Commanding a Brain-Controlled Wheelchair Using Steady-State Somatosensory Evoked Potentials

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***Abstract*— In this work, we propose a novel brain-controlled wheelchair, one of the major applications of brain–machine interfaces (BMIs), that allows an individual with mobility impairments to perform daily living activities independently. Specifically, we propose to use a steady-state somatosensory evoked potential (SSSEP) paradigm, which elicits brain responses to tactile stimulation of specific frequencies, for a user's intention to control a wheelchair. In our system, a user had three possible commands by concentrating on one of three vibration stimuli, which were attached to the left-hand, right-hand, and right-foot, to selectively control the wheelchair. The three stimuli were associated with three wheelchair commands: turn-left, turn-right, and move-forward. From a machine learning perspective, we also devise a novel feature representation by combining spatial and spectral characteristics of brain signals. In order to validate the effectiveness of the proposed SSSEP-based system, we considered two different tasks: 1) a simple obstacle-avoidance task within a limited time and; 2) a driving task along the predefined trajectory of about 40 m length, where there were a narrow pathway, a door, and obstacles. In both experiments, we recruited 12 subjects and compared the average time of motor imagery (MI) and SSSEP-based controls to complete the task. With the SSSEP-based control, all subjects successfully completed the task without making any collision while four subjects failed it with MI-based control. It is also noteworthy that in terms of the average time to complete the task, the SSSEP-based control outperformed the MI-based control. In the other more challenging task, all subjects successfully reached the target location.**

***Index Terms*— Brain–machine interfaces (BMIs), brain-controlled wheelchair, electroencephalography (EEG), steady-state somatosensory evoked potential (SSSEP), motor imagery (MI).**

I. Introduction

RECENT advances in brain–machine interfaces (BMIs), allowing people to communicate with external devices through thoughts rather than the peripheral nervous system [1]–[3] have witnessed their true potential for enhancing human performance, particularly for the disabled. For example, BMI technology has helped individuals with paralysis to drink water by steering a robot arm [4], [5], communicate by typing letters on a screen [6], and ambulate by controlling a powered wheelchair [7]. Of these advanced applications, in this paper, we focus on the so-called brain-controlled wheelchair based on non-invasive electroencephalography (EEG) signals.

According to the study initiated by the Christopher & Dana Reeve Foundation,[1] there are approximately 6 million people (1 in 50) with paralysis in the United States, caused by amyotrophic lateral sclerosis (ALS), spinal cord injury (SCI), brainstem stroke, and cerebral palsy, among other conditions. Although people with paralysis are unable to control their body freely, many may still think normally. In this respect, the brain-controlled wheelchair can help improve their quality of life by providing with independent mobility for their daily living activities. Therefore, the brain-controlled wheelchair has generated great interest in the field.

From an implementation perspective, the brain-controlled wheelchair system is composed of four parts: 1) EEG signal acquisition, 2) signal preprocessing, 3) feature extraction, and 4) user intention identification. The latter three steps are highly dependent on brain signal induction, i.e., the BMI paradigm. In the field, three different BMI paradigms are used: 1) oddball paradigm, which elicits a positive wave in response to rare events at a latency of 300 ms (P300) in near the central and parietal cortices [8]–[10], (2) steady-state visually evoked potential (SSVEP), which causes a high amplitude wave of a specific frequency in brain signals that matches the target stimulus in the occipital and parietal lobes [11], and 3) motor imagery (MI) paradigm, which evokes event-related (de)synchronized signals in the sensorimotor cortex [12], [13]. Despite their successful application to brain-controlled wheelchair, these paradigms are limited due to their requirements for visual attention to the stimuli (P300 and SSVEP) or an illiteracy problem[2] (MI). The advantages and disadvantages of these paradigms for brain-controlled wheelchair are summarized in Table I.

Recently, Müller-Putz *et al.* demonstrated that steady-state somatosensory evoked potential (SSSEP) induced by tactile stimulation could be used for BMIs [15]. The physiological background of this paradigm is that when it is given

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[1] http://www.christopherreeve.org/

[2] It is estimated that 20%–25% of subjects are unable to induce brain signals for MI-based BMIs [14].

TABLE I
ADVANTAGES AND DISADVANTAGES OF THE BMI PARADIGMS FOR BRAIN-CONTROLLED WHEELCHAIR

Paradigms	Characteristics	Advantages	Disadvantages
P300	Evoked/ endogenous	The system can extend to many classes with a high accuracy because of relatively evident signal patterns.	Many trials need to be conducted for commands extraction. (normally more than 5 times)
SSVEP	Evoked/ endogenous	The system can recognize user intention with a high accuracy in minimal training time.	The user experiences significant fatigue because of exposure to a visual stimulus for a long time.
MI	Spontaneous	The user can use induce brain patterns at his/her own will.	The number of commands is limited in motor imagery patterns, and intensive training may be required (long calibration time).
SSSEP	Evoked/ endogenous/ spontaneous	The user can induce brain signals at his/her own will as MI and further the patterns are relatively evident thanks to the use of external stimuli.	The screening is need to constructing vibration stimuli for stable accuracy in the system.

for a tactile stimulation, such as a periodic vibration at a specific frequency, a human brain elicits evoked potentials at the same frequency of the tactile stimulation. However, due to its poor performance in practical interfaces, SSSEP-based BMI has not been extensively investigated until Nam *et al.* devised a machine learning-based feature extraction method [16].

Motivated by the aforementioned work [15], [16], in this paper, we propose a novel SSSEP-based brain-controlled wheelchair system. Specifically, transducers for vibration stimulation at different frequencies were attached to a subject's hands and foot. A subject could thus control a powered wheelchair by selectively concentrating on one of the vibration stimuli provided to different body parts, i.e., hand or foot. It is noteworthy that previous brain-controlled wheelchair systems used the conventional BMI paradigms of P300 [17] or SSVEP [21], where the subject was required to keep their eyes focused on the target stimulus, thus losing their vision to the environment. In contrast, our SSSEP-based brain-controlled wheelchair system is free from such limitations. Due to the use of an evoked or endogenous paradigm, we can achieve high accuracy of identifying a user's intentions without being suffered from the illiteracy problem, which is one of the main challenges in an MI-based BMI.

For better identification of a subject's moving intention, we also proposed a new feature representation that combines spatial and spectral features. The rationale of our feature combination is based on the physiological characteristics of the human brain. The stimulation of different body parts induces spatially distinct patterns and the vibration stimulation with different frequencies, causing a change in the amplitudes of the respective frequencies, according to a subject's concentration on a specific stimulus.

To validate the effectiveness of our proposed system, we conducted an experiment where a subject was required to reach a goal line while avoiding obstacles located in their path. Our results from 12 subjects successfully demonstrated the feasibility and suitability of using an SSSEP paradigm with feature combinations for the brain-controlled wheelchair. The main contributions of our work are three-fold: 1) to the best of our knowledge, this is the first work to utilize SSSEP paradigm for BMI-based wheelchair control, 2) the combination of spatial and spectral features enhances classification accuracy, and 3) the general possible use of the BMI technology, not suffering from an illiteracy problem.

This paper is organized as follows. In Section II, we briefly introduce previous research regarding the brain-controlled wheelchair. The framework of our SSSEP-based wheelchair system, our methods for EEG pattern recognition, and experimental settings are detailed in Section III. The experimental results and discussion are presented in Section IV and Section V, respectively. Finally, we conclude by summarizing the proposed system and providing directions for future work in Section VI.

II. RELATED WORK

As mentioned previously, many research groups have broadly used three EEG potentials in the brain-controlled wheelchair system. Table II provides the brief characteristics of the existing systems.

P300-based wheelchair control systems were developed using visual stimuli (independently by Rebsamen *et al.* [17], Lopes *et al.* [18], and Iturrate *et al.* [19]). In these systems, the user focused on a visual stimulus to command a wheelchair with the oddball paradigm. Tactile P300-based systems were also developed by Kaufmann *et al.* [20]. The user concentrated on one of the stimuli that attached on the left or right thigh, abdomen, and lower neck to command a wheelchair to turn left or right and move forward or backward. In these P300-based systems, the user can control a wheelchair with high accuracy. However, many trials are needed for increased accuracy in this paradigm (typically more than five times).

The SSVEP-based wheelchair control systems were developed using visual flickering stimuli (independently by Müller *et al.* [21], Diez *et al.* [22], and Singla *et al.* [23]). In these systems, the user gazed at a visual flickering stimulus to command a wheelchair and controlled the wheelchair with high accuracy and minimal training. However, if users were exposed to a visual stimulus for a long period, they could experience significant fatigue and sore eyes. In addition, some patients (such as those with ALS or locked-in syndrome [LIS]) lose their volitional eye control in late disease stages. At the end stages of ALS, individuals lose the subtle vibrating

TABLE II
SUMMARY OF THE EXISTING BRAIN-CONTROLLED WHEELCHAIR SYSTEMS

Paradigms	Authors	# commands	Stimuli design
Visual - P300	Rebsamen *et al.* [17]	15	(2, 4, and 8 m) × (-60°, -30°, 0°, 30°, and 60°) as a grid
	Lopes *et al.* [18]	9	3 × 3 destination matrix on the screen as oddball
	Iturrate *et al.* [19]	6	Turn left-right(45° and 90°), moving forward, and back are displayed randomly on the screen
Tactile - P300	Kaufmann *et al.* [20]	4	Vibration stimuli on the left thigh, right thigh, abdomen, and lower neck
SSVEP	Müller *et al.* [21]	4	Flickering stimuli on the screen using 4 frequencies of 5.6, 6.4, 6.9, and 8.0 Hz
	Diez *et al.* [22]	4	Flickering stimuli on the screen using 4 frequencies of 37, 38, 39, and 40 Hz
	Singla *et al.* [23]	4	Flickering stimuli on the screen using 4 frequencies of 7, 9, 11, and 13 Hz and 4 colors of green, red, blue, and violet
MI	Gálan *et al.* [24]	3	Left hand imagination, rest, and word association
	K.-W. Choi [25]	3	Imagination of left/right-hand and foot movements
	Huang *et al.* [26]	5	Right wrist extension, left wrist extension and relaxation
Hybrid (P300 and SSVEP)	Li *et al.* [27]	4	4 stimuli as oddball and flickering stimuli within 7.5 Hz
Hybrid (MI and P300)	Long *et al.* [28]	5	Imagination of left/right-hand, foot, focusing on a specific flashing as oddball
Hybrid (MI and SSVEP)	Cao *et al.* [29]	7	Imagination of left/right-hand, and focusing on flashed in 7, 8, 9, and 11 Hz

movements of their eyes [30]. Therefore, wheelchair control systems, which are based on visual stimuli, cannot offer convenience and efficiency to all users.

MI-based wheelchair control systems were developed using event-related (de)synchronization patterns in the mu (8–13 Hz) and beta (14–30 Hz) bands (independently by Gálan *et al.* [24], K.-W. Choi [25], and Huang *et al.* [26]). The user imagined a movement of the left or right hand or foot to command a wheelchair, turning left or right or moving forward. In these systems, the user could control the wheelchair without any limitations on eye movements. However, the number of classes is limited, as discrimination between different motor imagery patterns becomes more difficult with increasing class number; therefore, intensive training may be required. Above all, the illiteracy problem has not yet been solved.

To overcome the limitations in each of these paradigms, several groups have developed hybrid systems using the P300, SSVEP, and MI paradigms. Li *et al.* developed a P300-SSVEP-based hybrid wheelchair control system [27]. This system can recognize user intention within a minimal number of trials, however, the user can experience more fatigue and sore eyes because of complex visual stimuli. Long *et al.* and Cao *et al.* proposed a hybrid wheelchair control system based on the MI-P300 [28] and MI-SSVEP [29]. In these systems, the user can control many wheelchair functions (e.g., acceleration, deceleration, speed, etc.). However, the user requires longer training because of the two modalities in these paradigms. These systems also do not consider the issue of illiteracy.

In this work, we proposed an SSSEP-based wheelchair control system, which has not yet been thoroughly evaluated. SSSEP can overcome the limitations of the aforementioned paradigms because it relies on a potential based on the somatosensory system in the human nervous system. Furthermore, the user can use this paradigm without any gaze limitation, as SSSEP is evoked by concentration on a vibration stimuli. Therefore, individuals can use the SSSEP-based wheelchair control system continuously and easily [31], [32]. Also, the number of wheelchair commands can be extended by using additional vibration stimuli.

III. MATERIALS AND METHODS

A. Participants

Twelve healthy subjects (1 female and 11 male, mean±standard deviation: 28± 2.5 [range: 24–34 years]) were recruited for our experiments. Seven subjects (S1, S2, S3, S4, S5, S8, and S10) had BMI experiences, while the other five subjects had no experience of BMI before. No subjects reported any neurological disorders. All experiments were conducted according to the principles expressed in the Declaration of Helsinki. This study was reviewed and approved by the Institutional Review Board at Korea University (1040548-KU-IRB-15-9-A-2) and written informed consent was obtained from all participants before the experiments.

B. Data Acquisition

1) Acquisition Environment for SSSEP: The human sensory systems have specific resonance ranges individually [34]. Therefore, the optimal frequency range of the somatosensory stimulation called as resonance-like frequency has to be investigated before using SSSEP-based BMI system [33]. To determine the subject-specific frequency, a screening measurement was conducted by stimulating the subject's index finger (left and right hand) and big toe of right foot with

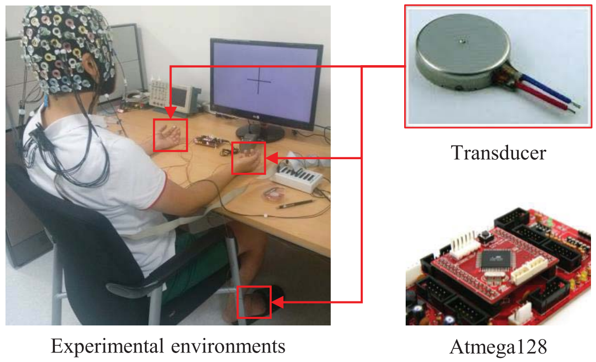


Fig. 1. Experimental environments for data acquisition. The vibratory stimulation was administered by a round shaped-vibration motor with a radius of 1 cm. The motor was controlled by a micro controller unit (MCU, Atmega128).

stimulation frequencies from 13 Hz to 35 Hz for 5 s, with an interval of 2 Hz [15]. The transducer, which evokes vibration stimuli, was controlled by a micro controller unit (MCU), Atmega128 (Fig. 1). The vibration frequency was constructed using the WinAVR open source software and programmed and downloaded onto the Atmega128. The MATLAB operated the vibration frequencies of the transducer. The transducers conducted using a box signal that has 50% duty cycle and a vibration amplitude of 3.67 voltage.

The subject concentrated on one of the attached transducers by following the command displayed on a screen. The subject concentrated when the term "Attention" was displayed. When a mathematical equation was displayed, the subjects calculated the equation (by either adding or subtracting randomly appearing numbers) to avoid concentrating on the transducer during the screening. After the screening acquired data were calculated using FFT to show power changes in the C3, Cz, and C4 channels during stimulation [15]. Three frequencies with the highest amplitudes during stimulation for the left and right hand and foot were selected as subject-specific vibration frequencies for the following experiment paradigm.

EEG signals were acquired via a BrainAmp (Brain Product) device with 30 Ag/AgCl electrodes according to the 10/20 international system (Fig. 2). The reference and grounding electrode were mounted on the FCz and Fpz respectively. The sampling frequency rate was 250 Hz, and a 60 Hz notch filter was applied to the EEG signal. All impedances were maintained below 10 kΩ.

The subject sat in a comfortable armchair facing a 24-in LCD computer screen (Fig. 1). The distance between the subject's eyes and the screen was approximately 60 cm. Each trial started by fixating on a cross in the middle of the screen. After 2 s, one of three arrows (left, right, and up) randomly appeared on the screen for 5 s. Once the arrow appeared, the subject concentrated on the vibration stimuli attached each part of the body (i.e., left-hand, right-hand, and right-foot) based on the arrow direction (Fig. 3). During the next 5 s, a fixation cross appeared on the screen again. For training classifiers, we collected 90 trials per subject in total (30 trials per class).

2) Acquisition Environment for MI: We also conducted an additional experiment using the MI paradigm to

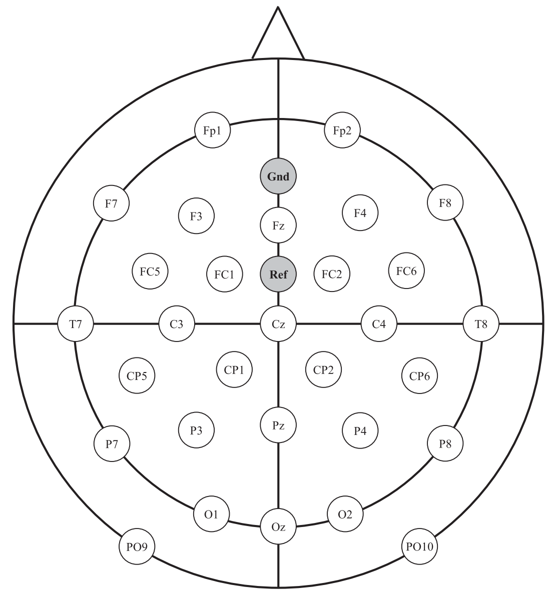


Fig. 2. Placements of the 30 electrodes used in our experiment (included reference and ground electrode) in international 10/20 system.

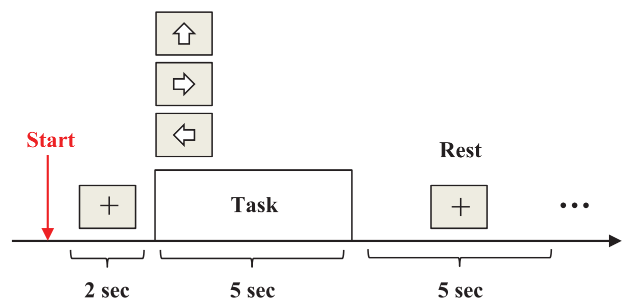


Fig. 3. Experimental paradigm for the data acquisition. When an arrow appeared on the monitor, the subject concentrated on one of three vibration stimuli based on the arrow (left direction-left hand, right direction-right hand, and up direction-foot).

compare performances, specifically for MI illiterate subjects. The same experimental paradigm was used for MI data collection. All subjects who participated in the SSSEP experiments also participated in the experiment. The subjects imagined movements of the left-hand, the right-hand, and the right-foot according to the arrows displayed on the screen (left, right, and up). We collected 90 trials (30 trials per class) from each subject.

C. Data Processing

In this work, we combined both spatial and spectral features to utilize best the physiological characteristics of EEG signals. Fig. 4 shows a schematic overview of the proposed feature extraction method.

For spatial-features (SF), we used a CSP algorithm that finds spatial filters to maximize the signal power difference between classes [35]–[39]. In our experiments, the CSP was trained by means of one-versus-rest (OVR) strategy, such as Left-hand versus Other, Right-hand versus Other, and Foot versus Other. In the transformation matrix from CSP, the

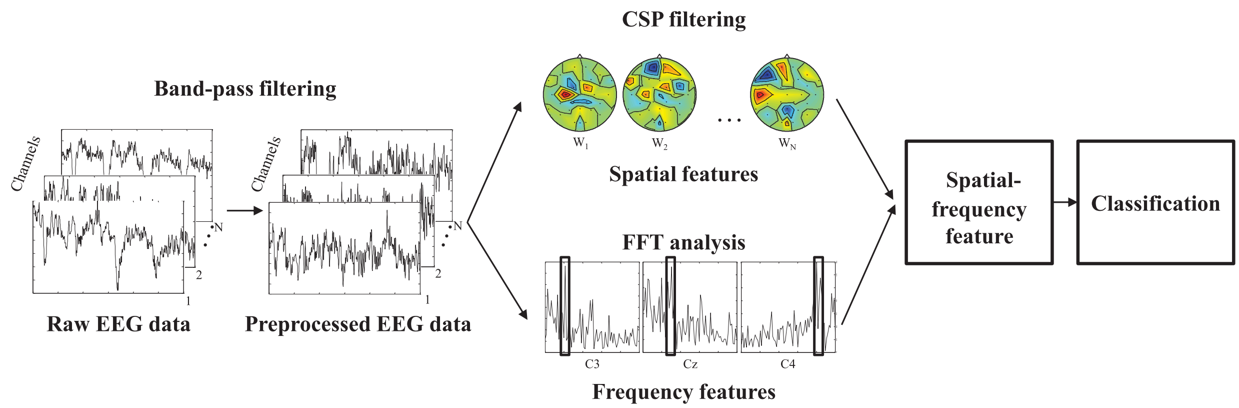


Fig. 4. Dataflow of the spatial-frequency feature extraction using FFT and CSP filtering from EEG data.

logarithmic variances of the first three and last three columns were used as a spatial feature.

For the extraction of the spectral features, called as frequency-feature (FF), we used FFT analysis in C3, Cz, C4 electrodes. Each amplitude of the three subject-specific frequencies was extracted from the acquired raw EEG data. The features (SF and FF) were concatenated

$$f = [a_1, \quad \ldots, \quad a_n, \quad b_{11}, \quad b_{12}, \quad \ldots, \quad b_{ij}] \qquad (1)$$

where n is the number of SFs, and i is the amplitude of three subject-specific frequencies. j is also the number of channels ($j \in \{C3, Cz, C4\}$). This feature was normalized by subtracting their empirical means and dividing by the empirical standard deviations as estimated on the training sets to re-scale the two types of features after feature concatenation.

For classification, we used regularized linear discriminant analysis (RLDA). The RLDA is a method that can improve classification performance by adding a regularization term to a covariance matrix [40]–[42] when there are an insufficient number of training samples. One parameter (γ) that controls the importance of the regularized term is a hyperparameter of a model. In our study, the value of γ was chosen using an analytic method to calculate the optimal shrinkage parameter for certain directions of shrinkage was found. This approach aims at minimizing the Frobenius norm between the shrunk covariance matrix and the *unknown* true covariance matrix σ. Let $(x_k)_i$ and $(\hat{\mu})_i$ denote the ith element of the vector x_k and $\hat{\mu}$, respectively, and s_{ij} denote the element in the ith row and jth column of $\hat{\sigma}$. Then we determine the value of γ with the following:

$$\gamma = \frac{n}{(n-1)^2} \frac{\sum_{i,j=1}^{d} \mathrm{var}_k(z_{ij}(k))}{\sum_{i \neq j} s_{ij}^2 + \sum_i (s_{ii} - v)^2} \qquad (2)$$

where $z_{ij}(k) = ((x_k)_i - (\hat{\mu})_i)((x_k)_j - (\hat{\mu})_j)$. In effect, this leads to stronger shrinkage as the large sample-to-sample variance of entries in the empirical covariance is penalized. Alternatively, a nested cross-validation technique, which is commonly used in the literature, can be also used for determination of γ, but because of its easy implementation and computational efficiency, in this work, we use this analytic approach.

Three RLDA classifiers were also trained by means of OVR strategy (i.e., Left-hand versus Other, Right-hand versus Other, and Foot versus Other) for our experiments. In a decision, one class that had the highest output value was determined as the final output.

IV. Experimental Results

To validate the effectiveness of our proposed SSSEP-based wheelchair system, we conducted two online and one offline experiments. Specifically, in the first online experiment, the subjects were asked to reach a target location within 5 min without making any collision to obstacles placed in the pathway. In the second online experiment, the subjects were asked to reach a target location with more challenging tasks, such as going through narrow pathways and a door. The offline experiment was to further analyze the effectiveness of the proposed SSF and to show the applicability of SSSEP-based BMI for BMI illiteracy.

A. Online Experiment 1: Simple Course With Obstacle-Avoidance

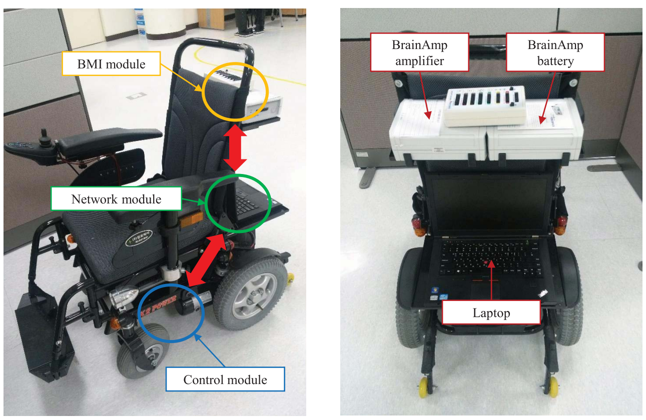
In the SSSEP-based wheelchair system, concentration on one stimulus was used to command the wheelchair. The stimuli (vibration motors) were attached to the left and right hands, and a foot, each of which corresponded to the commands of turn-left, turn-right, and move-forward.

Additional EMG signal was also used to make an emergency stop by moving the tongue. For the emergency stop, an electrode was attached to the right cheek, which measured the EMG signal from the tongue [25]. The EMG signal was sampled at 250 Hz. The intentional stop by the subject was recognized by a simple threshold value. If the power value of the EMG signal exceeded the threshold value, the wheelchair stopped slowly.

The K2 POWER model of WHEELOPIA, which has rear-wheel drive and a power-assist system on the manual wheelchair frame (Fig. 5), was used in this experiment as the wheelchair. The wheelchair system consisted of three main components: a BMI module, a network module, and a control module. In the BMI module, the EEG signal was recorded and analyzed for command extraction. The resultant command was transmitted to the control module via the network module. In the control module, the command was converted into an electrical signal and amplified to drive the two main wheel motors.

TABLE III
SUBJECT-SPECIFIC FREQUENCIES AND RESULTS OF MI- AND SSSEP-BASED WHEELCHAIR CONTROL EXPERIMENTS

Sub.	Sub.−specific frequencies [Hz]			SSSEP control		MI control		Joystick control [sec]
	Left hand	Right hand	Foot	Total time [sec]	EMG stop	Total time [sec]	EMG stop	
S1	21	15	23	158	6	>300 (Fail)	28	36
S2	19	13	29	105	4	>300 (Fail)	31	42
S3	25	13	29	113	5	>300 (Fail)	23	36
S4	15	13	23	86	3	109	5	43
S5	17	23	29	75	2	76	2	50
S6	17	31	25	69	1	71	1	47
S7	15	21	29	109	3	114	6	39
S8	13	19	31	115	4	136	9	46
S9	17	29	25	95	3	121	3	42
S10	23	17	19	132	6	>300 (Fail)	26	51
S11	21	17	13	102	3	105	2	43
S12	17	22	27	65	2	146	13	42
Mean±Std				102±26	4±1	173±95	12±11	43±4



(a) (b)

Fig. 5. (a) Modules of the SSSEP-based brain-controlled wheelchair system. The system consists of three main modules: BMI module, network module, and control module. EEG signals were acquired in the BMI module and transmitted to the control module via the network module. (b) Back view of our wheelchair system.

In this experiment, the subjects drove a wheelchair on the course with two obstacles (Fig. 6), based on MI and SSSEP, in a same day. In MI-based control experiments, three commands for the wheelchair (turn-left, turn-right, and move-forward) were extracted from the EEG signal of the subjects during the left-right hand and foot movement imagery. In SSSEP-based control experiments, the three commands for the wheelchair were extracted from the EEG signal of the subjects during concentration.

We used a motor driver (NT-M-DCDM2430, NTrex Co.) for smooth starting of the wheelchair. Using the motor driver, the wheelchair was moved during $4 \sim 5$ s by the control signal of 2 s from the network module (i.e., The Laptop) to motor driver within the control module.[3] And the wheels rotated at a 1:2 rate, when the command is related a turning (i.e., when turning left, the right wheel rotated in double time compared with the left wheel). A velocity of the wheelchair was approximately 0.3 m/s. The shortest pathway from the start to the goal line was approximately 10 m. For comparative analysis, reaching time by BMI control and the joystick method were measured. The joystick had only three commands (turn-left, turn-right, and move-forward).

Fig. 6 presents the trajectories of the wheelchair, which were made by subjects with both MI- and SSSEP-based controls. In MI-based wheelchair control, four subjects (S1, S2, S3, and S10) failed to reach the target location within 5 min. On the other hand, in SSSEP-based wheelchair control, all subjects successfully completed the task without making any collision.

Table III presents subject-specific vibration frequencies and the total control time in the obstacle-avoidance experiment. In MI-based control, the average reaching time was 173 ± 95 s and the emergency stops with EMG signals by tongue movement were made $12\pm$ 11 times. In SSSEP-based control, the reaching time was 102 ± 26 s on average, 71 s shorter than MI-based control, and the average number of emergency stops was 4 ± 1 times. It is interesting that the subject S6 who had not have any BMI experience, recorded the shortest time (71 s) among all subjects to complete the task successfully. For reference, the reaching time with a joystick control was 43 ± 4 s on average.

B. Online Experiment 2: Complex Course With Difficult Tasks

In this more challenging task, all subjects were also asked to drive a wheelchair to follow predefined trajectory, whose approximate length was 40 m, by moving through narrow straightways (F1 and F2), a doorway (D), and turning (R1, R2, and L) with no collision to obstacles (Fig. 7). For example, in F2 (the width is 0.61 m and length is 1.08 m), the wheelchair keep moving in the narrow pathway (the width is 1.37 m and length is 6.5 m).

[3]We used a motor driver (NT-M-DCDM2430), which can control two motors simultaneously. The motor driver can set a "The delay in acceleration" before the motor working, for smooth starting. We set as 1 s to "The delay in acceleration" for smooth starting of the wheelchair. And after the wheelchair moving, the wheels kept move for approximately $1 \sim 2$ s by the inertia effect. Therefore, the network module transferred the command signal of 2 s to the motor driver for movements of the wheelchair during $4 \sim 5$ s.

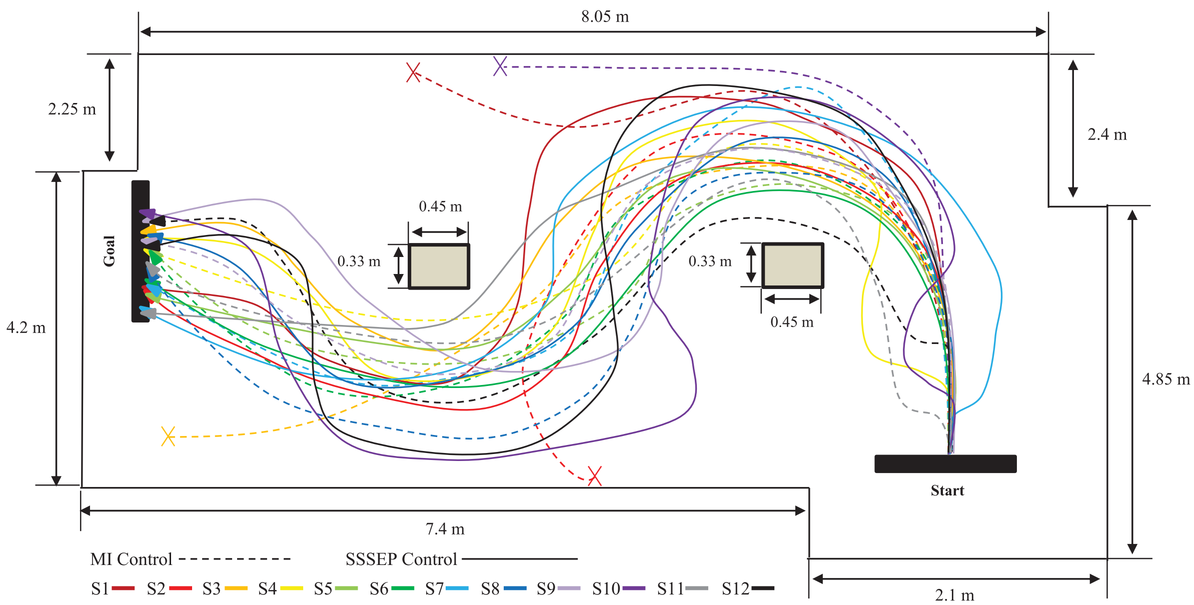


Fig. 6. Trajectories of a wheelchair controlled by MI- (dotted line) and SSSEP-induced (solid line) brain signals.

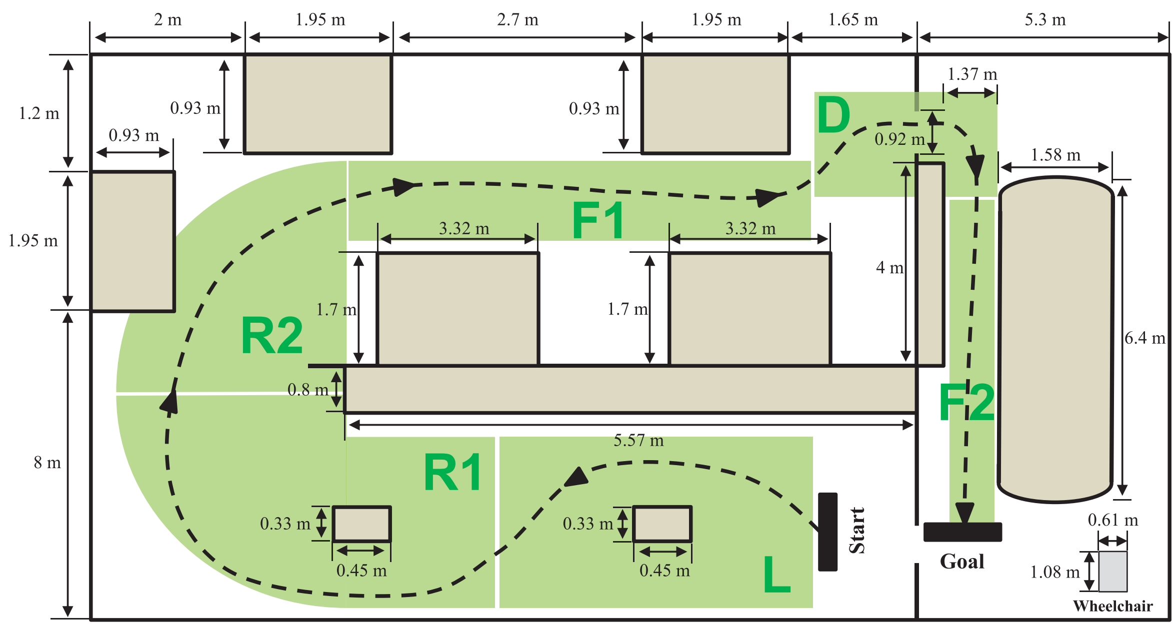


Fig. 7. Wheelchair control experiment with difficult tasks (L, R1, and R2: an obstacle-avoidance, F1 and F2: a narrow straightway, D: a doorway).

Table IV presents the results of the experiment with challenging tasks. All subjects also successfully reached the target location without any collision. The subjects recorded 298 ± 46 s on average to complete the task.

The entire experimental setup and concepts of our wheelchair system are uploaded to YouTube (https://youtu.be/xobotGROmAg).

C. Offline Experiment: Cross-Validation Analysis

To validate the effectiveness of the proposed spatial-frequency features, we conducted offline experiments using a 6-fold cross-validation in both MI and SSSEP. The acquired data, by MI and SSSEP, was divided to the 6-fold randomly without any overlap. And then, 5-folds were selected for training and remaining 1-fold was used for testing. The testing fold was changed in chronological. This process was iterated six times, and results were averaged to measure the accuracy.

In this experiment, the MI data was band-pass filtered in the range of 0.5 Hz and 40 Hz. And then, features were extracted using only CSP filtering. The SSSEP data was also band-pass filtered in the range of 0.5 Hz and 40 Hz. And then, three types of features were extracted using CSP filtering, FFT analysis, and feature combination. The CSP was trained by means of OVR strategy.

The RLDA was used in common as a classifier and was trained in the same manner. Specifically, three

TABLE IV
CONTROL TIME AND TRIALS OF SSSEP-BASED WHEELCHAIR CONTROL WITH DIFFICULT TASKS

Sub.	L		R1		R2		F1		D		F2		Total time [sec]
	Time	Trials	Time	Trials	Time	Trials	Time	Trials	Time	Trials	Time	Trials	
S1	56	1	40	1	42	1	25	2	51	3	57	1	271
S2	33	1	41	1	32	1	22	1	28	1	68	1	224
S3	48	1	52	1	37	1	28	1	45	5	91	1	301
S4	51	1	45	1	48	1	31	1	37	4	51	1	263
S5	46	1	40	1	34	1	42	1	60	7	71	1	293
S6	48	1	46	1	38	1	39	1	68	4	84	1	323
S7	42	1	52	1	55	1	35	1	50	3	43	1	277
S8	46	1	43	1	34	1	42	1	41	2	80	1	286
S9	36	1	40	1	35	1	32	1	45	3	73	1	261
S10	63	1	51	1	42	1	43	1	69	4	85	1	353
S11	75	1	48	2	46	1	35	2	57	6	131	2	392
S12	58	2	53	1	51	1	37	1	62	8	78	1	339
Mean±Std	50±11	1±0	45±5	1±0	41±7	1±0	34±6	1±0	51±12	4±2	76±22	1±0	298±46
Joystick	27	1	23	1	18	1	15	1	19	3	27	1	129

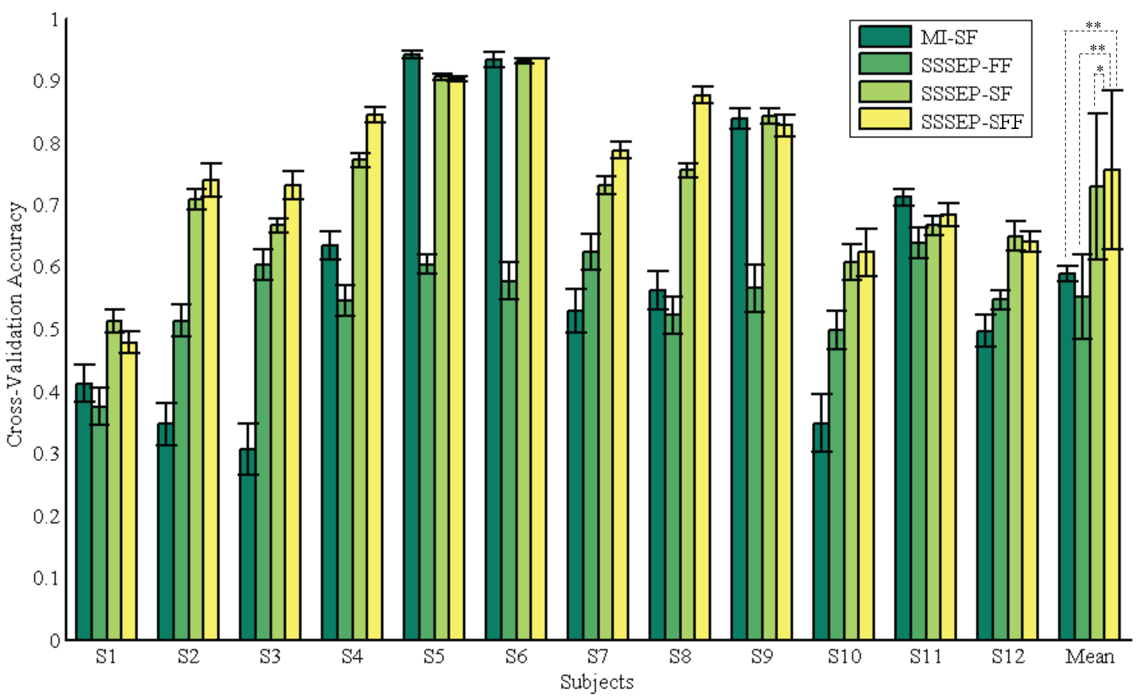


Fig. 8. Results of the cross-validation analysis within MI and the features of SSSEP (FF: the frequency feature, SF: the spatial feature, SFF: the spatial-frequency feature). The * and ** present a p-value from the paired t-test (*: $p < 0.05$, **: $p < 0.01$).

RLDA classifiers were also trained by OVR strategy. In a decision, one class that had the highest output value was determined as the final output.

Fig. 8 presents the cross-validation results of the acquired MI and SSSEP data. In this analysis, we investigated performances of the proposed SFF of SSSEP. The cross-validation was conducted, SSSEP first, using three features that are the FF by FFT analysis, the SF by CSP filtering, and the SFF by feature combination. In Fig. 8, various features had different performances in each of the subjects. Although the SF achieved high performance in four subjects (S1, S5, S9, and S12), the proposed SFF presented higher performance than the FF and SF in the other subjects. In order for better quantitative comparison among different feature types, we also performed statistical analysis via a paired t-test and the results were as follows: FF versus SFF ($p < 0.01$) and SF versus SFF ($p < 0.05$). Based on these results, the proposed SFF statistically outperformed the competing methods with a 95% confidence level.

To validate the feasibility of the SSSEP-based BMI among individuals with BMI illiteracy [14], MI-based cross-validation was also implemented in offline experiment (Fig. 8). As a result, three subjects (S2, S3, and S10) presented significantly improved accuracies. Specifically, the classification

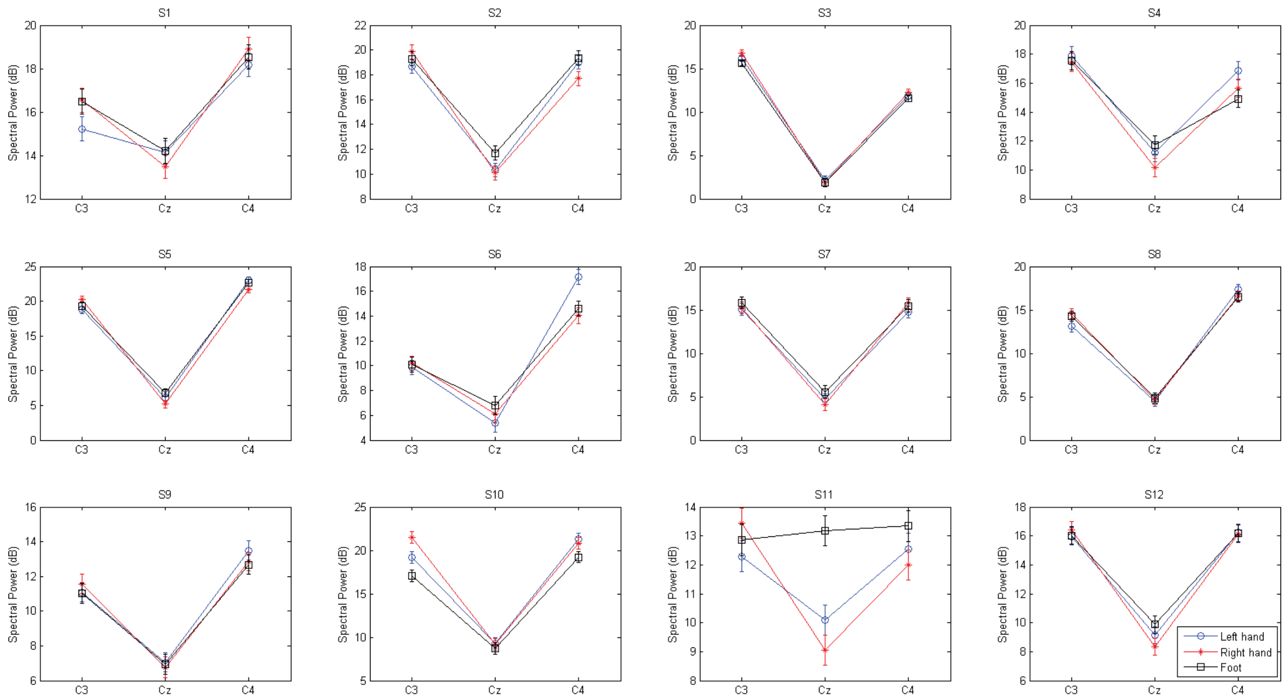


Fig. 9. Spectral power values of FF within all subjects from three tasks (concentrate on the vibration stimuli on the left-hand, right-hand, and foot).

accuracies of S2, S3, and S10 were 34.6± 3.4%, 30.6± 4.1%, and 34.7± 3.4%, respectively.

V. Discussion

In our experiments, all subjects were able to control a wheelchair by means of the MI- and SSSEP-based BMI. All subjects were even able to control with more challenging tasks of a narrow straightway and a doorway. While there was time variation among subjects, most subjects made many trials to go through a doorway (D), the task was not easy to go through even using a joystick (Table IV). Therefore, it is noteworthy that in an aspect of the wheelchair control, effectiveness of the SSSEP-based control was validated with more challenging tasks.

With the concern about tiredness after using BMI-based wheelchair control, we also asked subjects to complete a questionnaire after the experiments of wheelchair control based on MI and SSSEP. As a result, nine subjects answered that SSSEP-based control was less tired than MI-based control. Although more subjects were favorable to use SSSEP-based control in terms of tiredness, it would be interesting to further investigate the tiredness in a quantitative manner by analyzing EEG signals, which will be our forthcoming research issues.

In the feature extraction perspective, Nam *et al.* presented that the CSP could improve the discriminations of SSSEP after stimulation-specific frequency band filtering [16]. The main improvement of the results was based on stimulation-induced ERD/ERS features. In a similar way, Yao *et al.* had discovered and validated the feasibility of mechanical vibrotactile stimulation in the user's intention recognition [37], [38]. Even though they have utilized the vibrotactile stimulation and the CSP for improving the robustness of spatial features, however, they did not consider the spectral features which were an intrinsic characteristic of SSSEP. Hence, we employed the spacial as well as spectral information as a feature for the better classification of the SSSEP.

Fig. 9 presents the spectral power in three different tasks for all subjects. For S6 who achieved the best performance with FF-based cross-validation, the power values in each of the tasks (e.g., concentrating on the left-hand, right-hand or foot) was clearly distinguishable at each of the electrodes (C3, Cz, and C4). Spectral power values of the other subjects were also shown distinguishable values at each electrode. Based on these results, we argue that spectral features play an important role in improving performance with SSSEP-based BMI.

Fig. 10 presents each subject's topographical spatial patterns in SSSEP and MI tasks. Particularly, S3, who had 42.4% higher performance with SSSEP than performance with MI, presented that the SFs of each task were so similar. However, SFs in SSSEP task were more distinguishable spatially, corresponding to neurophysiological areas. The SFs in other subjects also presented that spatial patterns of the SSSEP task were more distinguishable spatially.

In general, the spatial-frequency feature helped improve performance in cross-validation analysis. Particularly, for S7, the FFs were not distinguishable at each electrode (Fig. 8). In this case, the spatial patterns were helpful to improve performance. The SFs were distinguishable from each task for S7 (Fig. 10). In this context, spatial-frequency features are helpful to enhance classification accuracy in SSSEP-based BMI.

Overall, the subjects' topographical spatial patterns in SSSEP were more distinguishable within the motor and somatosensory cortices than those in MI. The cross-validation of SSSEP performance was higher than MI in all subjects.

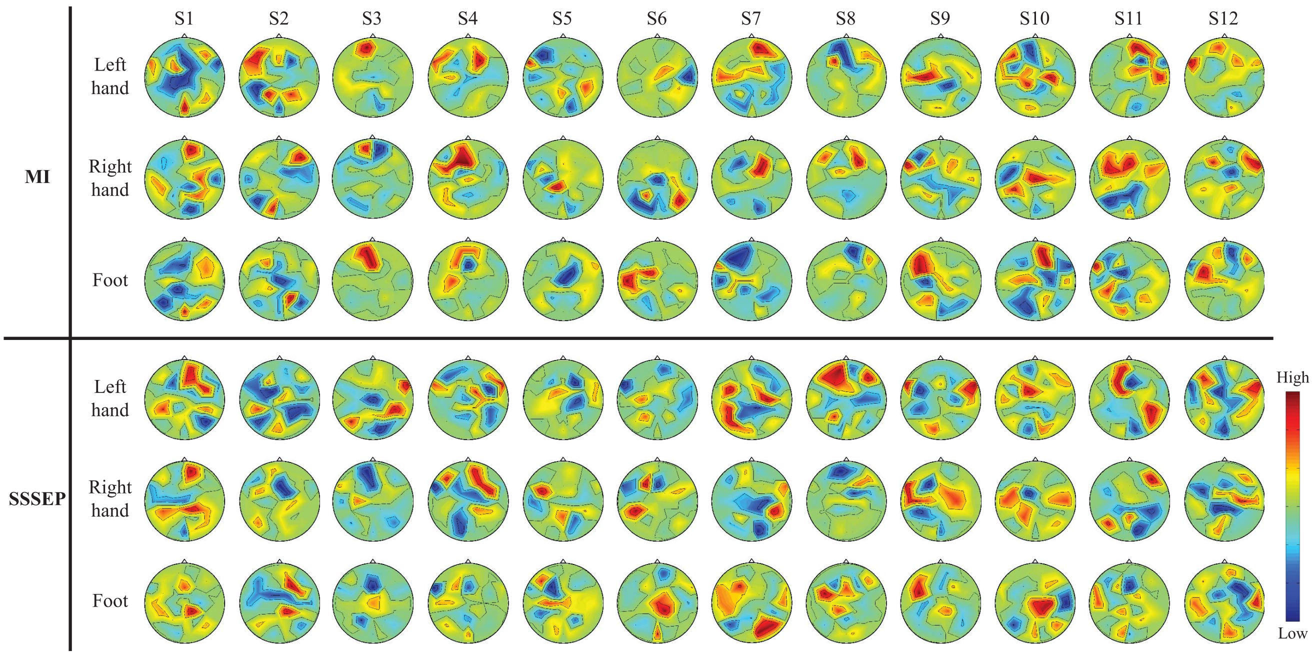


Fig. 10. Spatial patterns by the CSP filtering within the MI and SSSEP task.

In this context, SSSEP-based BMI is widely adaptable to various applications and can provide a stable performance to users.

As for SSSEP with BMI illiteracy, from the previous study, Ahn *et al.* reported that SSSEP-based BMI can be still applicable for the BMI illiteracy [43]. However, the SSSEP about only upper limb (i.e., left-hand and right-hand) was investigated and compared to MI. In this context, we also investigated that the SSSEP and MI about both limbs (i.e., left-hand, right-hand, and foot) to validate a possibility of SSSEP in the BMI illiteracy. To investigate more for BMI illiteracy with the both limbs, we acquired SSSEP and MI data within the same experimental environment. We also analyzed the cross-validation based on SSSEP and MI using the same methodology. As a result, four subjects (S1, S2, S3 and S10) were considered as BMI illiteracy because their spatial patterns were indistinguishable, and the MI-based cross-validation results were very low (at the chance level accuracy). However, the subjects were able to control a wheelchair successfully. These results validate the possibility of SSSEP-based BMI for BMI illiteracy.

In our experiments, the subjects (S4, S5, S6, S7, S8, and S9) showed an accuracy of higher than 75% could control a wheelchair in a relatively stable. For the subjects, it took to finish the task of obstacle-avoidance in simple course with SSSEP-based control only as approximately double as the time with a joystick control. Based on the results, we believe that at least the accuracy of 75% is need for efficient control in our wheelchair system. However, the performance of each subject depends on many factors such as concentration, individual vibration frequencies, tiredness, system-induced fatigue induced by the system, and signal processing methodology. These factors require additional investigation to determine how they influence performance with the SSSEP-based BMI.

In our system, EMG signals induced by tongue were used for only emergency stop. However, for those who even cannot move their own tongue, it is beneficial to use a secondary sensor such as a camera to recognize an emergent situation in a way of shared control. That can be our forthcoming research issue.

VI. Conclusion

In this study, we proposed an SSSEP-based wheelchair control system. The main contributions of our work are three-fold: 1) this is the first work to utilize SSSEP for BMI-based wheelchair control, 2) the combination of spatial and spectral features improves classification accuracy, and 3) SSSEP evoked better performance in individuals who had low performance with the MI-based BMI (illiteracy). We have provided evidence using data from online and offline experiments. In our experiments, all subjects finished the requested task with high performance (i.e., the wheelchair successfully reached the goal line without any collision). These results present the feasibility of an SSSEP-based wheelchair control system. SSSEP analysis demonstrated that spatial-frequency features could increase classification accuracy. Also, we confirmed the possibility of SSSEP-based BMI in BMI illiteracy subjects. The wheelchair control strategy was performed to avoid obstacles and collisions, but it is desirable to have an auxiliary autonomous navigation system to help the user accomplish such tasks. Also, such an auxiliary system would be beneficial for security reasons as well as prevent the user from becoming overly tired from using the SSSEP-based BMI system for long time intervals.

In future studies, a control system that supports the user in wheelchair navigation will be implemented. This includes a system to evade obstacles, avoid collisions, and pass through doorways, among other tasks. To further investigate the feasibility of an SSSEP-based wheelchair system for specific disability needs, further research is warranted with an ALS or SCI patient population.

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