/right) and the MI task (left/right) (standard, compatible, and incompatible). The results indicated a higher accuracy for the detection of commands with the same orientation between gaze and motor imagination. Thus, this effect should be taken into account while designing gaze-MI based BCI paradigms. Specifically, the experimental design could incorporate incompatible condition if the emphasis is on having a larger number of choices despite a slight dip in accuracy. This type of paradigms has been widely applied in cognitive psychology and neuroscience to study various cognitive abilities, e.g. the Simon effect [20]. They also used this paradigm for the diagnosis and characterization of psychiatric and neurological disorders [21],[22]. Further works will extend the proposed approach with optimized parameters to increase motor imagery detection.

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