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Collaborative Brain-Computer Interface for People with Motor Disabilities

Abstract

This research investigates the effects of collaboration mode, luminance contrast and motor disability on task performance, brain activity and satisfaction of users with motor disabilities who performed a robot control task using a collaborative brain-computer interface (C-BCI) based on steady-state visually evoked potentials (SSVEPs). Users can perform the task by himself/herself (individual mode), working together (simultaneous mode), or taking turns (sequential mode). Fourteen amyotrophic laterals sclerosis (ALS) participants and fourteen able-bodied participants of similar age were recruited from local ALS association and local communities. Results showed that participants in both groups had significantly better task performance and stronger brain activity in collaborative modes than individual mode. High luminance contrast produced significantly better task performance and stronger brain activity than low luminance contrast. There was no significant effect of motor disability between ALS participants and able-bodied participants. The two groups showed very similar task performance and brain activity. These results could provide precious empirical data and invaluable insights to the real-world applicability of the SSVEP-based BCI applications for people with motor disabilities.

IMAGE LICENSED BY GRAPHIC STOCK

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I. INTRODUCTION

Brain-computer interface (BCI) is a new interaction medium that allows users to communicate with the external world or control the external equipment without the use of normal pathways of peripheral nerves and muscles [1]. BCIs have shown to have the capability of providing great benefits to people with motor disabilities - increasing their quality of life both physically and spiritually [1]-[4]. BCIs can also reduce the burden oftentimes placed upon the caregiver [5]. Research has shown that both able-bodied users and people with motor disabilities can use BCI systems with acceptable accuracy levels for both communication and device control [4], [6].

Although BCI research has great promise, there are many challenges to overcome [7]–[9]. First, most BCI research focus on speed and accuracy. However, usability is more important for users; especially those with motor disabilities. As BCI is becoming an important tool in neurorehabilitation [10], [11], further research is required to develop more user-friendly BCI-based applications that cater for people with motor disabilities. Secondly, most BCI studies are single-user based and have not explored the integration of BCI into every day normal life, especially to support interactive work such as collaboration with other people [1], [12]. There has been a general lack of understanding regarding how BCIs should support collaborative work between users with motor disabilities and between users with and without motor disabilities under various task conditions. However, collaborative BCIs (C-BCIs) were shown to bring greater benefits to those with motor disabilities [13]. More studies regarding

C-BCIs will help to determine how the applications could be extended to real-life situations.

The objective of this research was to investigate the user performance, brain activity, and BCI design preference of people with motor disabilities (e.g., amyotrophic lateral sclerosis, stroke, spinal cord injury, etc.) using an SSVEP-based C-BCI, Brainbot [14], as a test bed.

There has been a general lack of understanding regarding how BCIs should support collaborative work between users.

II. LITERATURE REVIEW

A. Collaborative BCIs

While BCIs hold the promise to restore the communication and control ability of users with motor disability, BCI research has not fully addressed, yet, the social burdens of their disabilities (i.e., interaction with other people). People with motor disability have had little opportunity to work jointly with other people. Meanwhile, very few studies have explored the integration of BCI in normal life [1], [12], especially to support interactive work such as information exchange and collaboration with other people. New BCI applications have recently been validated, such as control of a robotic arm [15], neural prosthesis [16], [17], mobile humanoid robot [18], and smart home [19]. However, little emphasis is given to the value of BCI-supported collaborative work of people who have a motor disability.

Collaborative brain-computer interface (C-BCI) is defined in this study as a non-invasive electroencephalogram (EEG)-based BCI that supports collaboration in which, by working in a group of two, users can help each other and perform tasks jointly. Depending on the collaboration mode, users may take turns or work simultaneously to perform tasks at their own pace. However, there has been a general lack of understanding of, or inattention to, issues related to BCI-supported collaborative work. For example: Can people with motor disabilities perform a task jointly with other people (with or without motor disability) only through means of their brain activity? How then can BCIs best support their collaborative work? To empirically examine these new research questions, we developed a C-BCI for control – Brainbot, which allows participants to jointly move a ball by controlling a robot arm. It is intrinsic that C-BCIs, compared to individual BCIs, can provide greater benefit to those with motor disabilities. Collaboration can foster the sharing of knowledge, ideas, and skills, and plays an important role in areas of art, academia, business, and scientific research [20], [21]. Research has also indicated that group decisions are superior to individual decisions in many different aspects [22], [23].

More recently, researchers have begun to notice the advantage of C-BCIs and argued that C-BCIs should be investigated to better serve people with motor disabilities. Some initial research has been conducted showing the possibility and potential to develop C-BCIs [13], [24]–[28]. For example, Wang & Jung [27] have examined the performance of C-BCI in a task of movement planning and found that C-BCI setups could result in a better overall performance than a single user BCI system. Eckstein et al. [24] has examined the possibility of integrating the brain activity of group members in the decision making process and found that the combined neural activities could lead to decisions as accurate as the combined behavioral activities in less time. Additionally, Poli and his colleagues [25] investigated C-BCI in a space navigation task and found that C-BCIs produced significantly superior trajectories than single user BCI in a space navigation task. However, it should be noted that all of the aforementioned studies employed able-bodied participants. Also, previous research generally used much simpler tasks and users were not directly controlling any external equipment. Therefore, further research is needed to investigate the collaborative behavior of people with motor disabilities in more complex tasks.

SSVEP-based BCI is chosen for the following reasons - Firstly, SSVEP-based BCI requires almost no initial training, which provides a great advantage over most other BCI systems [29]. Secondly, research has shown that SSVEP-based BCI can provide fast and reliable communication as a non-invasive BCI [30], [31] and also has the advantage of high signal-to-noise ratio (SNR) and robustness to artifacts [32]. Finally, general design solutions exist for SSVEP. For example, LED is preferred to provide visual stimuli and low to medium frequency is generally used [33]. Therefore, SSVEP-based BCI is a good test bed for research relating to C-BCI.

B. Luminance Contrast

Luminance contrast describes the relative brightness of the light source in comparison to another light source and is an extremely important aspect of SSVEP-based BCI design. Research shows that both ambient luminance and contrast can affect the visual acuity of older adults [34]. Research shows that the amplitude of the evoked potentials is positively correlated to the logarithm of contrast [35]. Spekreijse [36] found that brightness and modulation depth can increase SSVEP amplitudes. Nam, Li, & Johnson [37] have shown a significant effect for interface color contrast on most P300 measures for able-bodied participants. Participants had significantly higher accuracy, larger information transfer rate (ITR), larger amplitude, and shorter latency in high interface color contrast as compared to low interface color contrast.

Zemon & Gordon [38] investigated the mechanisms of luminance contrast in humans using arrays of isolated-checks and discovered that a raster of dark squares, rather than bright squares, elicit larger responses when

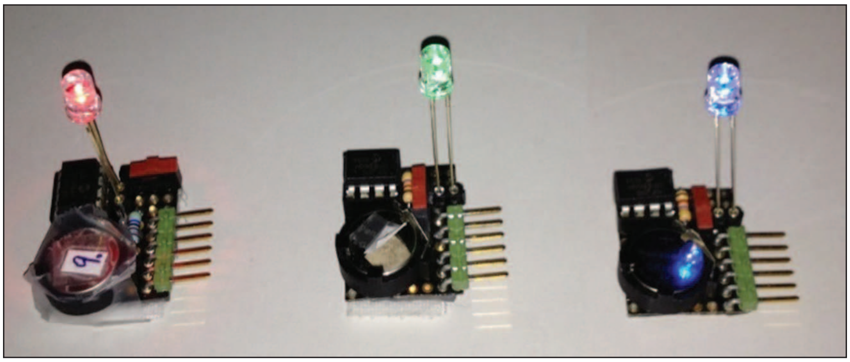

FIGURE 1 LED lights (from left to right: red, green, and blue).

emerging from a neutral background. Bieger & Garcia-Molina [39] investigated the effect of luminance contrast within BCI by testing eight conditions where both foreground and background stimuli luminance was varied. However, the results differed from Zemon & Gordon's findings [38] in that bright stimuli elicited larger responses over dark stimuli.

C. Motor Disability

Sellers & Donchin [3] have evaluated the effectiveness of a P300-based BCI system with 3 amyotrophic laterals sclerosis (ALS) patients and 3 non-ALS controls and found that non-ALS controls had higher average accuracy than ALS patients. Research by Volosyak et al. [4] evaluated the Bremen SSVEP based BCI with 32 participants including 8 handicapped users in a spelling task. Their result showed that able-bodied participants had significantly higher accuracy than handicapped participants. However, there was no significant difference for ITR. They concluded that there was almost no difference between the disabled and healthy subjects.

Münßinger et al. [40] examined the P300-Brain Painting with 3 ALS patients and 10 healthy participants. Their result showed that healthy participants had higher accuracy and ITR than ALS patients in both copy-spelling and copy-painting. Li and his colleagues [2] have examined the effects of interface type and screen size of a P300 Speller with 10 participants with severe motor disabilities and 10 able-bodied participants as a control group. Their results were consistent with Münßinger et al. [40]. Lim, Hwang, Han, Jung & Im [41] have examined the SSVEP-based BCI with the binary intentions classifications. Their results showed that healthy participants had higher average classification accuracy than the ALS patient.

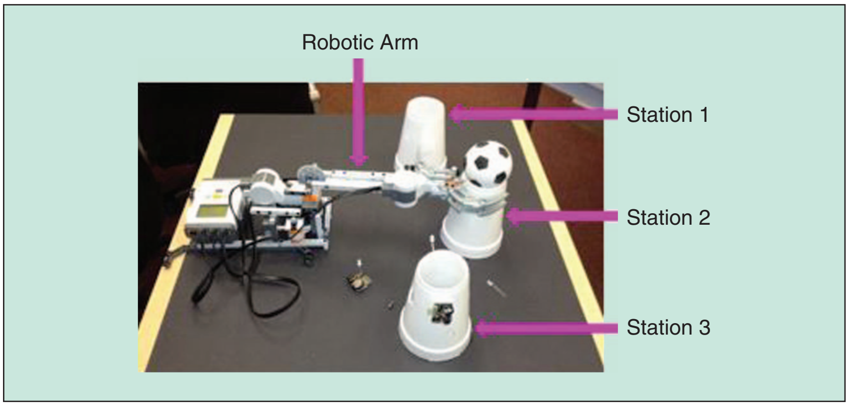

FIGURE 2 SSVEP-based robot control system.

III. METHODS

A. Participants

Fourteen participants (8 male, 6 female) with motor disabilities (ALS) were recruited from the local ALS association and community, with mean (M) age of 56.4 years old (Standard Deviation, $SD = 11.3$). Fourteen able-bodied participants of similar ages (8 male and 6 female) were recruited from the local community, with mean (M) age of 52.5 years old (Standard Deviation, $SD = 8.5$). Participants were rejected if younger than 18 years of age or if suffering or previously suffered from seizures, epilepsy, or skin allergies [42]. All eligible participants were compensated $20/hour for participation and provided with printed informed consent form. The study was approved by institutional review board (IRB) at North Carolina State University (NCSU).

B. Apparatus

The hardware included an amplifier (g.tec Medical Engineering), an EEG cap, electrodes, a g.GAMMAbox (g.tec Medical Engineering), EEG gel, syringes, blunt needles, and LED lights. The frequency detection software and SSVEP-based C-BCI were used, developed by BCI Lab at NCSU.

LED lights: Cost effective LED lights were developed as visual stimuli to elicit SSVEP responses. LEDs were highly customized and can be easily adjusted to different colors and frequencies via a programmable Micro Control Unit (Fig. 1).

Frequency Detection Software: A frequency detection software was developed to detect the frequency to which the participant is sensitive.

SSVEP-based C-BCI: Brainbot is a C-BCI and enables a pair of users to jointly perform a physical control task (Fig. 2). BrainBot consists of a robotic arm, three target locations (station 1 (St1), station 2 (St2) and station 3 (St3)), ten LEDs and a rubber ball. Brainbot is constructed using the LEGO Mindstorms NXT kit communicating with a computer via a Bluetooth medium.

In an example task, participants would be asked to grab (G) a ball, move and release (R) it to one of the three target locations (i.e., St1, St2, and St3) alone or collaboratively with their partner by focusing on the LED light corresponding to a desired action/motion. St2 is the neutral position, in which the robot arm and the ball is initially placed for any task.

In simultaneous mode, if no successful movement is made or a successful but incorrect one (not the same as the predefined path) is made, both participants need work together to make the correct movement again.

C. Independent Variables

1) Collaboration Mode

Three types of collaboration modes were used in this study. In each collaboration mode, participants are provided a predetermined sequence of "correct" movements. Any visual stimulus that has been chosen three times in a row constitutes a successful movement to be carried out by the robot. However, only movements following the predefined path constituted correct moves. For example, if the predefined path was $G \rightarrow St3 \rightarrow R$ and the participant(s) performed the following six movements $G \rightarrow St1 \rightarrow St3 \rightarrow St2 \rightarrow St3 \rightarrow R$, then only three of the sequential movements are considered "correct" (i.e. G, the first instance of St3, and R). Both the participants and the experimenters know the predefined paths. The BCI system will send any successful movement to the robot. The three collaboration modes are:

(a) Individual Mode (no collaboration): Each participant (1 and 2) performed the task individually. When a successful but incorrect movement (not the same as the predefined path) was made, the participant must correct it before making a subsequent movement in the predetermined path.

(b) Sequential Mode: Two participants (1 and 2) took turns performing the task as a group. When an incorrect movement was made, whoever made it must correct the movement before making a subsequent movement in the predetermined path. For two participants (1 and 2) to perform a 6-sequence control, the pattern would look like: **1-2-1-2-1-2**, where 1 and 2 represent participant 1 and participant 2, respectively. When one participant is working, the other participant is at rest.

(c) Simultaneous Mode: Two participants performed the task together (simultaneously) as a group. Each participant's brain signal was processed separately at first, and then combined together following the defined rule. There are three cases: (I) If there is no successful classification, no command will be sent to the robot; (II) If there is only one successful classification (either 1 or 2), the corresponding command will be sent to the robot; (III) If there are two successful classifications (i.e., both 1 and 2), then the average spectral power will be compared and the one with bigger spectral power will be chosen and the corresponding command will be sent to the robot.

If no successful movement is made or a successful but incorrect one (not the same as the predefined path) is made, both participants need work together to make the correct movement again. For two participants (e.g., 1 and 2) to perform a 6-sequence control, the pattern could be pretty random. For example, if participant 1 performed the first 3 sequences and participant 2 performed the second 3 sequences, the pattern would look like **1-1-1-2-2-2**.

2) Luminance Contrast

Web contrast [43] was used to define luminance contrast (C_W):

$$C_W = \frac{L_s - L_b}{L_b} \tag{1}$$

where L_s is the luminance of the visual stimulus and L_b is the luminance of the background. It is obvious to see that when the background is more luminous (i.e., brighter) than the visual stimulus, then $-1 < C_W < 0$. Likewise, when the background is darker than the visual stimulus, $C_W > 0$.

Luminance contrast was controlled by adjusting the background luminance. There were only two light sources in the lab: the visual stimuli (LED lights) and the room's overhead lights. Both light sources maintained a stable luminance. Two levels of background luminance were controlled: low (light off, 55 cd/m^2), and high (light on, 750 cd/m^2). The LED lights have luminance of 150 cd/m^2. Correspondingly, there were two levels of luminance contrast: 1.73 and –0.8.

3) Motor Disability

The participants were classified into two equal-sized groups: able-bodied participants and participants with motor disabilities (ALS participants).

D. Dependent Variables

1) Task Performance

Accuracy (%): Accuracy is the ratio of the number of correct robot movements over the total number of robot movements. For example, if the predefined path was $G \rightarrow St3 \rightarrow R$ and the participant performed six movements $G \rightarrow St1 \rightarrow St3 \rightarrow St2 \rightarrow St3 \rightarrow R$, then the accuracy would be 50% (3/6).

Information Transfer Rate (*ITR*) (*bits/min*): ITR has been widely used in BCI research [45] and conveys how many bits can be transferred per minute. It can be calculated by two steps. At first, the number of bits transferred per trial (B) would be calculated. Then, ITR can be obtained by dividing B by the duration of the trial. The following formula, defined by Pierce [44] and Wolpaw et al. [45], would be used to calculate the number of bits transmitted per trial:

$$B = \mathrm{Log}_2 N + A\mathrm{Log}_2 A + (1-A)\mathrm{Log}_2\left(\frac{1-A}{N-1}\right) \tag{2}$$

$$ITR = B/T \tag{3}$$

where N is the number of possible targets (number of visual stimuli in this study), A is the probability that the target was accurately classified (accuracy here), and T is the duration of the trial in minutes.

Task Completion Time (seconds): Task completion time measures the time duration needed to perform one trial.

2) Brain Activity

Spectral Power (mv^2): Spectral Power is defined as,

$$P = \lim_{T \to \infty} \frac{1}{2T} \int_{-T}^{T} x(t)^2 \, dt \qquad (4)$$

where $x(t)$ is the amplitude of the EEG signal and T is the duration of one cycle [46].

3) User Evaluations

User Preference: Participants were asked to choose their favorite experiment condition out of 6 conditions (3 collaboration modes × 2 luminance contrasts) when finished after the experiment.

E. Data Acquisition and Signal Processing

1) Data Acquisition

SSVEP brain waves were recorded using an EEG cap embedded with 16 channels (F_z, C_3, C_z, C_4, CP_z, P_7, P_3, P_z, P_4, P_8, PO_3, PO_z, PO_4, O_1, O_z, and O_2) based on the modified 10-20 system of the International Federation [47]. Brain signals from channel O_1 and O_2 were used as control signal. Figure 3 showed the electrode montage used in the study. Recordings were referenced to the left mastoid and grounded to location AF_z [42].

SSVEP brain waves were amplified with a g.USBamp amplifier (g.tec Medical Engineering). Data collection, online signal processing and offline data analysis were conducted using LabVIEW-based software developed by BCI Lab at North Carolina State University.

2) Signal Processing

Many methods have been used in the SSVEP signal classification, such as Harmonic Sum Decision (HSD) [16], [48], Canonical Correlation Analysis (CCA) [30], Linear Discriminant Analysis [49], and Minimum Energy Combination [31]. HSD was chosen in the current study for its efficiency and simplicity. Data processing included two phases: preprocessing and classification. In the preprocessing phase, raw EEG data was filtered and transformed into the frequency domain. In the classification phase, the brain signal was classified and

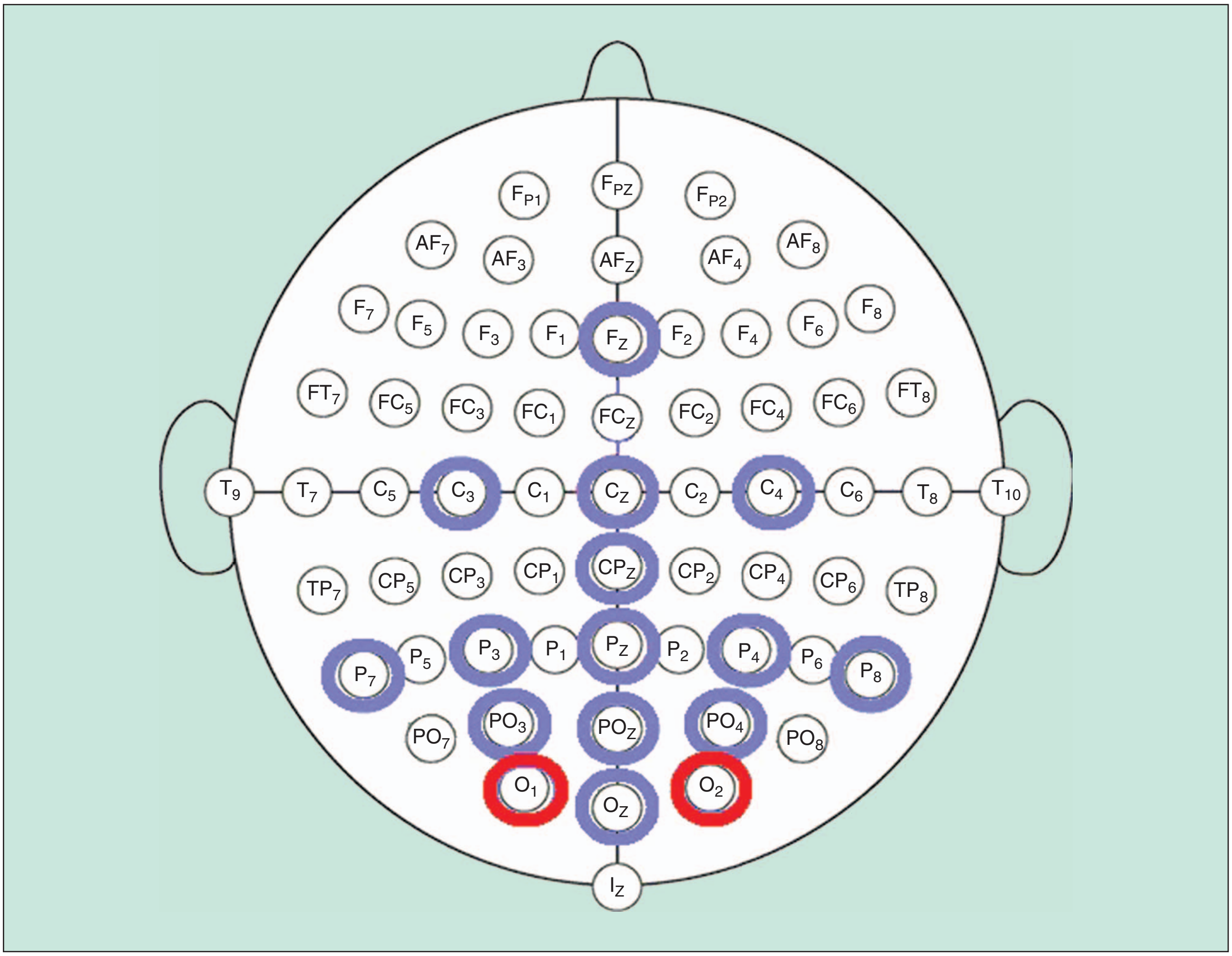

FIGURE 3 Electrode Montage.

a corresponding decision was sent to the NXT robot. EEG raw data was sampled with a rate of 512 Hz. It was filtered by a 0.1 Hz high pass filter and a 75 Hz low pass filter, notch filtered by 60 Hz. Then, the acquired time domain EEG data was transformed into frequency domain to get SSVEP response in the power spectrum by FFT. The time window was 3 seconds and the window sliding speed was 0.25 second. Next, the EEG data in frequency domain was adjusted by the baseline. After the process of normalization and averaging, the relative spectral data were sent to a classifier, in which the frequency with the maximum average spectral power would be chosen preliminarily. If a frequency was chosen 3 times in a row, it would result in a corresponding movement command, which would be sent to the robot to carry out. Figure 4 displayed the flow of the signal processing.

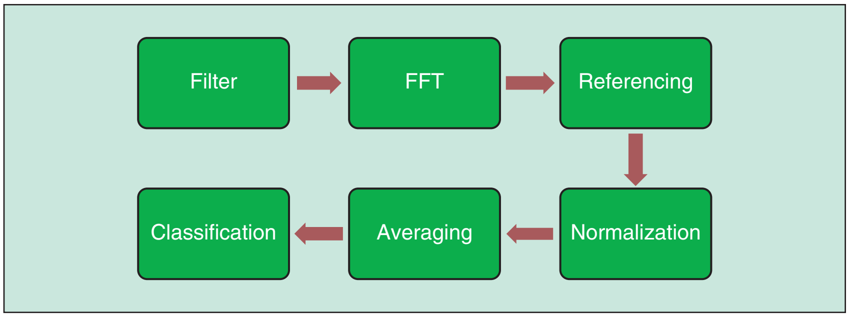

FIGURE 4 Signal Processing Diagram.

F. Experimental Task

In the study, each participant must perform predetermined sequence of six movements (G → St3 → R → G → St1 → R) in each condition either alone (individual mode) or together with the teammate (sequential or simultaneous mode). In other words, the participant must grab (G) the rubber ball in the neutral position (St2), then move to St3 and release (R) the ball, then grab (G) the ball and move to St1, then release (R) the ball.

Four movements were available in each task: G, R, St1 and St3. The four identified user-specific visual stimuli were used for each participant to optimize movement selection accuracy. The four visual stimuli were set up in front of the participant and apart from each other to prevent the interference based on the pilot test. The same layout of the visual stimuli was applied to each participant based on the pilot test. There were 6 conditions (3 collaboration modes ×2 luminance contrasts) for each participant with 1 trial in each condition. The 8 trials (4 trials in individual mode + 2 trials in sequential mode + 2 trials in simultaneous mode) were completely randomized in presentation to reduce any trial order effect. A 3-minute break was provided between each trial.

G. Procedure

All experiments were conducted in a quiet room. Before the experiment, participants were instructed on the basic procedure of the experiment and how to respond to visual stimuli. Participants were provided a comfortable chair and required to avoid any unnecessary gross body movement and to focus on the corresponding visual stimulus at each movement in a relaxed manner during the experiment. No interferences or hints were provided during the experiment.

At first, the user-specific visual stimulus (frequency & color) was determined for each participant based on spectral power values using the frequency detection software. During the process, the participant was asked to focus on LED lights with different frequencies and colors. The four LED lights with different frequencies which produced the biggest spectral power were chosen as the visual stimuli to control the robot.

Then, they performed the robot control task for 8 trials. Once the system is set up, participants were asked to close their eyes for 2 minutes for the system to record the baseline of EEG. Next, the participants were asked to open their eyes and perform the first task. When finished, a three-minute rest was given. Then, participants began the second task. This process was repeated until all 8 trials were completed. Next, each participant was required to complete a single questionnaire to evaluate the system and experimental condition. Finally, participants were compensated by cash and debriefed with the help of the experimenters. The whole procedure lasted approximately 1 hour.

H. Data Analysis

The study was a balanced 2 × 3 × 2 mixed design. There were two within-subjects factors (Collaboration Mode and Luminance Contrast), and one between-subjects factor (Motor Disability).

IV. RESULTS

Table 1 summarized the significant effects for performance measures.

TABLE 1 Summary of significance effects.

PERFORMANCE MEASURE	EFFECT	*F*-VALUE	*P*-VALUE
ACCURACY	COLLABORATION MODE	$F_{2,24} = 36.31$	<0.0001
	LUMINANCE CONTRAST	$F_{1,12} = 72.14$	<0.0001
COMPLETION TIME	COLLABORATION MODE	$F_{2,24} = 43.00$	<0.0001
	LUMINANCE CONTRAST	$F_{1,12} = 73.18$	<0.0001
ITR	COLLABORATION MODE	$F_{2,24} = 56.45$	<0.0001
	LUMINANCE CONTRAST	$F_{1,12} = 182.59$	<0.0001
SPECTRAL POWER	COLLABORATION MODE	$F_{2,24} = 8.70$	0.0014
	LUMINANCE CONTRAST	$F_{1,12} = 53.12$	<0.0001

The completion time decreased by 39.4% from individual mode to simultaneous mode, and decreased by 28.8% from low luminance contrast to high luminance contrast.

A. Task Performance

1) Accuracy (%)

The analysis revealed a significant main effect of collaboration mode ($F_{2,24}$ = 36.31, $p < 0.0001$) and luminance contrast ($F_{1,12} = 72.14$, $p < 0.0001$). Tukey's HSD test indicated that accuracy in simultaneous mode ($M = 0.868$, $SD = 0.126$) was significantly higher than that in sequential mode ($M = 0.728$, $SD = 0.115$) ($F_{1,12} = 38.43$, $p < 0.0001$) and individual mode ($M = 0.684$, $SD = 0.120$) ($F_{1,12} = 66.63$, $p < 0.0001$). However, accuracy was not significantly different between individual mode and sequential mode ($F_{1,12} = 3.85$, $p = 0.613$), although the mean accuracy in sequential mode was higher than that in individual mode. Accuracy in high luminance contrast ($M = 0.839$, $SD = 0.126$) was significantly higher in comparison to low luminance contrast ($M = 0.681$, $SD = 0.112$). Results revealed no significant effect of motor disability ($F_{1,12}$ = 0.01, $p = 0.9274$). Accuracy for ALS participants ($M = 0.762$, $SD = 0.147$) and able-bodied participants ($M = 0.758$, $SD = 0.139$) was not significantly different. No significant interaction effects were found between collaboration mode and motor disability ($F_{2,24} = 0.91$, $p = 0.4151$), luminance contrast and motor disability ($F_{1,12} = 0.23$, $p = 0.6405$), or collaboration mode and luminance contrast ($F_{2,24} = 1.65$, $p = 0.2125$).

2) Completion Time (seconds)

The analysis revealed a significant main effect of collaboration mode ($F_{2,24} = 43.00$, $p < 0.0001$) as well as a significant effect of luminance contrast ($F_{1,12} = 73.18$, $p < 0.0001$). Tukey's HSD test indicated that completion time in simultaneous mode ($M = 30.95$, $SD = 10.33$) was significantly shorter than that in sequential mode ($M = 45.19$, $SD = 12.23$) ($F_{1,12} = 40.62$, $p < 0.0001$), which was also significantly shorter than that in individual mode ($M = 51.10$, $SD = 11.63$) ($F_{1,12} = 7.01$, $p = 0.0141$). Meanwhile, completion time in high luminance contrast ($M = 35.29$, $SD = 10.32$) was significantly shorter than that in low luminance contrast ($M = 49.53$, $SD = 13.93$). The completion time also indicated the clinical difference. For example, the completion time decreased by 39.4% from individual mode to simultaneous mode, and decreased by 28.8% from low luminance contrast to high luminance contrast. However, the analysis revealed no significant effect of motor disability ($F_{1,12} = 0.48$, $p = 0.5005$). Completion time of ALS participants ($M = 43.55$, $SD = 13.08$) was not significantly different from able-bodied participants ($M = 41.28$, $SD = 15.18$). No significant interaction effects were found between collaboration mode and motor disability ($F_{2,24} = 3.12$, $p = 0.0622$), luminance contrast and motor disability ($F_{1,12} = 0.66$, $p = 0.4316$), or collaboration mode and luminance contrast ($F_{2,24} = 4.89$, $p = 0.0719$).

3) Information Transfer Rate (bits/minute)

The ANOVA revealed a significant main effect of collaboration mode ($F_{2,24}$ = 56.45, $p < 0.0001$) as well as a significant effect of luminance contrast ($F_{1,12} = 182.59$, $p < 0.0001$). Tukey's HSD test indicated that ITR in simultaneous mode ($M = 3.16$, $SD = 2.18$) was significantly higher than that in sequential mode ($M = 1.24$, $SD = 1.04$) ($F_{1,12} = 13.62$, $p < 0.0001$), which was significantly higher than that in individual mode ($M = 0.87$, $SD = 0.60$)($F_{1,12}$ = 6.01, $p = 0.0219$). ITR in simultaneous mode was also significantly higher than that in individual mode ($F_{1,12} = 59.72$, $p < 0.0001$). Meanwhile, ITR in high luminance contrast $M = 2.54$, SD = 1.97 was significantly higher than that in low luminance contrast ($M = 0.97$, $SD = 0.99$). However, the analysis revealed no significant effect of motor disability ($F_{1,12} = 0.05$, $p = 0.8209$). No significant interaction effects were found between collaboration mode and motor disability ($F_{2,24} = 1.54$, $p = 0.2345$), luminance contrast and motor disability ($F_{1,12} = 0.15$, $p = 0.7084$), and collaboration mode and luminance contrast ($F_{2,24} = 0.58$, $p = 0.5660$).

B. Brain Activity

The analysis revealed a significant main effect of collaboration mode ($F_{2,24} = 8.70$, $p = 0.0014$) as well as a significant effect of luminance contrast ($F_{1,12} = 53.12$, $p < 0.0001$). Tukey's HSD test indicated that spectral power in individual mode ($M = 0.787$, $SD = 0.269$) was significantly smaller than that in sequential mode ($M = 1.049$, $SD = 0.407$) ($F_{1,12} = 16.48$, $p = 0.0005$) and simultaneous mode ($M = 0.972$, $SD = 0.273$) $F_{1,12} = 8.15$, $p = 0.0087$. However, spectral power was not significantly different between sequential mode and simultaneous mode ($F_{1,12} = 1.45$, p = 0.2399), although the mean spectral power in sequential mode was higher than that in simultaneous mode. Meanwhile, spectral power in high luminance contrast ($M = 1.028$, $SD = 0.351$) was significantly bigger than that in low luminance contrast ($M = 0.844$, SD = 0.300). However, the analysis revealed no significant effect of motor disability ($F_{1,12} = 0.01$, $p = 0.9358$). Spectral power of ALS $M = 0.942$, $SD = 0.359$ and able-bodied participants ($M = 0.930$, $SD = 0.320$) was not significantly different. No interaction effects were found between collaboration mode and motor disability ($F_{2,24} = 0.44$, $p = 0.6481$), luminance contrast and motor disability ($F_{1,12} = 0.22$, $p = 0.6489$), or collaboration mode and luminance contrast ($F_{2,24} = 0.48$, $p = 0.6256$).

C. User Evaluations

A Two-way contingency analysis was conducted for user evaluations at first. Fisher's Exact Fisher Test was utilized because some cells had less than 5 observations [50]. If there was no association between the two factors, a one-way frequency analysis was conducted.

Table 2 summarizes ALS participants' user preference of experiment conditions.

The Fisher Exact Test showed that there is no association between collaboration mode and luminance contrast $(p = 0.3407)$. A one-way frequency analysis of collaboration mode revealed no significant difference in user preference $(\mathcal{X}_2^2 = 4,\ p = 0.1353)$. A one-way frequency analysis of luminance contrast revealed significant difference in user preference $(\mathcal{X}_1^2 = 7.1429,\ p = 0.0075)$ showing that ALS participants preferred high luminance contrast over low luminance contrast.

Table 3 summarizes able-bodied participants' user preference of experiment conditions.

The Fisher Exact Test showed no association between collaboration mode and luminance contrast $(p = 0.5385)$. A one-way frequency analysis of collaboration mode revealed no significant difference in user preference $(\mathcal{X}_2^2 = 0.2587,\ p = 0.5930)$. A one-way frequency analysis of luminance contrast revealed significant difference in user preference $(\mathcal{X}_1^2 = 4.5714,\ \ p = 0.0325)$ showing that able-bodied participants preferred high luminance contrast over low luminance contrast.

TABLE 2 Two-way contingency table of user preference for ALS participants.

COLLABORATION MODE		INDIVIDUAL	SIMULTANEOUS	SEQUENTIAL	TOTAL
LUMINANCE CONTRAST	LOW	0	1	1	2
	HIGH	4	7	1	12
TOTAL		4	8	2	14

TABLE 3 Two-way contingency table of user preference for ALS participants.

COLLABORATION MODE		INDIVIDUAL	SIMULTANEOUS	SEQUENTIAL	TOTAL
LUMINANCE CONTRAST	LOW	0	1	2	3
	HIGH	0	7	4	11
TOTAL		0	8	6	14

V. DISCUSSION

A. Effects of Collaboration Mode

Results showed that collaboration mode had a significant main effect on both task performance and brain activity. Simultaneous mode can produce significantly better task performance than individual mode. Sequential mode also produced a significantly better task performance than individual mode with the exception of accuracy (there was no significant difference).

Simultaneous Mode vs. Individual Mode: The results of this research are similar to those from Poli et al. [25], [13], Eckstein et al. [24], and Wang & Jung [27]. Research of group vs. individual showed that groups perform better than the average individual [51], [52], [53]. The result of the study was also consistent with this viewpoint.

Simultaneous mode provides an advantage over individual mode in SSVEP-based BCI in the form of group work efficiency. The error cancellation property of group work makes the simultaneous mode much more efficient than the individual mode. For example, in individual mode, the individual user had to make each movement alone and correct errors alone. In simultaneous mode, however, correct movement could be made if chosen by either participant. Meanwhile, the error could be corrected by either user. This mechanism greatly improved the accuracy as well as ITR and reduced the task completion time. Social facilitation could enhance brain activity in simultaneous mode tasks compared to individual mode tasks [54], [55]. Likewise, social facilitation could also contribute to greater task performance in simultaneous mode compared to individual mode. The presence of a teammate may cause each participant to have higher arousal level and enhanced focus to the visual stimulus [54], which in turn helped to produce stronger brain activity and greater task performance [56].

Sequential Mode vs. Individual Mode: Sequential mode is actually a modification of individual mode. The only difference is that two participants take turns completing the task, even though they can't help each other select movement or correct errors. In other words, each individual would perform only three movements rather than six, providing more opportunities for rest after each correct movement.

This is a critical advantage for sequential collaboration - less burden and more downtime - which could reduce the participant's tiredness, elevate the alertness, potentially produce better task performance (shorter completion time and bigger ITR) and stronger brain activity. Although the accuracy was not significantly higher in sequential mode (the average accuracy was higher), it is reasonable to believe that the advantage should be more significant as the number of movements increases in the task. As discussed earlier, social facilitation should also contribute to the advantage of sequential mode.

User preference also supports the popularity of the collaborative mode. Results showed that about 71.4% ALS participants and 100% able-bodied participants preferred collaborative mode. Participants commented that they "enjoyed the collaboration process with the teammate in the collaborative mode" and "were more efficient when controlling the robot together with the teammates", because they could get help from the teammate if they make a wrong move. However, some ALS participants expressed their concern about the collaborative mode. One ALS participant commented that she preferred

The error cancellation property of group work makes the simultaneous mode much more efficient than the individual mode.

the individual mode because she "was always in control of the process". Another ALS participant said he "couldn't believe in his teammate and would rather perform the task alone". These comments surfaced some very important research question: How can C-BCI system provide users with motor disabilities a greater sense of control? What training paradigm could bolster mutual trust? The result proves that the collaborative BCI is workable and more efficient than individual mode. It indicates the feasibility of developing more collaborative applications for those with motor disabilities in order to improve their quality of life.

B. Effects of Luminance Contrast

Results showed that luminance contrast had a significant main effect on task performance and brain activity. Participants had a significantly higher accuracy, a shorter completion time, a bigger ITR and a bigger spectral power in high luminance contrast compared to low luminance contrast. Nam et al. [37] and Li, Bahn, Nam & Lee [57] have obtained similar results in a P300-based BCI.

One explanation is that participants could perceive more intense stimuli in high luminance contrast when all other environmental factors remained unchanged. High luminance contrast could result in brighter, more noticeable visual stimuli compared to low luminance contrast, even when the visual stimuli were the same luminance. From visual sensory theory, rods will function more in high luminance contrast and make green and blue LED lights appear brighter [58]. Since more green and blue were used than red, high luminance contrast produced brighter visual stimuli. As revealed by Campbell & Maffei [35], the amplitude of evoked potentials was linearly increasing as the logarithm of the contrast of the stimulus. The spectral power in high luminance contrast was bigger than that in low luminance contrast. Meanwhile, participants could stay more alert and have better focus in high luminance contrast. Li et al. [57] showed that participants can lose focus when using BCIs. Higher luminance contrast may help participants to remain more focused so as to produce better task performance.

User preference also supports the popularity of the high luminance contrast. Results showed that significantly more participants preferred high luminance contrast. About 85.7% ALS participants and 78.6% able-bodied participants preferred high luminance contrast. Most participants commented that they could "catch" the stimuli more easily in high luminance contrast condition. Some participants said that it was easier to focus on the visual stimulus in high luminance contrast, while it was difficult in low luminance contrast because visual stimuli did not provide enough intensity and required too much concentration. On the other hand, some participants disliked high luminance contrast. One participant said that in high luminance contrast the visual stimuli were too bright while low luminance contrast was more user-friendly and allowed for longer durations of use. Another participant commented that high luminance contrast produced some sort of "burn" effect in the eyes that worsened with time. These comments advanced the following research questions: What level of luminance contrast is most user-friendly for long-term use? Is there a luminance contrast threshold? Further research is needed to answer those questions.

C. Effects of Motor Disability

It revealed no significant main effect of motor disability nor any interaction effect between motor disability and other factors. ALS participants exhibited comparable task performance to the able-bodied participants in all three modes, which differs from the previous research in [2], [3], [40], [41]. Li et al. [2] and Volosyak et al. [4] found that able-bodied participants had better task performance than participants with severe motor disabilities.

In an SSVEP-based BCI, participants need only focus on the visual stimulus, which brings into question whether ALS participants' motor disabilities could affect the quality and duration of focus. Li et al. [2] argued that participants with motor disability become easily fatigued in shorter duration of focus, which affected their performance in comparison to able-bodied participants. Piccione et al. [59] also found that participants with motor disabilities were unable to avoid head and/or eye movement, which are known to produce artifacts, disturb classification and harm performance.

However, the hypothesized "fatigue" from Li et al. [57] was not observed in this study. No ALS participants requested extra rest during the experiment, indicating that their motor disability didn't result in extra fatigue. Also, the hypothesized "head or eye movement" by Piccione et al. [59] was not observed in the experiment. ALS participants not utilizing wheelchairs (6 in the study) retained most motor abilities and could control head or eye movement as good as any able-bodied participant. ALS participants utilizing wheelchairs (8 in the study) were unable to move and rested their heads against the back of the wheelchair. In this sense, it is possible to argue that SSVEP-based BCI usage is unaffected by motor disability. Most BCI researchers also hold this paradigm [1], [3], [4], although this postulation has not been significantly supported with a large sample size. Therefore, the empirical data in this study should provide greater substantial support in favor of such a paradigm.

Results of this study indicated that ALS patients could use SSVEP-based BCI as accurately and efficiently as able-bodied people. It upholds the potential of BCI as an alternative method of communication and control for those with motor disabilities in communication and control. It also sheds light on the future research and development of BCI. However, it should be noted that this study didn't consider the different stages of ALS patients, which may affect their performance, as shown by McCane and the colleagues [60].

D. Effects of Collaboration Mode on Individual Performance

Results showed that participants had better task performance in collaborative mode than individual mode. Then the question is: Is it possible that collaboration elevates individual performance?

To explore this question, accuracy, average individual completion time and spectral power were retrieved from the simultaneous mode and sequential mode. The data was segregated by each individual participant's movement selections within the task. For example, if participant 1 performed four movements in one trial in simultaneous mode, then, participant 1's individual data in this trial would be based on those four movements. Since each individual participant may perform different number of movements in simultaneous mode, the individual task completion time would not be comparable. For comparison, average completion time was used in the analysis. ANOVA was conducted to evaluate the effects of collaboration mode on the individual performance.

1) Accuracy (%)

The analysis revealed a significant main effect of collaboration mode ($F_{2,52} = 26.23$, $p < 0.0001$). Tukey's HSD test indicated that the accuracy was significantly different between individual mode and simultaneous mode ($F_{1,26} = 52.20$, $p < 0.0001$), between individual mode and sequential mode ($F_{1,26} = 10.01$, $p = 0.0026$), and between simultaneous mode and sequential mode ($F_{1,26} = 16.50$, $p = 0.0002$). The individual accuracy in simultaneous mode ($M = 0.900$, $SD = 0.157$) was significantly higher than that in sequential mode ($M = 0.779$, $SD = 0.207$), which was also significantly higher than that in individual mode ($M = 0.684$, $SD = 0.147$).

2) Average Completion Time (seconds)

The analysis showed a significant main effect of collaboration mode ($F_{2,52} = 35.34$, $p < 0.0001$). Tukey's HSD test indicated that the average completion time was significantly different between individual mode and simultaneous mode ($F_{1,26} = 70.06$, $p < 0.0001$), between individual mode and sequential mode ($F_{1,26} = 19.84$, $p < 0.0001$), and between simultaneous mode and sequential mode ($F_{1,26} = 15.59$, $p = 0.0002$). The individual average completion time in simultaneous mode ($M = 3.75$, $SD = 2.70$) was significantly shorter than that in sequential mode ($M = 5.99$, $SD = 4.00$), which was also significantly shorter than that in individual mode ($M = 8.52$, $SD = 2.35$).

3) Spectral Power (mv^2)

The result revealed a significant main effect of collaboration mode ($F_{2,52} = 4.59$, $p = 0.0146$). Tukey's HSD test indicated that the individual spectral power in individual mode ($M = 0.808$, $SD = 0.387$) was significantly smaller than that in sequential mode ($M = 1.049$, $SD = 0.648$) ($F_{1,26} = 8.65$, $p = 0.0049$) and simultaneous mode ($M = 0.981$, $SD = 0.547$) ($F_{1,26} = 4.43$, $p = 0.0402$). However, the individual spectral power was not significantly different between simultaneous mode and sequential mode ($F_{1,26} = 0.70$, $p = 0.4069$).

Result revealed a significant main effect of collaboration mode for task performance and brain activity. It showed that collaboration not only improved the group performance, but also elevated the individual performance within the group. In other words, participants had significantly better performance collaborating as a group member rather than completing a task alone.

E. Other Issues

It should be noted that the ITR reported in this study is not as high as other studies. One reason is that we want to test the feasibility and sustainability of SSVEP-based collaborative BCI. To make sure that the system is sustainable for future use in real life, three successful selections in a row is needed to make a robot movement or make a correction. These greatly increased the task completion time. We elevate the difficulty level of the task on purpose. Actually, most participants can use one successful selection to make a robot movement or make a correction. In the current system, the participant will take at least 200% more time as it is actually needed to focus on the visual stimuli and produce the command to move the robot. Meanwhile, the robot is a very simple LEGO demo. The Grab/Release movement takes around 1 second each and other robot movement around the 3 stations takes around 2 second each. During that time, the BCI system will not work in order to guarantee that the robot will not receive another command during the movement. On the whole, the robot movement will take around 40~45% of the task completion time. We believe that more advanced robots will integrate with the BCI system more efficiently and greatly reduce the task time, and therefore increase the ITR.

VI. CONCLUSION

This study investigated the effects of collaboration mode, luminance contrast and motor disability on task performance, brain activity and user evaluations. Results revealed significant main effects of collaboration mode and luminance contrast, while no effect of motor disability. These results could provide precious empirical data and invaluable insights to the real-world applicability of the SSVEP-based BCI applications for people with motor disabilities. Most importantly, this research demonstrated that people with motor disabilities can use C-BCI as efficient as able-bodied people, which proved the potential of C-BCI to help those with motor disabilities. Future research should focus on the layout of the visual stimuli when there are more targets so as to prevent the interference between each other. Different stage of the ALS patients should also be considered in order to customize the applications for all potential users. Meanwhile, the collaboration in this study uses a method of combination based on each participant's selection. Future research may attempt combining all the participants' brain signal at first and then process the combined EEG to get a selection.

References

[1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control," *Clin. Neurophysiol.*, vol. 113, no. 6, pp. 767–791, June 2002.

[2] Y. Li, C. S. Nam, B. B. Shadden, and S. L. Johnson, "A P300-based brain-computer interface: effects of interface type and screen size," *Int. J. Hum.-Comp. Interact.*, vol. 27, no. 1, pp. 52–68, 2010.

[3] E. W. Sellers and E. Donchin, "A P300-based brain-computer: Initial tests by ALS patients," *Clin. Neurophysiol.*, vol. 117, pp. 538–548, Mar. 2006.

[4] I. Volosyak, H. Cecotti, D. Valbuena, and A. Gräser, "Evaluation of the Bremen SSVEP based BCI in real world conditions," in *Proc. IEEE 11th Int. Conf. Rehabilitation Robotics*, Kyoto, 2009, pp. 322–331.

[5] Y. Wang, B. Hong, X. Gao, and S. Gao, "Implementation of a brain-computer interface based on three states of motor imagery," in *Proc 29th Annu. Int. Conf. IEEE EMBS*, 2007, pp. 5059–5062.

[6] E. M. Mugler, C. A. Ruf, S. Halder, M. Bensch, and A. Kübler, "Design and implementation of a P300-based brain-computer interface for controlling an internet browser," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 6, pp. 599–609, 2010.

[7] T. Ebrahimi, J. M. Vesin, and G. Garcia, "Brain-computer interface in multimedia communication," *IEEE Signal Process. Mag.*, vol. 20, no. 1, pp. 14–24, 2003.

[8] A. Kübler, E. M. Holz, A. Riccio, C. Zickler, T. Kaufmann, S. C. Kleih, P. Staiger-Sälzer, L. Desideri, E. J. Hoogerwerf, and D. Mattia, "The user-centered design as novel perspective for evaluating the usability of BCI-controlled applications," *PLoS One,* vol. 9, no. 12, pp. 1–22, 2014.

[9] M. A. Lebedev and M. A. Nicolelis, "Brain-machine interfaces: Past, present and future," *Trends Neurosci.*, vol. 29, no. 9, pp. 536–546, Sept. 2006.

[10] K. K. Ang and C. Guan, "Brain-computer interface for neurorehabilitation of upper limb after stroke," *Proc. IEEE*, vol. 103, no. 6, pp. 944–953, May 2015.

[11] K. K. Ang, K. S. G. Chua, K. S. Phua, C. Wang, Z. Y. Chin, C. W. K. Kuah, W. Low, and C. Guan, "A randomized controlled trial of EEG-based motor imagery brain-computer interface robotic rehabilitation for stroke," *Clin. EEG Neurosci.*, vol. 46, no. 4, pp. 310–320, 2014.

[12] Y. T. Wang, Y. Wang, and T. P. Jung, "A cell-phone based brain-computer interface for communication in daily life," *J. Neural Eng.*, vol. 8, no. 2, pp. 1–5, 2011.

[13] R. Poli, C. Cinel, F. Sepulveda, and A. Stoica, "Improving decision-making based on visual perception via a collaborative brain-computer interface," in *Proc. IEEE Int. Multi-Disciplinary Conf. Cognitive Methods in Situation Awareness and Decision Support*, 2013, pp. 1–8.

[14] C. S. Nam, J. Lee, and S. Bahn, "Brain-computer interface supported collaborative work: Implications for rehabilitation," in *Proc. 35th Annu. Int. Conf. IEEE EMBS*, Osaka, Japan, 2013, pp. 269–272.

[15] J. K. Chapin, K. A. Moxon, R. S. Markowitz, and M. A. L. Nicolelis, "Real-time control of a robot arm using simultaneously recorded neurons in the motor cortex," *Nat. Neurosci.*, vol. 2, no. 7, pp. 664–670, July 1999.

[16] G. R. Muller-Putz and G. Pfurtscheller, "Control of an electrical prosthesis with an SSVEP-based BCI," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 1, pp. 361–364, Jan. 2008.

[17] A. B. Schwartz, X. T. Cui, D. J. Weber, and D. W. Moran, "Brain-controlled interfaces: Movement restoration with neural prosthetics," *Neuron*, vol. 52, no. 1, pp. 205–220, Oct. 2006.

[18] C. J. Bell, P. Shenoy, R. Chalodhorn, and R. P. N. Rao, "Control of a humanoid robot by a noninvasive brain–computer interface in humans," *J. Neural Eng.*, vol. 5, no. 2, pp. 214–220, June 2008.

[19] G. Edlinger, C. Holzner, C. Guger, C. Groenegress, and M. Slater, "Brain-computer interfaces for goal orientated control of a virtual smart home environment," in *Proc. 4th Int. IEEE/EMBS Conf. Neural Eng.*, 2009, pp. 463–465.

[20] P. Isenberg, "Information visualization in co-located collaborative environments," in *Proc. Grace Hopper Celebration of Women in Computing*, 2007, pp. 223–229.

[21] P. Isenberg and S. Carpendale, "Interactive tree comparison for co-located collaborative information visualization," *IEEE Trans. Visual. Comp. Graphics*, vol. 13, no. 6, pp. 1232–1239, 2007.

[22] N. L. Kerr and R. S. Tindale, "Group performance and decision making," *Annu. Rev. Psychol.*, vol. 55, pp. 623–655, Feb. 2004.

[23] P. R. Laughlin, B. L. Bonner, and A. G. Miner, "Groups perform better than the best individuals on letters-to-numbers problems," *Organ. Behav. Hum. Decis. Process.*, vol. 88, no. 2, pp. 605–620, July 2002.

[24] M. P. Eckstein, K. Das, B. T. Pham, M. F. Peterson, C. K. Abbey, J. L. Sy, and B. Giesbrecht, "Neural decoding of collective wisdom with multi-brain computing," *NeuroImage*, vol. 59, pp. 94–108, Jan. 2012.

[25] R. Poli, C. Cinel, A. Matran-Fernandez, F. Sepulveda, and A. Stoica, "Towards cooperative brain-computer interfaces for space navigation," in *Proc. Int. Conf. Intelligent User Interfaces*, Santa Monica, CA, 2013, pp. 149–160.

[26] A. Stoica, "Multimind: Multi-brain signal fusion to exceed the power of a single brain," in *Proc. 3rd Int. Conf. Emerging Security Technologies*, Lisbon, 2012, pp. 94–98.

[27] Y. Wang and T. P. T. Jung, "A collaborative brain-computer interface for improving human performance," *Plos One*, vol. 6, no. 5, pp. 1–11, May 2011.

[28] P. Yuan, Y. Wang, W. Wu, H. Xu, X. Gao, and S. Gao, "Study on an online collaborative BCI to accelerate response to visual targets," in *Proc. 34th IEEE EMBS Conf.*, San Diego, CA, 2012, pp. 1736–1739.

[29] C. Guger, B. Z. Allison, B. Groβwindhager, R. Prückl, C. Hintermüller, C. Kapeller, M. Bruckner, G. Krausz, and G. Edlinger, "How many people could use an SSVEP BCI?," *Front. Neurosci*, vol. 6, pp. 1–6, Nov. 2012.

[30] G. Bin, X. Gao, Z. Yan, B. Hong, and S. Gao, "An online multi-channel SSVEP-based brain-computer interface using a canonical correlation analysis method," *J. Neural Eng.*, vol. 6, no. 4, pp. 1–6, 2009.

[31] I. Volosyak, "SSVEP-based Bremen-BCI interface–boosting information transfer rates," *J. Neural Eng.*, vol. 8, no. 3, pp. 1–11, 2011.

[32] J. P. Dmochowski, A. S. Greaves, and A. M. Norcia, "Maximally reliable spatial filtering of steady state visual evoked potentials," *NeuroImage*, vol. 109, pp. 63–72, Apr. 2015.

[33] D. Zhu, J. Bieger, G. G. Molina, and R. M. Aarts, "A survey of stimulation methods used in SSVEP-based BCIs," *Comput. Intell. Neurosci.*, vol. 2010, no. 2010, pp. 1–12, 2010. Article ID 702357, doi:10.1155/2010/702357.

[34] E. Elton, D. Johnson, C. Nicolle, and L. Clift, "Supporting the development of inclusive products: The effects of everyday ambient illumination levels and contrast on older adults' near visual acuity," *Ergonomics*, vol. 56, no. 5, pp. 803–817, 2013.

[35] F. W. Campbell and L. Maffei, "Electrophysiological evidence for the existence of orientation and size detectors in the human visual system," *J. Physiol.*, vol. 207, no. 3, pp. 635–652, 1970.

[36] H. Spekreijse, "Analysis of EEG responses in man evoked by sine wave modulated light," Ph.D. thesis, Universiteit van Amsterdam, The Netherlands, 1966.

[37] C. S. Nam, Y. Li, and S. Johnson, "Evaluation of P300-based brain-computer interface in real-world contexts," *Int. J. Hum.-Comp. Interact.*, vol. 26, no. 6, pp. 621–637, 2010.

[38] V. Zemon and J. Gordon, "Luminance-contrast mechanisms in humans: visual evoked potentials and a nonlinear model," *Vision Res.*, vol. 46, no. 24, pp. 4163–4180, 2006.

[39] J. Bieger and G. Garcia-Molina, "Light stimulation properties to influence brain activity: A brain-computer interface application," Phillips Research, Amsterdam, The Netherlands, Tech. Note TN-2010-00315, 2010.

[40] J. I. Münβinger, S. Halder, S. C. Kleih, A. Furdea, V. Raco, A. Hösle, and A. Kübler, "Brain painting: First evaluation of a new brain-computer interface application with ALS-patients and healthy volunteers," *Front. Neurosci.*, vol. 4, no. 182, pp. 1–11, 2010.

[41] J. H. Lim, H. J. Hwang, C. H. Han, K. Y. Jung, and C. H. Im, "Classification of binary intentions for individuals with impaired oculomotor function: 'Eyes-closed' SSVEP-based brain-computer interface (BCI)," *J. Neural Eng.*, vol. 10, no. 2, pp. 9–18, 2013.

[42] B. Allison, T. Lüth, D. Valbuena, A. Teymourian, I. Volosyak, and A. Gräser, "BCI demographics: How many (and what kinds of) people can use an SSVEP BCI?," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 2, pp. 107–116, Apr. 2010.

[43] P. Whittle, "The psychophysics of contrast brightness," in *Lightness, Brightness, and Transparency*, A. L. Gilchrist, Ed. Hillsdale, NJ: Lawrence Erlbaum, 1994, pp. 35–110.

[44] J. R. Pierce, *An Introduction to Information Theory: Symbols, Signals and Noise*. New York: Dover, 1980, pp. 145–165.

[45] J. R. Wolpaw, H. Ramoser, D. J. McFarland, and G. Pfurtscheller, "EEG-based communication: Improved accuracy by response verification," *IEEE Trans. Rehabil. Eng.*, vol. 6, no. 3, pp. 326–333, Sept. 1998.

[46] S. K. Mitra, *Digital Signal Processing: A Computer-Based Approach, with DSP Laboratory Using MATLAB*. New York: McGraw-Hill, 2002.

[47] F. Sharbrough, G. E. Chatrian, R. P. Lüders, H. M. Nuwer, and T. W. Picton, "American electroencephalographic society guidelines for standard electrode position nomenclature," *J. Clin. Neurophysiol.,* vol. 8, no. 2, pp. 200–202, 1991.

[48] G. Sanchez, P. F. Diez, E. Avila, and E. L. Leber, "Simple communication using a SSVEP-based BCI," *J. Phys. Conf. Ser.*, vol. 332, no. 1, Dec. 2011.

[49] R. S. Leow, F. Ibrahim, and M. Moghavvemi, "Development of a steady state visual evoked potential (SSVEP)-based brain computer interface (BCI) system," in *Proc. Int. Conf. Intelligent and Advanced Systems*, Kuala Lumpur, Malaysia, 2007, pp. 321–324.

[50] J. J. Higgins, *Introduction to Modern Nonparametric Statistics*. Pacific Grove, CA: Brooks/Cole, 2003.

[51] R. P. Baron, N. L. Kerr, and N. Miller, *Group Process, Group Decision, Group Action*. Pacific Grove, CA: Brooks/Cole, 1992.

[52] R. Brown, *Group Processes*, 2nd ed. Oxford, UK: Blackwell, 2000.

[53] S. Wuchty, B. F. Jones, and B. Uzzi, "The increasing dominance of teams in production of knowledge," *Science*, vol. 316, no. 5827, pp. 1036–1039, May 2007.

[54] J. R. Aiello and E. A. Douthitt, "Social facilitation from Triplett to electronic performance monitoring," *Group Dyn.*, vol. 5, no. 3, pp. 163–180, Sept. 2001.

[55] N. Triplett, "The dynamogenic factors in pace-making competition," *Am J. Psychol.*, vol. 9, no. 4, pp. 507–533, July 1898.

[56] M. Steriade and R. W. McCarley, *Brainstem Control of Wakefulness and Sleep*. New York: Plenum, 1990.

[57] Y. Li, S. Bahn, C. S. Nam, and J. Lee, "Effects of luminosity contrast and stimulus duration on user performance and preference in a P300-based brain-computer interface," *Int. J. Hum.-Comp. Interact.*, vol. 30, no. 2, pp. 151–163, 2014.

[58] C. D. Wickens, J. D. Lee, Y. D. Liu, and S. Gordon-Becker, *An Introduction to Human Factors Engineering*, 2nd ed. Upper Saddle River, NJ: Prentice Hall, 2004.

[59] F. Piccione, F. Giorgi, P. Tonin, K. Priftis, S. Giove, S. Silvoni, G. Palmas, and F. Beverina, "P300-based brain computer interface: Reliability and performance in healthy and paralyzed participants," *Clin. Neurophysiol.*, vol. 117, no. 3, pp. 531–537, Mar. 2006.

[60] L. M. McCane, E. W. Sellers, D. J. McFarland, J. N. Mak, C. S. Carmack, D. Zeitlin, J. R. Wolpaw, and T. M. Vaughan, "Brain-computer interface (BCI) evaluation in people with amyotrophic lateral sclerosis," *Amyotroph. Lat. Scl. FR. Degen.*, vol. 15, no. 3-4, pp. 207–215, Feb. 2014.