Classification of Selective Attention Within Steady-State Somatosensory Evoked Potentials From Dry Electrodes Using Mutual Information-Based Spatio-Spectral Feature Selection

KEUN-TAE KIM1, JAEHYUNG LEE2, HYUNGMIN KIM1,3, CHOONG HYUN KIM1, AND SONG JOO LEE1,3
1Center for Bionics, Biomedical Research Institute, Korea Institute of Science and Technology, Seoul 02792, South Korea
2Research and Development Center, KOH YOUNG TECHNOLOGY, Inc., Yongin 16864, South Korea
3Division of Bio-Medical Science and Technology, KIST School, Korea University of Science and Technology, Seoul 02792, South Korea

Corresponding author: Song Joo Lee (songjoolee@kist.re.kr)

This work was supported in part by the Institute of Information and Communications Technology Planning and Evaluation (IITP) grant funded by the Korean Government (Development of Non-Invasive Integrated BCI SW Platform to Control Home Appliances and External Devices by User’s Thought via AR/VR Interface) under Grant 2017-0-00432, and in part by the National Research Council of Science and Technology (NST) grant by the Korean Government (MSIT) under Grant CAP-18-01-KIST.

ABSTRACT Nowadays, the steady-state somatosensory evoked potential (SSSEP)-based brain-computer interfaces (BCIs) has been developed for improving the quality of daily life for people with physical disabilities. However, due to its poor performance of recognizing selective attention tasks and inattention (rest)-state, the SSSEP-based BCI has not been widely used for practical interfaces. In this paper, we propose a mutual information-based spatio-spectral feature selection method for recognizing selective attention tasks and inattention (rest)-state using dry electrodes considering a real-life application, when vibration stimuli were applied to both index fingers. In our methods, the filter-bank common spatial pattern (FBCSP) was used for extracting spatio-spectral features of the SSSEP. Then, discriminative features were selected using a mutual information-based best individual feature (MIBIF) algorithm. The regularized linear discriminant analysis (RLDA) used as the classifier. The feasibility of the proposed method was demonstrated through eight healthy subjects using the vibration stimuli induced SSSEP with spatially clear and distinguishable patterns for SSSEP-based BCI. From our study, the proposed method showed the best classification accuracy with a kappa value of 0.35 ± 0.17. Furthermore, based on the ANOVA with posthoc tests, the proposed method showed significantly higher accuracy as 57.9% in decoding three classes (p-value < 0.01) compared to the fast Fourier transform (FFT) and common spatial pattern (CSP)-based previous feature extraction methods. Consequently, the proposed FBCSP and MIBIF-based methods and findings can further help to improve decoding performance and develop the SSSEP-based BCI systems for real-world applications.

INDEX TERMS Steady-state somatosensory evoked potential, selective attention, brain-computer interface, dry electrode.

I. INTRODUCTION Over the last few years, the non-invasive brain-computer interface (BCI) using Electroencephalogram (EEG) has been developed for people with paralysis (such as amyotrophic lateral sclerosis, brainstem stroke, spinal cord injury, etc.) to communicate with external devices [1]–[3]. Especially, electroencephalography (EEG)-based BCI technology has helped individuals with paralysis to type letters on a screen [4]–[6] to control a powered wheelchair [7], [8] and to ambulate...
with a lower-limb gait exoskeleton [9], [10]. For controlling the external devices, various BCI paradigms have been also developed to recognize the user’s intentions. In general, three BCI paradigms have been widely developed and used to the BCI: 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 [11], [12]; 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 [13], [14]; and 3) motor imagery (MI) paradigm, which evokes the event-related (de)synchronized signals in the sensorimotor cortex [15]. The P300 and SSVEP-based BCIs have a high information transfer rate for interfacing with extra devices [33]. However, these potentials are limited due to their requirements for visual attention to continuous stimuli. Consequently, the user may experience significant fatigue because of exposure to a prolonged visual stimulus. Especially, with advancing our technologies of wearable exoskeleton systems, there has been an attempt to use BCI for executing commands to move the system [10]. For example, it could be tiresome for patients to focus on the visual stimuli to evoke P300 or SSVEP while they are walking with the exoskeleton system. Indeed, there have been extensive studies using the MI-based BCIs that use user-induced spontaneous brain patterns at his/her own will [8]. The user has no gaze restriction because it can be used without any visual stimuli. However, the intensive MI training session may be required to using the system, and the number of commands can be limited in motor imagery patterns, as discrimination between different motor imagery patterns becomes more difficult with increasing class numbers [8]. Therefore, despite the successful BCI applications using the aforementioned potentials, the limitations still exist. To overcome the limitations, Müller et al. demonstrated that steady-state somatosensory evoked potential (SSSEP) induced by tactile stimulation could be used for BCIs [16], [17]. The physiological background of the SSSEP is that when a periodic vibration is given at a specific frequency, a human brain elicits evoked potentials near the frequency of the tactile stimulation. The SSSEP-based BCI can overcome the limitations of the aforementioned three BCI paradigms because it relies on the somatosensory nervous system. Besides, the number of BCI commands can be extended by using additional vibration stimuli.

For classifying user’s intentions, machine learning and pattern recognition-based feature extraction methods (within the temporal, spectral, and spatial domain) have been developed from various research groups. Nam et al. validated that the spatial feature based on common spatial pattern (CSP) with band-pass filtering can show high performance than using raw signals to decode the user’s intentions [18]. Yi et al. suggested a filter-bank CSP (FBCSP)-based feature extraction method within dividing frequency bands for an MI-based BCI with electrical stimulation-induced SSSEP [19]. Also, Kim et al. proposed spatio-spectral feature extraction methods using CSP filtering and the Fast Fourier Transform (FFT) analysis for the SSSEP-based wheelchair control algorithm [8]. While various methods exist for the classifying users’ intentions using SSSEP, the decoding accuracy still needs to be improved.

Therefore, various feature selection and fusion methods were developed for improving the decoding accuracy [20], [21]. Bhattacharyya et al. proposed the feature selection technique based on differential evolution and learning automata [20]. The experimental results, using the BCI competition III dataset IVa, showed the feature selection technique can improve the classification accuracy [20]. Baig et al. presented the optimal feature subset selection, based on the Differential Evolution optimization algorithm for the MI-based BCI [21]. The BCI competition III dataset IVa was also used for performance evaluation. The experimental results showed the significance of the evolutionary algorithm in selecting the best features [21]. Furthermore, the mutual information-based best individual feature (MIBIF) algorithm was applied to the MI-based BCI with good decoding accuracy [22], [23]. In the study [22], the decoding accuracy of FBCSP with the MIBIF algorithm in the MI-based BCI using the BCI competition III dataset IVa, that includes 2-class motor imageries, showed higher performance as 90.3±0.7% than other feature selection methods (such as the mutual-information-based feature selection (MIFS), the fuzzy-rough set-based feature selection (FRFS), etc).

In this paper, we aimed to improve the decoding accuracy of the user’s intention (i.e. selective attention) based on the SSSEP and to investigate the efficiency of the dry electrode-based SSSEP-BCI to the real-world environments. The main contributions of our study are two-fold. First, we applied the FBCSP-based feature extraction and MIBIF-based feature selection method to classify a left and right direction using selective attention with SSSEP for the first time. To investigate the effectiveness of the feature selection method, we also compared several previous methods, such as the fast Fourier transform (FFT) and common spatial pattern (CSP). Second, we investigated the decoding accuracy within the EEG data which were acquired by dry electrodes for considering the SSSEP-based applications in real-world environments.

The remainder of this paper is organized as follows, Section II presents the data collection and details the proposed method. Section III presents the results of comparisons among the previous methods and the proposed method. Then, the results are discussed in Section IV. Finally, our conclusion and future work are presented in Section V.

II. METHODS AND MATERIALS
Eight healthy subjects were recruited for our experiments (Table. 1). Six subjects were male and two subjects were female. Furthermore, seven subjects were right-handed and one subject was left-handed. All subjects had no experience of BCI before. No subjects reported any neurological

VOLUME 8, 2020
disorders. All subjects read and signed an informed consent form approved by the Institutional Review Board of the Korea Institute of Science and Technology prior to the experiment.

When somatosensory stimulations are applied for SSSEP-based BCI, each subject could have different vibration frequency ranges to maximize brain activities shown as the highest power spectrum amplitude near the stimulation frequencies [24]. The frequency is called a resonance-like frequency [25]. To determine the subject-specific vibration frequency, a screening session was conducted by stimulating the subject’s left and right index finger, respectively, with stimulation frequencies from 20 Hz to 40 Hz in 2 Hz steps in a pseudorandomized order for 2 sec [16], [25]. In the screening session, the subjects sat in a comfortable chair while the vibration stimulator attached to their index finger. Then, to avoid concentrating on the vibration stimulation, the subject concentrated on the screen that mathematical equations or quizzes were displayed. The vibration frequency was checked using an accelerometer (352A71, PCB Piezotronics Inc.) attached to the left or right index finger. The maximum error in the vibrating frequency was less than 1 Hz. The vibration stimulation was customized using a weight (MB1103W) and coreless DC motor (MB2607-0335, Nury Electric Co., Ltd.).

For the acquisition of the SSSEP, the subject concentrated on one of the attached vibration stimuli on index fingers by following the displayed commands (White circle, green circle, green arrow, and red circle) on a screen (Fig. 2). Each trial started by the white circle in the middle of the screen for 2 sec (without any vibration). After the white circle, the green circle appeared on the screen with vibration stimuli, based on the individual resonance-like frequencies, at the left and right hands during 2 sec. Then, one of the arrows randomly appeared, as the cue, on the screen for 1 sec. After the arrow disappeared, the subject concentrated on the vibration stimuli attached to each part (left and right hands) based on the arrow direction for 3 sec. Finally, the red circle was appeared for 2 sec for resting. The SSSEP data were collected 20 trials per subject in total (10 trials per class).

EEG signals were acquired via an actiCHamp (Brain Product) device with 23 dry electrodes (Fp1, F3, F7, FC5, FC3, FC1, C3, C5, CP3, CP5, CP1, CP6, CP4, CP2, Cz, C2, C4, FC6, FC4, FC2, F4, F8, and Fp2) according to the international 10/20 system (Fig. 3). The reference and grounding electrode was mounted on the FCz and Afz, respectively. The sampling frequency was 500 Hz, and a 60 Hz notch filter was applied to remove power noise.

Fig. 4 shows a schematic diagram for the proposed method. In data processing, we used a filter-bank common spatial pattern (FBCSP) that finds spatial filters to maximize the signal power difference between classes at each sub-frequency band. The raw EEG data were divided into 12 sub-frequency bands. The size of each band was 3 Hz within 2 Hz steps (16-19, 18-21, ..., and 38-41 Hz). Then, the CSP was trained by means of one-versus-rest (OVR) strategy (Left-hand vs. Others, Right-hand vs. Others, and Rest vs. Others) in each sub-frequency band. The logarithmic variance of the first two columns and last two columns ($m_1 = 2$) in each transformation matrix (from CSP) were then extracted and concatenated as a feature. The feature vector for $i$th trial is formed as follows

$$v_i = [v_{1,i}, v_{2,i}, \ldots, v_{b,i}],$$

where $v_i \in \mathbb{R}^{1 \times (b \times 2m)}$, $i = 1, 2, \ldots, n$; $n$ denotes the total number of trials in the data. And $b$ denotes the number of the
sub-frequency bands (in our study \( b = 12 \)). The training data that comprised the extracted feature data and the true class labels are denoted as

\[
\tilde{V} = \begin{bmatrix}
\tilde{v}_1 \\
\tilde{v}_2 \\
\vdots \\
\tilde{v}_n
\end{bmatrix}, \quad \tilde{y} = \begin{bmatrix}
y_1 \\
y_2 \\
\vdots \\
y_n
\end{bmatrix}
\]  

respectively to make a distinction from the evaluation data, where \( \tilde{V} \in \mathbb{R}^{n \times (bn \times 2m)} \); \( \tilde{y} \in \mathbb{R}^{n \times 1} \); \( \tilde{v}_i \) and \( \tilde{y}_i \) denote the feature vector and true class label from the \( i \) th training trial, \( i = 1, 2, \ldots, n \); and \( n \) denotes the total number of trials in the training data.

The discriminative features were then selected by the MIBIF algorithm [23]. The MIBIF is based on the filter approach. The mutual information of each feature is computed and sorted in descending order. The first features are then selected. The MIBIF algorithm is described as follows:

- Step 1: Initialize set of features \( F = \{ f_1^\alpha, f_2^\alpha, f_{b \times 2m}^\alpha \} = \tilde{V} \) and set of true labels \( C = \tilde{y} \) from equation (2) whereby \( f_j^\alpha \in \mathbb{R}^{n \times 1} \) is \( j \)th column vector of \( \tilde{V} \), and the true label of each trial \( \tilde{y} \in \{ 1, 2 \} \). Initialize set of selected features \( S = \emptyset \).
- Step 2: Compute the mutual information of each feature \( f_j \in F \) with each class label \( \omega = \{ 1, 2 \} \in C \). Compute \( I(f_j; \omega) = I(f_j; \omega) \hat{=} 1, 2, \ldots, (b \times 2m) \) using

\[
I(f_j; \omega) = H(\omega) - H(\omega | f_j),
\]

where \( H(\omega) = - \sum_{\omega=1}^{2} p(\omega) \log_2 p(\omega) \); and the conditional entropy is

\[
H(\omega | f_j) = - \sum_{\omega=1}^{2} \sum_{i=1}^{n} p(\omega | f_{j,i}) \log_2 p(\omega | f_{j,i}),
\]

where \( f_{j,i} \) is the feature value of the \( i \)th trial from \( f_j \) [23].
- Step 3: Sort all the features in descending order of mutual information computed in step 2 and select the \( k \) features. Mathematically, this step is performed as follows until \( |S| = k \)

\[
F = F \setminus f_j, S = S \cup f_j | I(f_j; \omega) = \max_{j=1,2,\ldots,(b\times2m),f_j\in F} I(f_j; \omega),
\]

where \( \setminus \) denotes set-theoretic difference; \( \cup \) denotes set union; and \( | \) denotes given the condition.

To validate the effectiveness of the proposed method (FBCSP with MIBIF), we conducted an offline analysis using 10-fold cross-validation within the previous feature extraction methods and the proposed method:

- CSP: In this method, the feature extracted using only CSP filtering without any preprocessing [18]. The logarithmic variance of the first two and last two columns in the transformation matrix was used as the spatial feature.
- FFT with CSP: This method was proposed in [8] by Kim et al. First, the spectral feature was extracted at each vibration (on the left and right hand) frequency using FFT analysis at C3, Cz, and C4 electrodes. Then the spatial feature was extracted by CSP filtering. Finally, the spectral and spatial features were concatenated as a feature.
- FBCSP: Recently, this method was widely used in SSSEP studies [19], [28]. In this method, the spatial features are extracted in each sub-frequency band. For our study, the spatial features of 12 sub-frequency bands (16-19, 18-21, ... and 38-41 Hz) were concatenated.
- MIBIF(Vib): In this proposed method, after the aforementioned ‘FBCSP’, discriminative features were selected using the MIBIF algorithm in each class. The number of discriminative features was decided by a simple with a cross-validation procedure. For our study, the EEG data at the period when the green circle was displayed with vibration stimuli were used as the ‘Rest’ class.
• MIBIF(noVib): This method was conducted for comparison with rest with/without vibration stimuli. The EEG data at the period when the white circle was displayed without vibration stimuli were used as the ‘Rest’ class.

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 when there is an insufficient number of training samples [26], [27]. Therefore, three RLDA classifiers (Left-hand vs. Others, Right-hand vs. Others, and Rest vs. Others) were also trained using the OVR strategy. Consequently, one class that had the highest output value of the three RLDA classifiers was determined as a final output (Fig. 4). Furthermore, to compare the performance of the proposed method, the linear discriminant analysis (LDA) and support vector machine (SVM) were also used with the FBCSP with MIBIF method.

For the cross-validation, the acquired SSSEP data were divided into the 10-fold randomly without any overlap. And then, 9-folds were selected for training and the remained 1-fold was used for testing. The testing fold was changed in chronological order. This process was iterated 10 times, and results were averaged to measure the accuracy in each method. In order to obtain a better quantitative comparison between the previous and proposed methods, we performed statistical analysis via the ANOVA with posthoc tests. Bonferroni correction was done for multiple comparisons. The $p < 0.05$ indicates a statistical significance. Cohen’s kappa coefficients were also reported. The kappa value is a measure for classification performance removing the effect of the accuracy of random classification [32]. The kappa value is calculated as

$$\text{kappa} = \frac{\text{acc} - \text{rand}}{1 - \text{rand}}$$

where acc is the classification accuracy and rand is the result of random classification [32]. The $p$-value and kappa value were calculated by using the accuracies derived from the 10 by 10 cross-validation of each method.

III. RESULTS
To investigate the effect of the number of features ($k$) within the MIBIF algorithm, we first implemented a simulation that could confirm the accuracies in terms of the number of MIBIFs (Fig. 5). In this simulation, 1-48 MIBIFs selected in the concatenated spatial feature (12 sub-frequency bands $\times$ first two and last two columns in the transformation matrix) which were extracted from the CSPs. Fig. 5 shows the averaged accuracies of 10-fold cross-validation within all subjects. For the cross-validation, the acquired SSSEP data were divided into the 10-fold randomly without any overlap. And then, 9-folds were selected for training and 1-48 MIBIFs selected. And the remained 1-fold was used for testing. The testing fold was changed in chronological order. Consequently, over 10 features did not show any improvement in the classification accuracy. Therefore, for the proposed method, we used 10 selected MIBIFs in all analyses.

Fig. 6 presents the 10-fold cross-validation results of previous and proposed methods using the acquired SSSEP data. In Fig. 6 the proposed method (FBCSP and MIBIF with RLDA) shows the highest accuracy (within multiclass classification: left-hand vs. right-hand vs. rest). As the average accuracies (3 classes) were 48.8%, 48.0%, 55.8%, 56.4%, 55.3%, 48.7% and 57.9%, the proposed method shows a better performance than other methods. Furthermore, the main factor of ANOVA was showed $p < 0.01$. For the detail followed by the Bonferroni posthoc tests, the significant differences ($p < 0.01$) were revealed between the ‘CSP with RLDA’ and ‘FBCSP with RLDA’, between the ‘CSP with RLDA’ and ‘MIBIF with RLDA(Vib)’, between the ‘CSP with RLDA’ and ‘MIBIF with SVM(Vib)’, between the ‘CSP with RLDA’ and ‘MIBIF with RLDA(noVib)’, between the ‘FFT+CSP with RLDA’ and ‘FBCSP with RLDA’, between the ‘FFT+CSP with RLDA’ and ‘FBCSP with RLDA(Vib)’, between the ‘FFT+CSP with RLDA’ and ‘MIBIF with SVM(Vib)’, between the ‘FFT+CSP with RLDA’ and ‘MIBIF with RLDA(noVib)’, between the ‘CSP with RLDA’ and ‘MIBIF with SVM(Vib)’, between the ‘CSP with RLDA’ and ‘MIBIF with SVM(Vib)’, between the ‘CSP with RLDA’ and ‘MIBIF with SVM(Vib)’. However, there no significant differences in other cases. Based on these results of statistical analysis, we can conclude that the FBCSP or MIBIF-based feature extraction methods showed higher performances than CSP or FFT+CSP-based feature extraction. It can be also concluded that the RLDA or SVM classifier has higher performance than the LDA classifier.

To make it clearer in regard to the effectiveness of the MIBIF, we calculated Cohen’s kappa coefficient among the ‘FBCSP with RLDA’, ‘MIBIF with RLDA’ and ‘MIBIF with SVM’ (Table 2). In Table 2, the proposed method (MIBIF with RLDA) has the highest kappa value (0.35±0.17). It means that the proposed method can classify with smaller errors in each class respectively, than other methods.
FIGURE 6. 10-fold cross-validation results within previous feature extraction methods (CSP, FFT+CSP, FBCSP) with RLDA and the proposed method (FBCSP with MIBIF) with LDA, SVM, and RLDA classifiers. Each bar indicates the averaged accuracy and standard derivation of the 10-fold cross-validation (** means that the p-value is < 0.01).

TABLE 2. Kappa values in each methods.

| Sub. | RLDA | SVM |
|------|------|-----|
|      | FBCSP| MIBIF| MIBIF|
| S1   | 0.26 | 0.43 | 0.47 |
| S2   | 0.61 | 0.56 | 0.49 |
| S3   | 0.30 | 0.40 | 0.37 |
| S4   | 0.03 | 0.05 | 0.01 |
| S5   | 0.40 | 0.39 | 0.28 |
| S6   | 0.15 | 0.16 | 0.26 |
| S7   | 0.38 | 0.34 | 0.41 |
| S8   | 0.53 | 0.47 | 0.36 |
| Mean±Std. | 0.33±0.19 | 0.35±0.17 | 0.33±0.15 |

Furthermore, to make it clearer in regard to the effectiveness of the MIBIF in aspect feature extraction, the feature distributions between the ‘FBCSP’ and the proposed ‘MIBIF’ were further investigated.

Fig. 7 shows the extracted feature distribution of all tasks (the left hand, right hand, and resting with vibration stimuli) using the ‘FBCSP with RLDA’ and the ‘MIBIF with RLDA’. For Fig. 7, all trials (10 trials per each class) in each subject were used to presenting the feature distribution. The dimension of each extracted feature, from ‘FBCSP with RLDA’ and ‘MIBIF with RLDA’, were also reduced to 2-dimension using the principal component analysis (PCA) for a scattering. In Fig. 7, each color represents each class. In general, the ‘MIBIF with RLDA’ and the ‘FBCSP with RLDA’ shows a discriminative feature distribution in all subject. However, the proposed ‘MIBIF with RLDA’ shows more discriminative distribution in inter-classes with several subjects. For instance, in S1, the clustering of features that were extracted using the ‘MIBIF with RLDA’ in each class is higher than the ‘FBCSP with RLDA’. For instance, in S1, the clustering of features that were extracted using the ‘FBCSP with MIBIF’ in each class is higher than the ‘FBCSP with RLDA’. It means that the features from the ‘FBCSP with MIBIF’ were more distinguishable to classify. Also, in S4, the features that were extracted using the ‘MIBIF with RLDA’ show a more distinguishable distribution than the ‘FBCSP with RLDA’. These results can be interpreted that the proposed method can extract the more discriminative features for the classification of the user’s tasks.

Additionally, we conducted a topological analysis between the ‘FBCSP with RLDA’ and ‘MIBIF with RLDA’. Fig. 8 presents the representative topographical spatial patterns within the ‘FBCSP with RLDA’ and the proposed method. For the patterns of left- and right-hand in the ‘FBCSP with RLDA’, the first and second columns of the transformation matrix (from the CSP) at each special frequency band (left-hand and right-hand, respectively), which has the resonance-like frequency, were averaged. For the pattern of the ‘Rest’, the first and second columns of the transformation matrix in both frequencies of left- and right-hand were averaged. In the proposed method ‘MIBIF with RLDA’, selected features in each frequency band, which included the resonance-like frequencies of left- and right-hand, was used. Likewise, for the patterns of the ‘Rest’, selected features in both frequencies of left- and right-hand were averaged. As shown in Fig. 8, the spatial patterns (left- and right-hand) of the proposed method were spatially clearer and more distinguishable corresponding to the neuro-physiological areas than that from the ‘FBCSP with RLDA’.

IV. DISCUSSIONS

Up to the authors’ best knowledge, for the first time, the EEG signals were acquired by the dry electrodes for applying SSSEP-based BCI to the real-world application. In previous motor imagery studies [30], [31], using the dry electrodes showed less classifying performance than using the wet electrodes in the cross-validation because of lower signal quality. In our results (Fig. 6), despite using the
dry electrodes, the proposed method showed higher performance than other methods. However, the quality of the EEG signals from a dry electrode can low easily because the electrode can lose contact temporally with the subject’s scalp by small head movements [31]. Therefore, source separation techniques, such as the independent component analysis (ICA), can be required to extract significant signals and remove the artifact for real-world environment applications.

We applied the MIBIF algorithm to improve the accuracy for recognizing selective attention of the left and right directions and inattention (rest)-state. Our study showed that the proposed method can help to improve the classification accuracy of the selective attention and inattention and show spatially clear and distinguishable patterns for vibration stimuli-induced SSSEP-based BCIs. In the previous twitch-based multiclass SSSEP study, Pokorny et al. [29], the cross-validation accuracy for multi-class (concentrating on left-hand, right-hand, and idle class) were averaged 48.6% within 14 subjects using C-2 tactor (Engineering Acoustics, Inc., Casselberry, Florida, USA) with finger clip to induce SSSEP [29]. Unlike our experimental setup, the EEG signals from 29 channels focused on the somatosensory cortex and the EOG signals from 3 channels were recorded [29]. In order to have constant contact pressure between the tactors and fingers, finger clips were used [29]. The tactile stimulation pattern consisted of a twitch-based sinusoidal carrier signal which was amplitude modulated with a rectangular stimulation signal of the respective stimulation frequency. For the data analysis in [29], the features were extracted with the logarithmic lock-in amplifier system (LAS) and the multi-class shrinkage LDA was also used as the classifier. The LAS is an algorithm of filtering small sinusoidal signals out of random noise, or out of a mixture of different signals [16]. In our experimental results (Fig. 6), the proposed method showed higher performances (56.4%, and 57.9%) compared to the previous study as 48.6% [29]. Despite considering the differences in stimuli inducing SSSEP and in the number of subjects from the previous study and the current study, our approach is valuable. The proposed method in our study showed approximately 10% higher classifying performance than the previous study. Further studies to generalize our findings are needed.
Furthermore, in our study, due to the limitation of the system using dry electrodes, we could not monitor the impedances whether those were below 10 kΩ or not. The proposed method can improve the classifying performance within a wet-type electrodes-based experimental environment. Therefore, we have a plan to acquire the EEG signals using wet-type electrodes and conduct additional experiments for further performance comparison.

In Table 2, the kappa values calculated as averaged 0.35±0.17. To the best of authors’ knowledge, the kappa value in the selective attention tasks was calculated for the first time. Therefore, it is difficult to compare our averaged kappa value with that from the previous studies about selective attention [16], [17], [29]. However, a comparison of kappa values between subjects in our study could be made. The classification accuracies of specific subjects (S4 and S6) were much lower than other subjects in our study. Especially, in the case of S4, the kappa value is lower than 0.1 and classification accuracies also similar to random classification. It can be interpreted that the previous methods (FFT, CSP, FBCSP-based feature extraction and LDA, SVM, RLDA-based classification) and the proposed method were not suitable to classify for SSSEP data of S4. Therefore, it may need to apply deep learning, such as the convolutional neural network (CNN), for our further study for considering cases like the S4. Interestingly, the S4, showing the lowest kappa value, is one of the two female subjects in our experiments. From our study, it is difficult to investigate the effect of genders on the classification accuracies of selective attention. Further gender-matched experiments may be needed regarding this matter. The age and/or handedness can also contribute to the classification accuracies. In our experiment, the subjects were almost the early 20s and the right-handed. More experiments with the matched gender, age, handedness could be implemented to further investigate the effects of gender, age, and handedness on the classification accuracies of selective attention in our future work.

In our study, we also investigated that the inattention(rest)-state with/without vibration. In Fig. 6, the performance with vibration was lower than without vibration. However, the difference was very small (below 1%) and there was no statistically significant difference. Consequently, it was shown that with/without vibration was not significant to recognize a user’s inattention(rest)-state in the SSSEP-based BCI systems. Additional studies on a larger population might be needed to generalize the current findings.

V. CONCLUSIONS

In this study, we proposed the mutual information-based spatio-spectral feature selection method using FBCSP and MIBIF. Our study showed that the proposed method is better performance than other methods to classify left, right, and rest states. However, the performance of each subject depends on various subject-specific factors such as concentration level, individual vibration frequencies, tiredness, etc. These factors require additional investigation to determine how they could affect performance within the SSSEP-based BCI, especially with dry electrodes. Therefore, further investigation of applying the proposed method for subject-specific SSSEP-BCI on various subjects such as healthy and neurologically impaired patients.

REFERENCES

[1] N. Birbaumer and L. G. Cohen, “Brain-computer interfaces: Communication and restoration of movement in paralysis,” J. Physiol., vol. 579, no. 3, pp. 621–636, Mar. 2007.

[2] A. Kübler, B. Kotchoubey, J. Kaiser, J. R. Wolpaw, and N. Birbaumer, “Brain–computer communication: Unlocking the locked in,” Psychol. Bull., vol. 127, no. 3, pp. 358–375, Feb. 2001.

[3] I. Wolpaw, N. Birbaumer, D. McFarland, G. Pfurtscheller, and T. Vaughan, “Brain-computer interfaces for communication and control,” Clin. Neurophysiol., vol. 113, no. 6, pp. 767–791, Jun. 2002.

[4] N. Birbaumer, N. Ghanayim, T. Hinterberger, I. Iversen, B. Kotchoubey, A. Kübler, J. Perelmouter, E. Taub, and H. Flor, “A spelling device for the paralysed,” Nature, vol. 398, no. 6725, pp. 297–298, Mar. 1999.

[5] M.-H. Lee, J. Williamson, D.-O. Won, S. Fazli, and S.-W. Lee, “A high performance spiking system based on EEG-EOG signals with visual feedback,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 26, no. 7, pp. 1443–1459, Jul. 2018.

[6] D.-O. Won, H.-J. Hwang, D.-M. Kim, K.-R. Muller, and S.-W. Lee, “Motion-based rapid serial visual presentation for gaze-independent brain–computer interfaces,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 26, no. 2, pp. 334–343, Feb. 2018.

[7] D. Huang, K. Qin, D.-Y. Wei, J. Xie, Chen, and O. Bai, “Electroencephalography (EEG)-based brain–computer interface (BCI): A 2-D virtual wheelchair control based on event-related desynchronization/synchronization and state control,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 20, no. 3, pp. 379–388, May 2012.

[8] K.-T. Kim, H.-J. Suk, and S.-W. Lee, “Commanding a brain-controlled wheelchair using steady-state somatosensory evoked potentials,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 26, no. 3, pp. 654–665, Mar. 2018.

[9] A. Kilicarslan, S. Prasad, R. G. Grossman, and J. L. Contreras-Vidal, “High accuracy decoding of user intentions using EEG to control a low-body exoskeleton,” in Proc. 35th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC), Osaka, Japan, Jul. 2013, pp. 5606–5609.

[10] N.-S. Kwak, K.-R. Muller, and S.-W. Lee, “A lower limb exoskeleton control system based on steady state visual evoked potentials,” J. Neural Eng., vol. 12, no. 5, Oct. 2015, Art. no. 056009.

[11] D. J. Krusienski, E. W. Sellers, F. Cabestaing, S. Bayoudh, D. J. McFarland, T. M. Vaughan, and J. R. Wolpaw, “A comparison of classification techniques for the P300 speller,” J. Neural Eng., vol. 3, no. 4, pp. 299–305, Dec. 2006.

[12] I.-H. Kim, J.-W. Kim, S. Haufe, and S.-W. Lee, “Detection of braking intention in diverse situations during simulated driving based on EEG feature combination,” J. Neural Eng., vol. 12, no. 1, Feb. 2015, Art. no. 016001.

[13] R. Ortner, B. Z. Allison, G. Korisek, H. Gaggel, and G. Pfurtscheller, “An SSVEP BCI to control a hand orthosis for persons with tetraplegia,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 19, no. 1, pp. 1–5, Feb. 2011.

[14] D.-O. Won, H.-J. Hwang, S. Daehne, K.-R. Müller, and S.-W. Lee, “Effect of higher frequency on the classification of steady-state visual evoked potentials,” J. Neural. Eng., vol. 13, no. 1, Dec. 2015, Art. no. 016014.

[15] H. Yuan and B. He, “Brain–computer interfaces using sensorimotor rhythms: Current state and future perspectives,” IEEE Trans. Biomed. Eng., vol. 61, no. 5, pp. 1425–1435, May 2014.

[16] G. R. Müller-Putz, R. Röcher, C. Neuper, and G. Pfurtscheller, “Steady-state somatosensory evoked potentials: Suitable brain signals for brain–computer interfaces?,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 14, no. 1, pp. 30–37, Mar. 2006.

[17] C. Breitwieser, C. Pokorny, and G. R. Müller-Putz, “A hybrid three-class brain–computer interface system utilizing SSSEPs and transient ERP’s,” J. Neural. Eng., vol. 13, no. 6, Dec. 2016, Art. no. 066015.

[18] Y. Nam, A. Cichocki, and S. Choi, “Common spatial patterns for steady-state somatosensory evoked potentials,” in Proc. 35th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC), Osaka, Japan, Jul. 2013, pp. 2255–2258.
[19] W. Yi, S. Qiu, K. Wang, H. Qi, X. Zhao, F. He, P. Zhou, J. Yang, and D. Ming, “Enhancing performance of a motor imagery based brain–computer interface by incorporating electrical stimulation-induced SSSEP,” J. Neural Eng., vol. 14, no. 2, Apr. 2017, Art. no. 026002.

[20] S. Bhattacharyya, A. Sengupta, T. Chakraborti, A. Konar, and D. N. Tibarewala, “Automatic feature selection of motor imagery EEG signals using differential evolution and learning automata,” Med. Biol. Eng. Comput., vol. 52, no. 2, pp. 131–139, Feb. 2014.

[21] M. Z. Baig, N. Aslam, H. P. H. Shum, and L. Zhang, “Differential evolution algorithm as a tool for optimal feature subset selection in motor imagery EEG,” Expert Syst. Appl., vol. 90, pp. 184–195, Dec. 2017.

[22] K. Keng Ang, Z. Yang Chin, H. Zhang, and C. Guan, “Filter bank common spatial pattern (FB CSP) in brain-computer interface,” in Proc. IEEE Int. Joint Conf. Neural Netw. (IEEE World Congr. Comput. Intell.), Jun. 2008, pp. 2390–2397.

[23] K. K. Ang, Z. Y. Chin, C. Wang, C. Guan, and H. Zhang, “Filter bank common spatial pattern algorithm on BCI competition IV datasets 2a and 2b,” Frontiers Neurosci., vol. 6, p. 39, Mar. 2012.

[24] N. R. Galloway, “Human brain electrophysiology: Evoked potentials and evoked magnetic fields in science and medicine,” Br. J. Ophthalmol., vol. 74, no. 4, p. 255, Apr. 1990.

[25] G. R. Müller-Putz, C. Neuper, and G. Pfurtscheller, “Resonance-like frequencies of sensorimotor areas evoked by repetitive tactile stimulation,” Biomedizinische Technik/Biomed. Eng., vol. 46, nos. 7–8, pp. 186–190, 2001.

[26] B. Blankertz, S. Lemm, M. Treder, S. Haufe, and K.-R. Müller, “Single-trial analysis and classification of ERP components—A tutorial,” NeuroImage, vol. 56, no. 2, pp. 814–825, May 2011.

[27] J. H. Friedman, “Regularized discriminant analysis,” Amer. Statist. Assoc., vol. 84, no. 405, pp. 165–175, Oct. 1987.

[28] Z. Chen, X. Zhao, Z. Wang, K. Wang, W. Yi, F. He, and H. Qi, “A hybrid brain computer interface driven by motor imagery of right hand versus right forearm,” in Proc. 9th Int. Conf. Awareness Sci. Technol. (iCAST), Fukuoka, Japan, Sep. 2018, pp. 79–83.

[29] C. Pokorny, C. Breitwieser, and G. R. Müller-Putz, “The role of transient target stimuli in a steady-state somatosensory evoked potential-based brain–computer interface setup,” Frontiers Neurosci., vol. 10, p. 152, Apr. 2016.

[30] I. Domingos, F. Deligianni, and G. Yang, “Dry versus Wet EEG Electrode Systems in Motor Imagery Classification,” Imperial College London, UK, 2017.

[31] J. Saab, B. Bhatte, and M. Grosse-Wentrup, “Simultaneous EEG recordings with dry and wet electrodes in motor-imagery,” in Proc. 5th Int. Brain–Computer Interface Conf. (BCI), 2011, pp. 312–315.

[32] A. Schlögl, F. Lee, H. Bischof, and G. Pfurtscheller, “Characterization of four-class motor imagery EEG data for the BCI-competition 2005,” J. Neural Eng., vol. 2, no. 4, pp. L14–L22, Dec. 2005.

[33] S. Amiri, A. Rabbi, L. Azinifar, and R. Razeli-Rezai, “A Review of P300, SSVEP, and Hybrid P300/SSVEP Brain-Computer Interface Systems,” InTech Publisher, 2013

KEUN-TAE KIM received the B.S. degree in computer information science and the Ph.D. degree in brain and cognitive engineering from Korea University, South Korea, in 2012 and 2019, respectively. He is currently a Postdoctoral Fellow with the Biomedical Research Institute, Korea Institute of Science and Technology, Seoul, South Korea. His research interests include brain–computer interfaces, myoelectric interfaces, signal processing, pattern recognition, and machine learning.

JAEHYUNG LEE received the B.S. degree in system management engineering and the M.S. degree in industrial engineering from Sungkyunkwan University, South Korea, in 2014 and 2017, respectively. He is currently an Assistant Manager with KOH YOUNG TECHNOLOGY Inc. His research interests include brain–computer interfaces, signal processing, and usability of medical devices.

HYUNGMIN KIM received the B.S. and M.S. degrees in mechanical engineering from Seoul National University, Seoul, South Korea, in 1998 and 2001, respectively, and the Ph.D. degree in biomedical engineering from the University of Bern, Bern, Switzerland, in 2011. Then, he entered himself into the medical industry, developed medical and dental imaging softwares and surgical navigation systems at Cybermed, Inc., Seoul, for six years. He was a Research Scientist with the Institute for Surgical Technology and Biomechanics, Bern. He recently served as a Research Fellow with the Department of Radiology, Harvard Medical School, Boston, USA. He is currently serving as a Principal Research Scientist with the Biomedical Research Institute, Korea Institute of Science and Technology, Seoul, South Korea, and an Associate Professor with the Division of Bio-Medical Science and Technology, KIST School, University of Science and Technology (UST), Seoul, South Korea. His research interests include neural interface, neuromodulation, and focused ultrasound.

CHOONG HYUN KIM received the Ph.D. degree in mechanical engineering from Hanyang University, Seoul, South Korea, in 2001. He is currently a Senior Research Scientist with the Center for Bionics, Korea Institute of Science and Technology (KIST), Seoul. His current research interests include gait analysis, gait rehabilitation, fall detection using medical signal process, engineering application for injury prevention, and machine element design.

SONG JOO LEE received the Ph.D. degree in biomedical engineering from Northwestern University, Evanston, IL, USA. She was a Research Assistant and a Postdoctoral Fellow with the Sensory Motor Performance Program (SMPP), Rehabilitation Institute of Chicago (RIC), Chicago, IL, USA. She is currently a Senior Research Scientist with the Center for Bionics, KIST, South Korea, and an Associate Professor with the Division of Bio-Medical Science and Technology, KIST School, University of Science and Technology (UST), Seoul, South Korea. Her research interests include neuromechanics, human–machine interaction, biomedical modeling, engineering application for injury prevention and rehabilitation, rehabilitation robotics, and muscle physiology.