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Significant improvement in one-dimensional cursor control using Laplacian electroencephalography over electroencephalography

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Abstract

Objective. Brain–computer interfaces (BCIs) based on electroencephalography (EEG) have been shown to accurately detect mental activities, but the acquisition of high levels of control require extensive user training. Furthermore, EEG has low signal-to-noise ratio and low spatial resolution. The objective of the present study was to compare the accuracy between two types of BCIs during the first recording session. EEG and tripolar concentric ring electrode (TCRE) EEG (tEEG) brain signals were recorded and used to control one-dimensional cursor movements. *Approach*. Eight human subjects were asked to imagine either 'left' or 'right' hand movement during one recording session to control the computer cursor using TCRE and disc electrodes. *Main results*. The obtained results show a significant improvement in accuracies using TCREs (44%–100%) compared to disc electrodes (30%–86%). *Significance*. This study developed the first tEEG-based BCI system for real-time one-dimensional cursor movements and showed high accuracies with little training.

Keywords: brain–computer interface (BCI), electroencephalography (EEG), Laplacian EEG, tripolar concentric ring electrode (TCRE)

(Some figures may appear in colour only in the online journal)

1. Introduction

Brain–computer interfaces (BCIs) are systems that detect changes in brain signals related to human intentions, typically translating intention into a control signal to communicate between the brain and the external world such as computer applications [1]. These new communication systems have the potential to substantially increase and improve the quality-of-life of people suffering from severe motor disabilities including paralysis, and provide a new way for able-bodied people to control computers or other devices (e.g., robot arm, artificial limb or computer cursor). The most important clinical applications of BCI systems include brain-derived communication in paralyzed and locked-in patients [2, 3] and restoration of motor function in patients with spinal cord injuries [4].

BCIs enable users to control devices with direct brain communication using electroencephalographic (EEG) activity recorded from electrodes placed on the scalp (noninvasive BCI) [5, 6] or with activity recorded from on or within the brain (Invasive BCI) [7, 8]. The EEG is a noninvasive method to monitor brain electrical activity; however EEG signals have low signal to noise ratio (SNR), low spatial resolution, and are contaminated by various artifacts from other sources. These characteristics limit measuring the spatial distribution of brain electrical activity and thus necessitate significant preprocessing [6]. Invasive BCIs face substantial technical difficulties and clinical risks as they require that recording

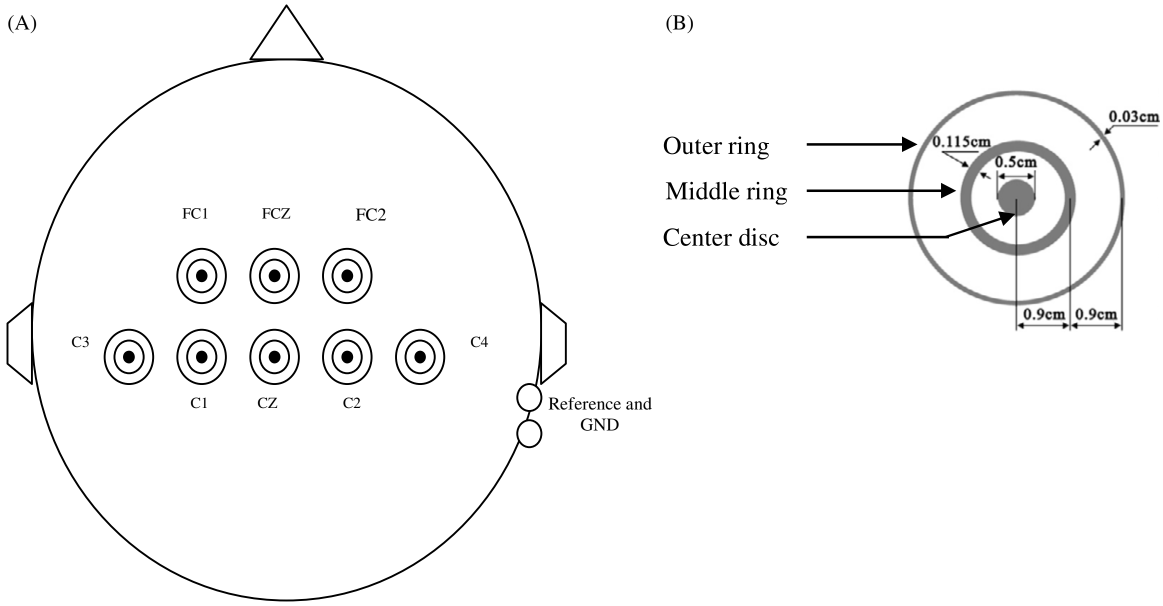

Figure 1. (A) Schematic illustration of the electrode montage. The EEG signal is recorded from the outer ring of the TCRE electrodes. EEG and tEEG signals were recorded from the same location concurrently. (B) Schematic of TCRE electrode.

electrodes be implanted in or on the cortex and function well for long periods, with risks of infection and other damages [8].

Recently, improvements have been developed to make EEG more accurate by increasing the spatial resolution. One such improvement is the application of the surface Laplacian to the EEG, the second spatial derivative. Tripolar concentric ring electrodes (TCREs) (see figure 1(B)) automatically perform the Laplacian on the surface potentials. Previously we have shown that TCRE EEG (tEEG) has significantly better spatial selectivity, SNR, localization, approximation of the analytical Laplacian, and mutual information than conventional EEG with disc electrodes [9, 10]. These findings suggest that tEEG may be beneficial for neurological disorders analysis like seizure detection [11, 18].

An important concern in BCI research is to control the computer cursor such as able-bodied persons do. Cursor control requires the subject to learn how to adapt their brain signals by using different thought patterns for different tasks [12]. Studies in recent years have shown that EEG-based BCI has great potential in achieving one-dimension cursor control [13–15]. However, these systems usually require long-term training in regulating brain signals and the performance in long-term use is often not robust [16]. For example, Wolpaw *et al* (2004) performed over twenty sessions per subject, at a rate of two to four per week to develop high-accuracy cursor control (i.e., >90%) [6]. Slow training of subjects and low spatio-temporal resolution is still a serious problem [12]. In order to make future BCI convenient, the training time must be minimized without loss of accuracy.

The objective of this research project was to compare accuracy of one-dimensional ('left'–'right') cursor control between EEG and tEEG. A secondary objective was to determine if high accuracies could be accomplished in a single training session. We demonstrate that tEEG signals can enable users to control a one-dimensional computer cursor rapidly and accurately with significantly higher accuracy compared to the EEG signals during their first session.

The rest of the paper is structured as follows: section 2 presents a general description of the dataset used in this work and the procedure employed is explained in detail. Section 3 presents the obtained results with a general discussion. Finally, some conclusions with future work are offered.

2. Methodology

2.1. Laplacian electroencephalography (tEEG)

The scalp surface Laplacian is an alternative method for presenting EEG data with higher spatial resolution. It has been shown that the surface Laplacian is proportional to the cortical potentials and improves the high spatial frequency components of the brain activity near the electrode [19]. To obtain the Laplacian, we take a new approach by using unique sensors and instrumentation for recording the signal [9, 20]. The unique sensor configuration which measures the Laplacian potential directly is the TCRE (figure 1, panel B) [9, 10]. Two differential signals from each electrode were combined algorithmically for a tEEG derivation of the signal as reported previously in [9]. Briefly, the algorithm is two-dimensional and weights the middle ring and central disc difference sixteen times greater than the outer ring and central disc difference (16*(middle–disc) – (outer–disc) where disc is the central disc, middle is the middle ring, and outer is the outer ring of the TCRE. The outer ring was used as the disc electrode (figure 1, panel B)). In our previous work [22] we have shown that the outer ring signal has a 0.99 correlation to disc electrode signals. All the signal processing was performed using Matlab (Mathworks, Natick, MA, USA).

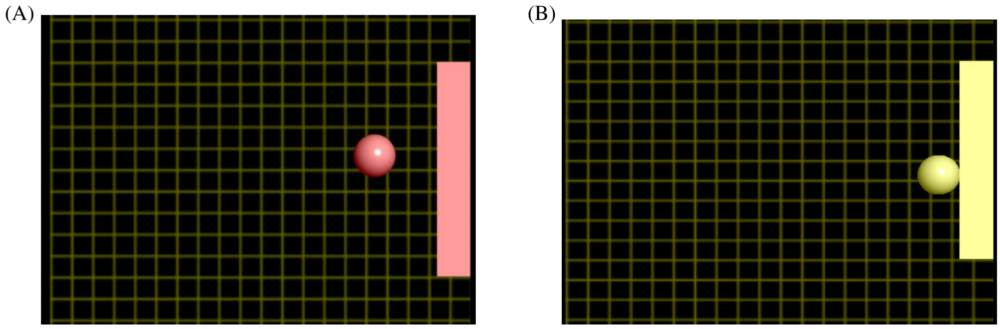

Figure 2. Screenshot of the real-time application for cursor control. The ball is the cursor and the rectangle is the target. (A) Before the ball hit the target and (B) when the ball hit the target, the color of the target turned green.

2.2. Data recording

The brain signals were gathered from eight healthy subjects (1–8, ages 24–40, two female). The subjects were naïve to neuro-feedback training and their task was to move a cursor, in the form of a ball, from the center of the screen to a target. The target was a pink rectangle which appeared in the 'left' or the 'right' of the periphery of the screen. The cursor width was 10% of the screen width. Figure 2 shows a screenshot of the real-time application.

During BCI operation, subjects were seated in a chair, facing a computer screen which was placed about 1.5 m in front of the subject. The subjects were asked to remain motionless during the recording process to reduce the introduction of artifacts. The BCI2000 [16] software application was used to acquire and process in real-time signals recorded from eight surface electrodes (C3, C1, Cz, C2, C4, FC1, FCz, FC2) according to the international 10–20 system, with reference and ground from the right mastoid process (see figure 1 panel A). Skin-to-electrode impedances were maintained below 5 kΩ. Signals from all the channels were first pre-amplified with a gain of 6, then amplified, filtered (0.1–100 Hz) and digitized (sampling frequency was 256 Hz) with a gUSB amplifier (g.tec GmgH, Schiedlberg, Austria). For a direct comparison between EEG and tEEG cursor accuracy TCREs were placed once and used for both experiments. The subjects were blinded to whether EEG or tEEG was being used for BCI.

3. Procedure

In this paper, for achieving one-dimension cursor control two stages were used: (1) features identification during an offline analysis, and (2) online one-dimensional BCI cursor control (real-time one-dimensional cursor control). The two stages are described in the following section (see figure 3).

3.1. Offline analysis for features identification

The offline analysis was performed to determine which components and features of the signal the user could most easily modulate for BCI control. First we determined which EEG and tEEG features (i.e., signal amplitudes at particular frequency bands and particular electrode locations) were correlated with a particular motor imagery task, and might thus be the basis for BCI experiments.

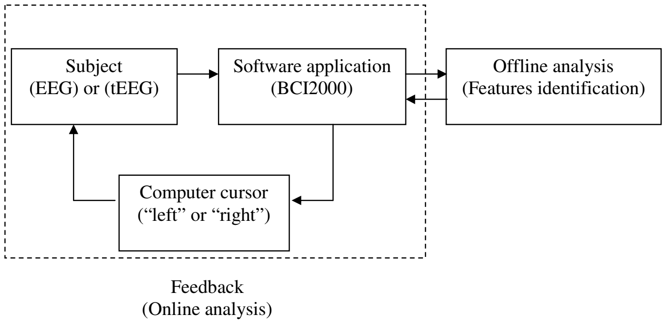

Figure 3. Procedure of one-dimensional computer cursor control.

To measure and characterize responses to motor imagery, each subject had to imagine 'left' and 'right' hand movements, following a fixed repetitive time scheme of an arrow pointing 'left' or 'right' for 2 s, and to rest while the screen was blank for 1 s. The appearance of the arrow was random and each 'left' or 'right' task was repeated ten times. Moreover, the data were collected just for one session (to assure that the subject was a first-time BCI user). The session consisted of five runs, and each run consisted of 20 trials for 100 trials total.

For these analyses, we converted the time-series EEG and tEEG data into the frequency domain, with 2 Hz wide bins from 0 to 140 Hz, using an autoregressive model of order 20 (BCI200 function) to produce a set of frequency spectra for each location and for each task and rest. We then calculated the statistical difference for the distribution of frequency amplitudes at each location and frequency (i.e., values of r^2, which indicated what fraction of the signal variance at that location and frequency was due to the condition of task and rest). This procedure was performed to identify features that could be modulated by the subject using imagined tasks.

Electrodes for each subject were identified for a selected frequency band that exhibited a high correlation with the imagined right hand movement task (i.e. the largest value of r^2) for both EEG and tEEG signals (see table 1). From the feature plot (figure 4) it is observed that the largest r^2 value in the selected frequency band appeared in the C3, C1, and FC1 electrodes located on the left motor cortex (figure 1). Furthermore, we selected up to three electrodes, from the frequency bands that we monitored. An electrode was selected if the r^2 value was dark red ($r^2 > 0.09$). The amplitudes of these features (frequency band and electrodes) were used by

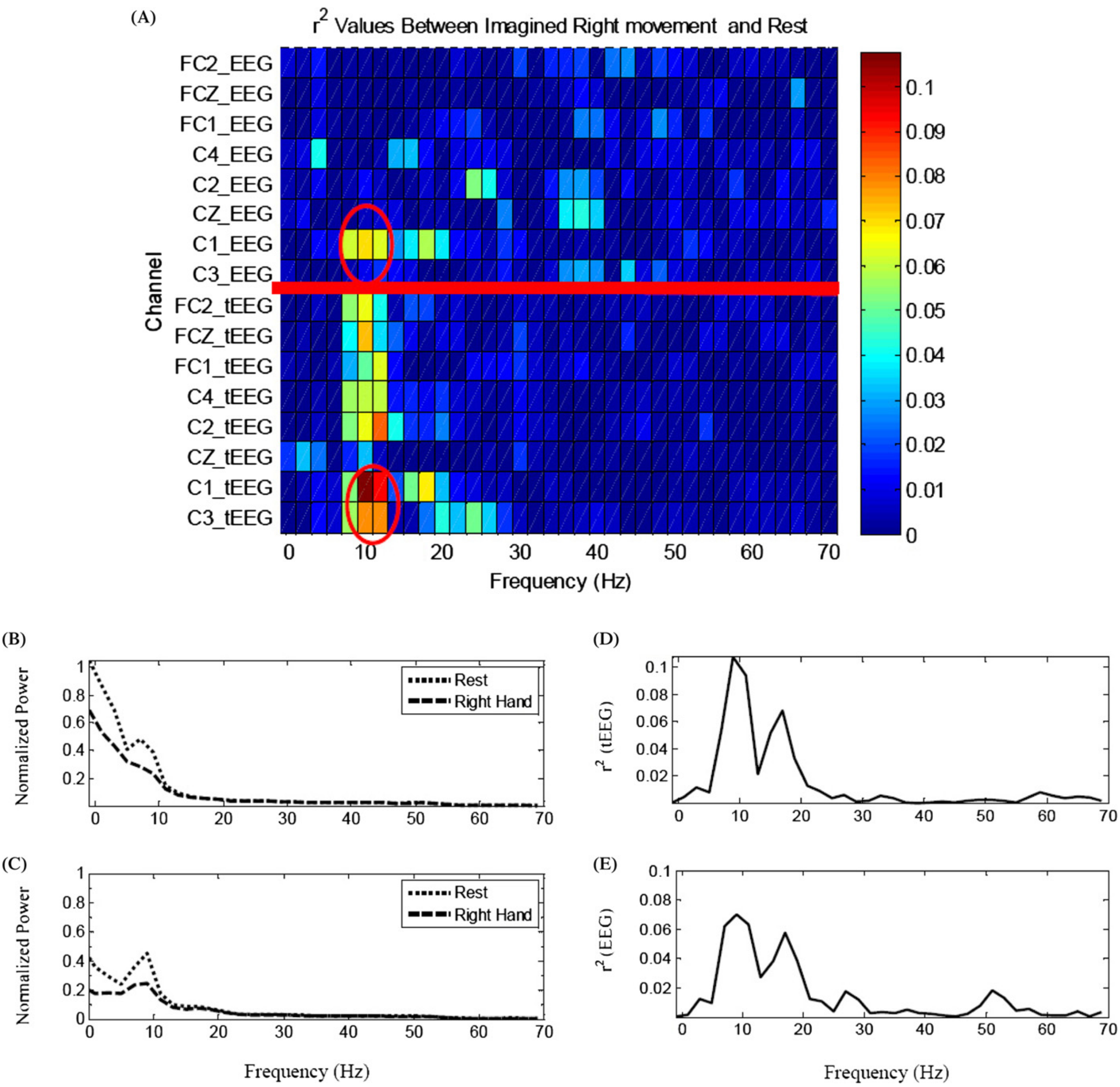

Figure 4. Example of an analysis comparing between tEEG and EEG signals for the 'right' hand imaginary and rest. (A) Values of r^2 for all the electrodes locations and frequencies for both tEEG and EEG signals. Normalized power from channel C1 for (B) tEEG and (C) EEG. The corresponding r^2 spectrum measures the amplitude variation for (D) tEEG (E) and EEG for electrode C1.

Table 1. The average rates of online experimental results for each subject using both EEG and tEEG signals and their corresponding electrode locations and frequency bands for 'right' hand imaginary task.

	Electrode locations		Frequency band (Hz)		Hit accuracy (%)	
Subjects	EEG	tEEG	EEG	tEEG	EEG	tEEG
1	C3, FC1	C1, FC1	8.5–10.5	10.5–12.5	54.8	63.8
2	C3	C1, C3	8.5–10.5	8.5–10.5	44.1	55.1
3	C1, FC1	C1, C3, FC1	8.5–10.5	10.5–12.5	57.7	71
4	C1, C3, FC1	C3	18.5–20.5	16.5–18.5	61.8	72.4
5	C1	C1, C3	8.5–10.5	10.5–12.5	62.9	71
6	C1, C3, FC1	C1, C3, FC1	28.5–30.5	24.5–26.5	66.3	83.5
7	C1, FC1	C1, C3	16.5–18.5	16.5–18.5	60.3	71.6
8	C3	C1, C3	20.5–22.5	16.5–18.5	65.1	73.2

the subject to move the cursor to the 'right' toward the target on the screen during the online procedure. During rest the cursor moved to the 'left'.

Figure 4 shows an example analysis calculated for one subject performing imagined 'right' hand movement and rest. The top panel (A) shows the values of r^2 for each channel and frequency for both EEG and tEEG signals. It can be seen that some signals at particular locations and frequencies exhibit a difference between the task and rest such as C1, which was used for the remainder of figure 4. Panel B shows the average tEEG spectra for 'right' hand movement and rest and Panel C shows the same for EEG. Panel D shows the r^2 values for tEEG and Panel E for the EEG. This same process was followed for each subject during a no-feedback session and the features (i.e., electrode locations and frequency band) that had the highest values of r^2 were determined for each subject.

3.2. Online testing

The order of the EEG or tEEG closed-loop control was randomized without the subject knowing which they were performing. The closed-loop BCI experiments, the real-time testing, were performed with the subject receiving online feedback. The feedback consisted of one-dimensional cursor imaginary movement controlled by the EEG or tEEG features. Moreover, the subjects received feedback that was proportional to the extracted features identified in the methods of section 3.1. To translate the extracted features into a set of signals that moved the cursor toward the target during the online feedback, the amplitudes of an identified frequency band were summed linearly for the identified electrodes [23]. The weights were chosen so that the cursor moved to the 'right' with task performance and to the 'left' during rest. The weights were selected manually to set this configuration. Initially, we performed a trial task for each subject using EEG and an initial weight value of (1). We monitored the speed of the ball and adjusted the weight so that the cursor moved from the center to the target within 2 s for each subject. The same weights determined for the EEG were also used for the tEEG. The EEG and tEEG features were integrated over time to yield the current cursor position.

The subject's goal was to move the cursor horizontally so that it hit the appropriate (i.e., 'left' or 'right') target. Data were collected from each subject for 10 runs, each run comprised 20 trials. The runs were separated with short breaks. The random 'left' or 'right' target appeared 2 s prior to the cursor (a ball) which appeared in the center of the screen. The trial ended 1 s after a hit, miss, or abort with a total run duration of approximately 8 s. The feedback duration was 2 s with a maximum duration of 4 s. One session comprised ten runs for approximately 2.7 min per run and approximately 27 min for a session. Data were collected for only one session from each subject. The cursor was visible and controllable throughout the whole run. Once the cursor hit the target, the color changed from pink to green to show the successful performance. Since there were two possible outcomes in each trial, the expected probability in the absence of any control was 0.5.

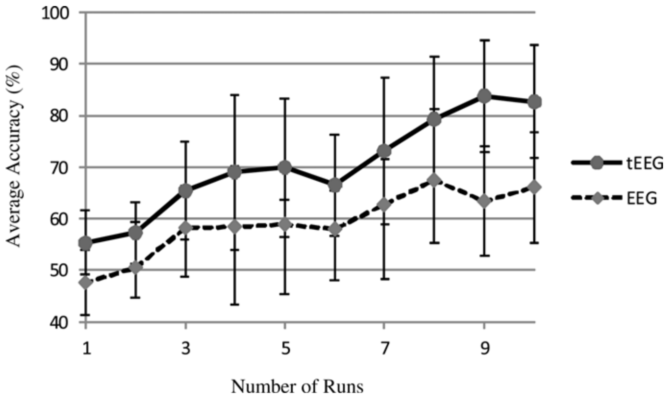

Figure 5. Average accuracy for tripolar concentric ring electrode (TCRE) (continuous line) and disc electrode (dashed line). The values are mean ± SD.

4. Results and discussion

In this study, we report the first tEEG-based BCI system for one-dimensional real-time cursor movements. Furthermore, we emphasize that the system requires only one session of an offline analysis for features identification (∼27 min) and online testing (∼27 min) resulting in proficient operation. The procedure for achieving one-dimensional cursor control had two stages. In the first stage, the data were collected from naïve subjects and analyzed using an offline process to determine which features could be used for BCI control. In the second stage the subjects attempted control of the computer cursor.

During offline analysis, the signal amplitudes related to the electrodes and frequencies with the most significant task (i.e., the highest values of r^2) were identified as features to be used to control cursor movement in the subsequent online BCI experiments. The r^2 is a measure of how relevant a signal is to the presented target [21]. An analysis example comparing tEEG and EEG signals for the right-hand imaginary and rest is shown in figure 4. The analysis of r^2 (figure 4 panel D and panel E) demonstrate that the relevant signal is focused in mu and beta frequency. Moreover, figure 4 panel B and C, shows that the normalized power of these frequency bands decreased during task execution.

In the online analysis, the subjects controlled a cursor (moving the cursor to the left or right edge of the screen to hit the target) with their EEG or tEEG signals. The obtained accuracies are comparable to other noninvasive and invasive BCI studies aimed at one-dimensional cursor control [6, 8, 17 and 21]. For examples in [6] human subjects try to control at first a one-dimensional movement and then moved to a two-dimensional movement using a noninvasive BCI. The tasks were performed from 2–4 times a week with a 92% hit rate achieved. In [17], the subjects controlled a cursor in one-dimensional direction by imagined movements. All data of each subject were recorded on the same day without subject training. The average accuracy of all subjects obtained online in the feedback application was 90.5%.

Over short training periods (∼27 min), all eight users achieved significant control of the computer cursor. Figure 5 shows the average group accuracy during online cursor control obtained from each user for the period of ten runs. The average rates of online experimental results for each subject using both disc and tripolar electrodes are shown in table 1. The maximum hit rate reached 86% using EEG (Subject 4) and reached 100% using tEEG (Subjects 3 and 6). The grand average hit rate and standard deviation for EEG and tEEG was 59.1% $\pm$ 7.13 and 70.2% $\pm$ 8.13, respectively (figure 5). One-way analysis of variance (ANOVA) with blocking factor levels corresponding to eight human subjects was used to confirm that there was a significant difference in the mean BCI hit rate between data corresponding to conventional disc EEG and tripolar concentric ring Laplacian tEEG ($p < 0.0001$). These results show that there is a significant difference in accuracy of the tEEG to disc EEG for new users in real-time one-dimensional cursor control.

Comparing the obtained results from EEG and tEEG signals, the cursor control accuracy using tEEG, on average, was significantly higher than for the disc EEG. When moving the cursor in one dimension, two of the eight subjects were able to hit 100% of the targets within one session (∼27 min) using tEEG. We believe that this increased accuracy in a shortened time will help users train on the BCI quicker.

We always used the features that provided the highest r^2 for each electrode type. Many times the electrode locations used for EEG and tEEG overlapped and sometimes the frequency bands also overlapped. Although, the performance of tEEG over EEG may be partially due to different selection of features, we believe this improvement is also due to tEEG having higher spatial resolution, lower mutual information, and better SNR than EEG which provides more specific features.

5. Conclusion

In this paper, we have shown a significant improvement in accuracy for one-dimensional BCI real-time center out cursor control using tEEG compared to EEG in humans after minimal training. The obtained results indicate that tEEG-based BCI could provide one-dimensional control that is more accurate with shorter training time requirements than EEG-based BCI. All eight subjects demonstrated reliable control achieving an average of 70.2% using tEEG-based BCI and an average of 59.1% using EEG-based BCI. As a result, the average improvement of the tEEG-based BCI over the EEG-based BCI was more than 15%. Using TCREs allowed us to collect the tEEG and EEG data from the same locations at the same time for comparison.

Our future studies will focus on two-dimensional cursor control to determine the hit accuracies are for tEEG and EEG signals.

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