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Comparative analysis of features extracted from EEG spatial, spectral and temporal domains for binary and multiclass motor imagery classification

Seung-Bo Lee[1], Hyun-Ji Kim[1], Hakseung Kim, Ji-Hoon Jeong, Seong-Whan Lee, Dong-Joo Kim*

Department of Brain and Cognitive Engineering, Korea University, Anam-dong, Seongbuk-gu, Seoul, South Korea

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ABSTRACT

The electroencephalogram (EEG) remains the predominant source of neurophysiological signals for motor imagery-based brain-computer interfaces (MI-BCIs). Various features can be derived from three distinctive domains (i.e., spatial, temporal and spectral); however, the efficacies of the existing feature extraction methods when discriminating complex multiclass MI tasks have yet to be reported. This study investigates the performances of EEG feature extraction techniques from varying domains against different levels of complex, multiclass MI tasks. Ten healthy volunteers underwent multiple complex MI tasks via a robotic arm (i.e., hand grasping and wrist twisting; grasp, spread, pronation and supination). The discrimination performances of various feature extraction (i.e., common spatial patterns (CSP), time domain parameters (TDP), and power spectral density (PSD)) and classification methods for EEG were tested to perform binary (hand grasping/wrist twisting), ternary ((A) grasp/spread/wrist twisting and (B) hand grasping/pronation/supination) and quaternary (grasp/spread/pronation/supination) discrimination. Based on the available data, the combination of shrinkage-regularized linear discriminant analysis (SRLDA) and TDP achieved the highest accuracy. The findings suggest that multiclass complex MI-BCI task discrimination could gain more benefit from analyzing simple and symbolic features such as TDP rather than more complex features such as CSP and PSD.

1. Introduction

A brain-computer interface (BCI) provides a direct communication channel between the brain and an external device beyond the brain's normal output channels of peripheral nerves and muscles. Improving the quality of life for patients with neurological disorders and/or injuries lies at the center of BCI studies. BCI systems estimate user intent via neurophysiological signals—primarily electroencephalogram (EEG) signals. Because neurophysiological signals reflect a combined cognitive status [4], selecting the appropriate aspects of EEG traces is of paramount importance in BCI applications [2]. The EEG traces used to manipulate BCI-controlled devices include sensorimotor rhythms [12], steady-state visual evoked potentials [17], error-related potentials (ErRPs) [1,8], and motor imagery (MI) [16]. Among these, the EEG traces of MI have been shown

* Corresponding author.
E-mail address: dongjookim@korea.ac.kr (D.-J. Kim).
[1] These authors contributed equally to this study.

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to be applicable for automatically controlling external devices, partially due to their advantage of not requiring neuromuscular mediation [3]. The MI-BCI converts the user's motor intention into a command by detecting MI states in real time. Users can also activate brain patterns during MI depending on their own intentions. Nonetheless, accurately discriminating EEG signals remains a major challenge for MI-BCIs [22].

A variety of attempts have been made to better extract relevant features from EEG for MI-BCI. As a neurophysiological signal that is commonly measured at multiple locations, an EEG can be analyzed at three prominent domains, i.e., spatial, temporal and spectral [6,10,19,20,24]. One widely used algorithm for extracting spatial features is the common spatial patterns algorithm (CSP), which shows strengths in MI tasks such as left and right hand movements [20] or movements of the hands, feet and tongue [6]. The time domain parameters method (TDP) focuses on the temporal aspects of EEG signals; its advantage lies in its low computational complexity while retaining acceptable performance for discriminating among simple MI tasks (e.g., classifying MI of the left or right hand or foot movements) [24]. Finally, the power spectral density (PSD) parameters can extract features hidden in the spectral domains of EEG signals which can be helpful for discriminating among simple MI tasks (e.g., left or right hand movements [10]).

The aforementioned feature extraction methods each have advantages; however, they have been tested against only a few (2–4 classes) of relatively simple MI tasks. For instance, changes in left or right hand or foot movements induce different signals in different regions [19] that can be identified without much effort. Furthermore, the majority of the previous attempts for EEG-based MI feature extraction did not utilize an actual robotics setup. Thus, for MI-BCI to be helpful in practical situations, the conventional feature extraction methods should be tested against more complex MI tasks, preferably with real robotics systems.

This study investigates the performances of the conventional EEG feature extraction techniques from varying domains against binary and multiclass MI-BCI systems and used the results to manipulate a robotic arm. The conventional feature extraction methods are tested against more complex MI tasks. The remainder of this article is organized as follows: the framework of our MI-based robotic arm system, experimental settings and EEG data analysis methods are described in the Materials and Methods section. The findings and their implications for future research are presented in the Sections 3 and 4.

2. Materials and methods

In accordance with the study objective, a BCI-operated robotic arm system was utilized. EEG signals were acquired from healthy volunteers who underwent MI-mediated complex hand movement tasks. The primary objective of this study was to investigate the efficacies of the features extracted from varying EEG domains in multiclass discrimination of complex MI-BCI tasks. In this investigation, three conventional feature extraction methods (i.e., CSP, TDP and PSD) were specifically selected due specifically to their wide availability and ease of implementation to achieve objectivity while retaining a certain level of validity in the findings. A detailed explanation is provided below.

2.1. Participants

Thirteen healthy subjects (all males, right-handed, average age of 26.8 ± 1.8 years) were recruited to participate in the experiment. None of the subjects had experience with BCI experiments prior to this study, and they had no known cognitive deficits. The study was approved by the Institutional Review Board (IRB) at Korea University (1040548-KU-IRB-17-172-A-2). All the subjects provided written informed consent before the experiments.

2.2. Apparatus

In this study, an apparatus was designed to measure upper-limb motor imagery performance. The major elements of the apparatus were (1) neurophysiological signal measurement, (2) a robotic arm environment and (3) a network module. The experimental apparatus and environment are illustrated in Fig. 1.

2.2.1. Neurophysiological signal measurement

EEG signals were noninvasively acquired utilizing an EEG recording system (BrainVision Recorder, BrainProduct GmbH). The signals were recorded using 64 Ag/AgCl electrodes following 10/20 international systems: all the channels were referenced to FCz and grounded to the FPz position. Electrode impedance was maintained below 10 k. The EEG signals were digitized at a rate of 1000 Hz and filtered using a 60 Hz notch filter. A bandpass filter of 8–30 Hz was later applied for feature extraction.

2.2.2. Robotic arm environment

Visual feedback was provided by a robotic arm (WAM Arm, Barrett Technology Inc.), which was a seven-degree of freedom human-like robotic arm with three fingers (Barrett hand, Barrett Technology Inc.) to foster enhanced feelings of embodiment toward the robot. The WAM system included three main components, a WAM PC, WAM hardware and a power supply with line cord. The WAM PC includes control software coded in the C++ language that allows a user to execute desired tasks. Using this software, the control function of the robotic arm was modified in accordance with the experiments.

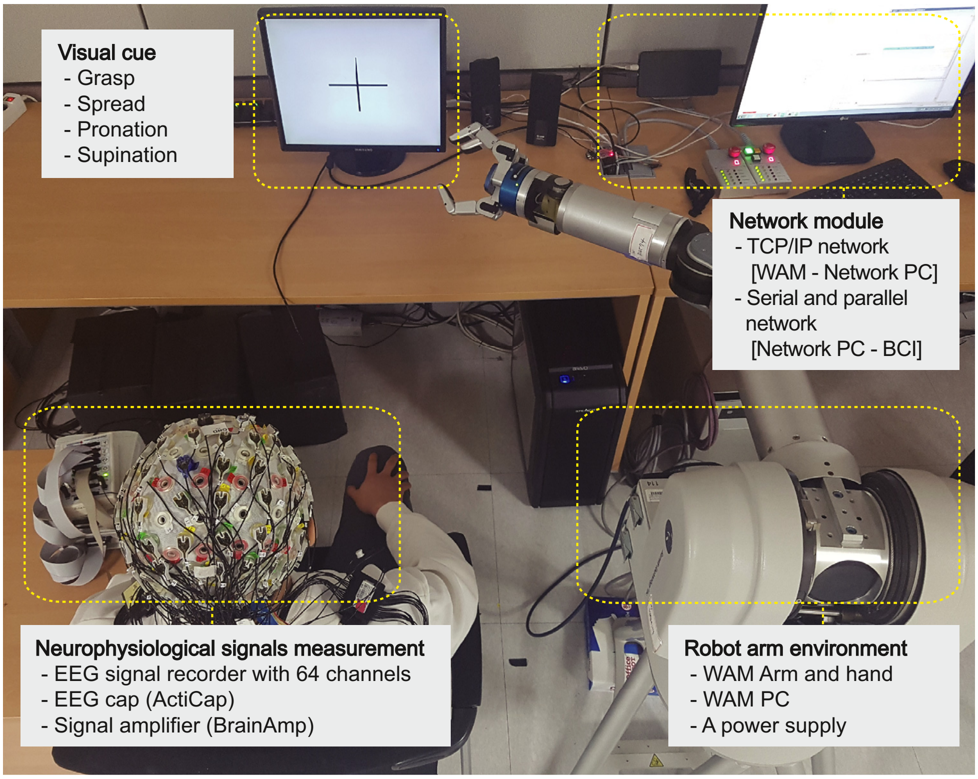

Fig. 1. Experimental apparatus and environment. A subject performs motor imagery of upper-limb movements following instructions provided by visual cues displayed on a monitor.

The WAM hardware includes the WAM arm, the Barrett hand and a WAM wrist, and it is able to perform numerous tasks (i.e., reaching, grasping, twisting, and so on).

2.2.3. Network module

The network module mediates between the control and the BCI modules and transmits a trigger message to the recording software. The two modules were connected by the TCP/IP network, which sent the movement cue and the time indices of the movement trigger from each module. The parallel and serial networks between the BCI module and each recording software were also constructed.

2.3. Experiment paradigm

The subject sat in an armchair facing a computer monitor. The robotic arm (WAM Arm) was located to the right of the subject. The experiment consisted of four movement imagery trials, i.e., hand grasping (grasp and spread) and wrist twisting (pronation and supination) (Fig. 2A). Each trial was designed as shown in Fig. 2B. At the start of each trial, the computer monitor displayed a black screen for 2 s, followed by a ‘Rest’ instruction for 3 s. Next, during the ‘Visual cue’ period, the subject was asked to concentrate on the movement of the robotic arm, which was one of four movements, for 3 s. The subject performed MI following the robotic arm movement during the subsequent 4-second period (Fig. 2C). For training classifiers, 100 trials per subject were collected in total (25 trials per class).

2.4. Feature extraction

2.4.1. CSP

The CSP uses spatial filters to maximize the variance of EEG signals of one class while simultaneously minimizing the variance from other classes [20]. The EEG signals for a single trial are observed as a time series, $x_t = [x_1(t), \ \ldots, x_k(t)]^\mathrm{T}$, $1 \le t \le r \times l$, where r is the sampling rate, l is the time length of a single trial and k is the number of channels. Let the matrix X be denoted as $[x_1, \ldots, x_N]$ (where N is the number of samples and has the same value as $r \times l$) and each column is a recording vector. Then, CSP is a method for finding a spatial filter w that satisfies Eq. (1):

$$\max_w \left(\frac{w^\top X_1{}^\top X_1 w}{w^\top X_2{}^\top X_2 w} \right) = \max_w \left(\frac{w^\top C_1 w}{w^\top C_2 w} \right) \tag{1}$$

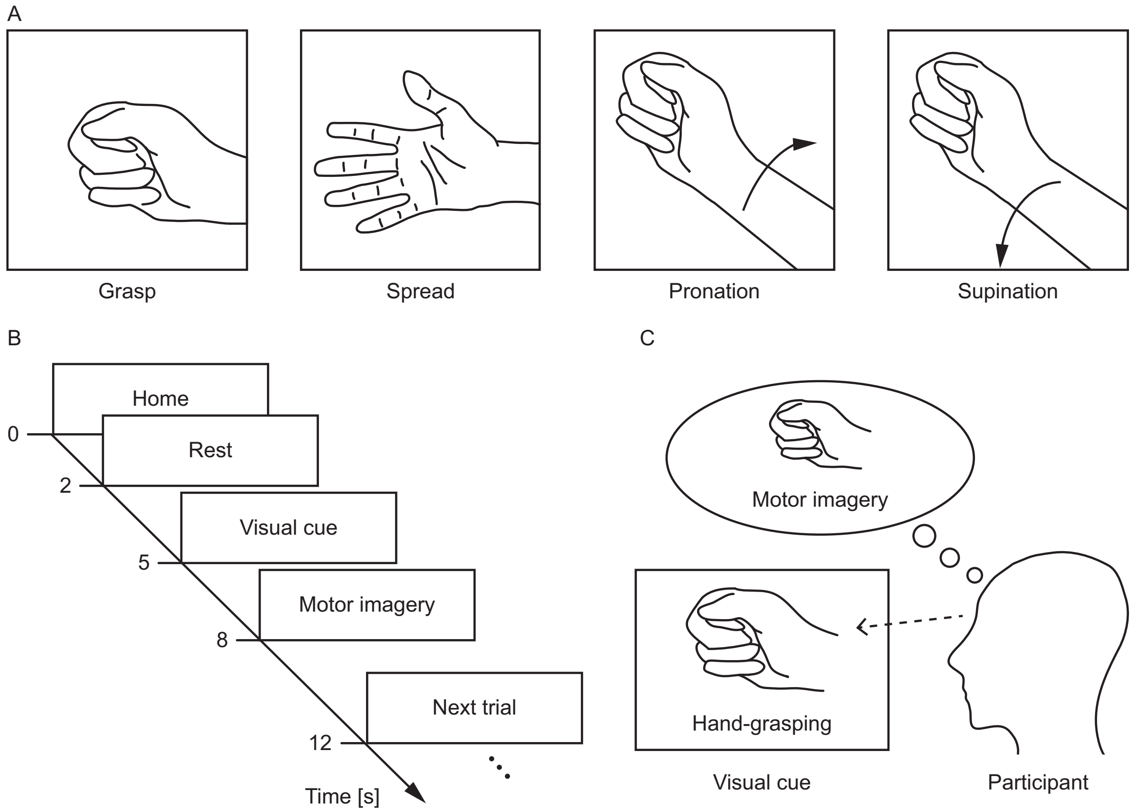

Fig. 2. Experimental paradigm for the MI tasks. (A) The experiment included four MI tasks (grasp, spread, pronation and supination). (B) Each trial consisted of a pre-rest period of 2 s, a rest period of 3 s, a visual stimulation period of 3 s and a motor task period of 4 s. (C) During the MI task, participants imagined performing the movements for one of four hand tasks, which were stimulated by robotic arm movements during the visual stimulation period.

where C_i is the spatial covariance matrix from class i. Using the Lagrange multiplier method to optimize Eq. (1), the following Eq. (2) is derived:

$$L(w, \lambda) = -w^\top C_1 w + \lambda (w^\top C_2 w - 1) \tag{2}$$

To solve the Lagrange multiplier optimization, the derivative $\frac{\partial}{\partial w} L(w, \lambda) = 0$. Then, the optimization is transformed into a generalized eigenvalue as follows:

$$\max_w \left(\frac{w^\top C_1 w}{w^\top C_2 w}\right) = \max_w \left(\frac{w^\top \lambda C_1 w}{w^\top C_1 w}\right) = \max_w (\lambda) \tag{3}$$

The spatial filters that optimize (1) are the eigenvectors of $C_2^{-1} C_1$ with the largest and smallest eigenvalues. These extracted features are used as the logarithm of the signal variance after projection onto the filters w for ease of calculation. Topographical patterns of the CSP are presented in Fig. S1 (Supplementary material).

2.4.2. TDP

The TDP is inspired by Hjorth parameters [11,24], which describe the Activity, Mobility and Complexity of a target signal and are defined as follows:

$$\text{Activity} = \text{var}(x(t)) \tag{4}$$

$$\text{Mobility} = \sqrt{\frac{\text{Activity}(\frac{dx(t)}{dt})}{\text{Activity}(x(t))}} \tag{5}$$

$$\text{Complexity} = \frac{\text{Mobility}(\frac{dx(t)}{dt})}{\text{Mobility}(x(t))} \tag{6}$$

Table 1
Details of the classification class.

Experiment	BCI classes	
Experiment 1	Binary classification:	Hand grasping (grasp + spread) vs. wrist twisting (pronation + supination)
Experiment 2	Ternary classification:	(A) Grasp vs. spread vs. wrist twisting (pronation + supination) (B) Hand grasping (grasp + spread) vs. pronation vs. supination
Experiment 3	Quaternary classification:	Grasp vs. spread vs. pronation vs. supination

where Activity is the signal power, Mobility is the mean frequency and Complexity is the change in frequency. The TDP, with the number of derivatives P used as a parameter, can be calculated as follows:

$$P_i = \mathrm{var}\left(\frac{d^i x(t)}{dt^i}\right).(i = 0,\ 1,\ 2) \tag{7}$$

In practice, the TDP implies the characteristics of variance; for complex curves that consist of numerous superimposed elements, the TDP reflects the average of basic elements computed from the complex curves themselves [11]. The distribution of the TDP is shown in Fig. S2 (Supplementary material).

2.4.3. PSD

Information from a signal as a stochastic process that reflects the distribution of its power in the spectral domain is extracted by spectral density methods. The PSD is a Fourier transform (FT) of the autocorrelation function provided by the stationary signal. In real world EEG applications, the complete characteristics of the random signal are not available; thus, its spectral content should be estimated from discrete time samples [15]. In our work, the coefficients of the autoregressive model were estimated using the Yule-Walker method [10] applied to discrete EEG sampling data. The general autoregressive AR(p) is described as follows:

$$x_t = \sum_{i=1}^{p} \phi_i x_{t-i} + \zeta_t \tag{8}$$

where p is the appropriate order of AR(p) and the corresponding coefficients are $\emptyset_t$. PSD estimated by the Yule-Walker equation is defined as follows:

$$\gamma_m = \sum_{k=1}^{p} \phi_k \gamma_{m-k} + \sigma^2 \delta_m \tag{9}$$

where $m = 0, \ldots, p$, γ_m is the autocovariance function of x_t, σ is the standard deviation of the noise, and δ^m is the Kronecker delta function [13]. Assuming $p = 1$, $\gamma_1 = \emptyset_1\gamma_0$ and $\mathrm{AR}(1) = \frac{\gamma_1}{\gamma_0} = \emptyset_1$, for $p = 2$, $\gamma_1 = \emptyset_1\gamma_1 + \emptyset_2\gamma_{-1}$, $\gamma_2 = \emptyset_1\gamma_1 + \emptyset_2\gamma_0$, $\mathrm{AR}(1) = \frac{\gamma_1}{\gamma_0} = \frac{\emptyset_1}{1-\emptyset_1}$, and $\mathrm{AR}(2) = \frac{\gamma_2}{\gamma_0} = \frac{{\emptyset_1}^2 - {\emptyset_1}^2 + \emptyset_2}{1-\emptyset_2}$. Using this approach, AR(p) is estimated and used as the PSD feature. A graph of the PSD is shown in Fig. S3 (Supplementary material).

2.5. Classification

Four types of conventional, widely used machine learning techniques, including linear support vector machine (LSVM) [5], radial basis function (RBF), kernel support vector machine (KSVM) [18], gradient boosting (GB) [26] and shrinkage-regularized linear discriminant analysis (SRLDA) [14], were applied to classify MI using the CSP, TDP and PSD. The two variants of SVM are well-established methods for classification problems in BCIs [23]. GB was selected for its multiclass discrimination ability, and SRLDA was selected because it is one of the most frequently used classifiers in MI studies [14]. Combined with the three feature extraction techniques (CSP, TDP and PSD), these four classifiers were employed for binary, ternary and quaternary classification of complex MI tasks (Table 1).

2.6. Statistical analysis

All statistical analyses were conducted with SPSS 24.0 (IBM Corp., Chicago, Illinois, USA). Non-parametric tests were performed due to the small number of subjects. Consequently, the Mann-Whitney U test was used to evaluate statistically significant differences between the groups. A value of $p < 0.01$ was considered statistically significant.

3. Results

In this section, the classification accuracy of features from three domains (CSP, TDP and PSD) was presented to identify the tendency of each feature in specific tasks. In addition, three series of multiclass experiments were conducted to compare the effectiveness of three feature extraction methods and four classifiers (LSVM, KSVM, GB and SRLDA).

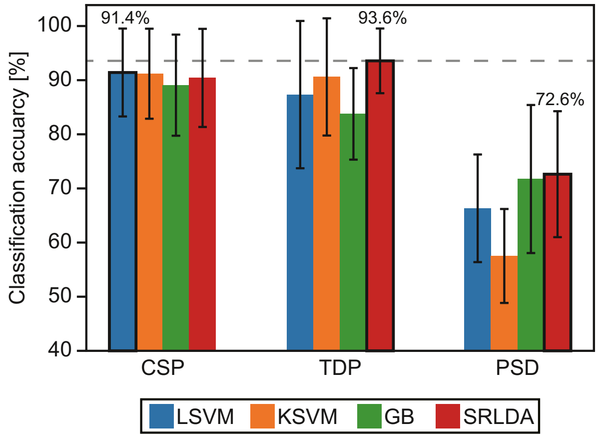

Fig. 3. Comparison of the feature extraction-classifier combinations' accuracies for discriminating hand grasping and wrist twisting. Bars with a bold border represent the highest accuracy of classifier for each feature extraction method and the error bars represent the standard deviation for each feature extraction-classifier combination.

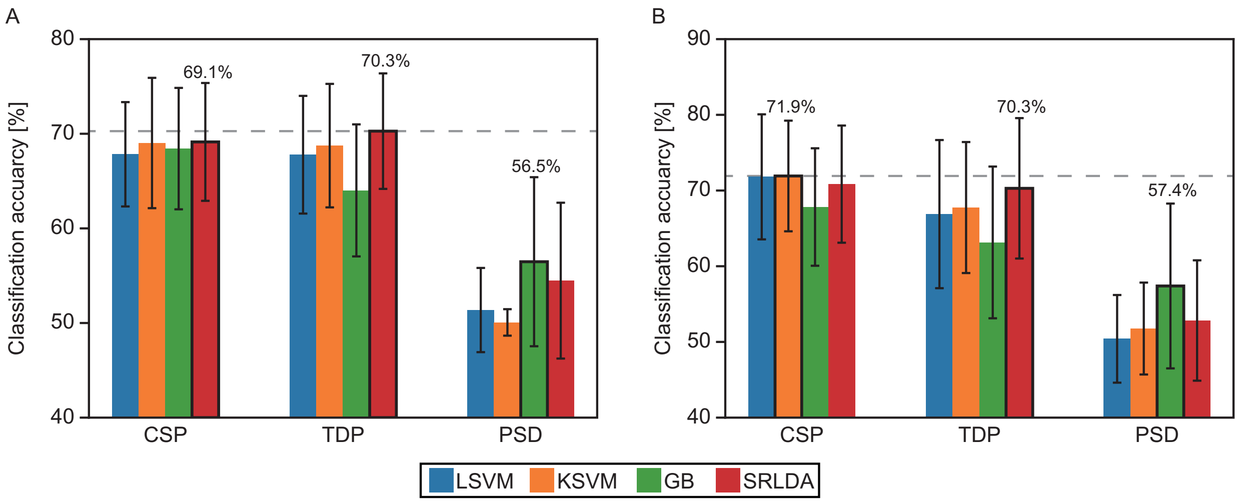

Fig. 4. Comparison of the feature extraction-classifier combinations' accuracies for discriminating (A) hand grasping, pronation and supination, and (B) wrist twisting, grasp and spread. Bars with a bold border represent the highest accuracy of classifier for each feature extraction method and the error bars represent the standard deviation for each feature extraction-classifier combination.

3.1. Experiment (I): binary classification

For the first series of classification experiments, a binary classification of MI tasks (i.e., hand grasping (grasp and spread) versus wrist twisting (pronation and supination)) was conducted. The classification accuracy of the binary classification is shown in Fig. 3. The TDP with SRLDA showed the best classification accuracy among all the feature extraction method and classifier combinations (93.6 ± 6.0%). The CSP exhibited the next best classification capacity with LSVM as the optimal classifier (91.4 ± 8.1%). For the TDP and CSP, GB was the worst classifier for binary classification, exhibiting remarkably poor performance when combined with the TDP (CSP: 89.1 ± 9.3%, TDP: 83.8 ± 8.5%). PSD, especially when coupled with KSVM, achieved the lowest performances among the three feature extraction methods; the accuracy did not exceed 75% for all classifiers.

3.2. Experiment (II): ternary classification

To verify the performances of the feature extraction-classification combinations in a 3-class discrimination task, the movements were separated into two specific classification experiments: hand grasping was divided into grasp and spread for ternary classification A, and wrist twisting was divided into pronation and supination for ternary classification B. Fig. 4 shows the accuracy of the various combinations in the ternary classification task, hand grasping versus pronation versus supination (classification A) and grasp versus spread versus wrist twisting (classification B). Again, the best classification performance was achieved by the combination of the TDP and SRLDA for ternary classification A, although a slight decrease

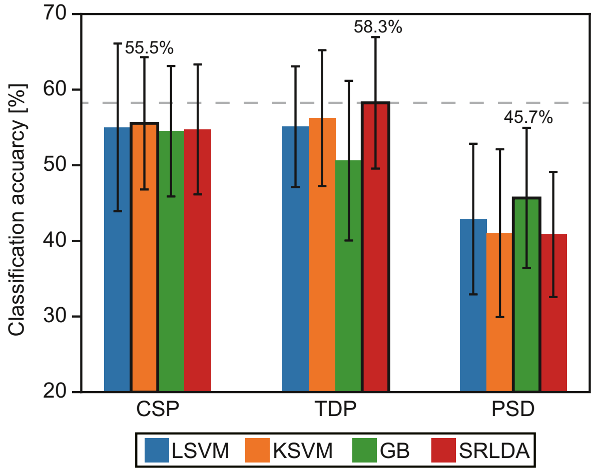

Fig. 5. Comparison of the feature extraction-classifier combinations' accuracies for discriminating grasp, spread, pronation and supination. Bars with a bold border represent the highest accuracy of classifier for each feature extraction method and the error bars represent the standard deviation for each feature extraction-classifier combination.

in performance occurred compared to the binary classification (70.3 ± 6.1%). In classification B, the CSP, which yielded an accuracy below 70% in classification A, showed improved performance with greater than 70% accuracy, except when combined with GB (LSVM: 71.8 ± 8.3%, KSVM: 71.9 ± 7.3%, GB: 67.8 ± 7.8%, SRLDA: 70.8 ± 7.7%). PSD showed low accuracy (mostly below 60%) compared to the other two feature extraction methods. A decline in performance compared to the binary classification was observed over all the combinations.

3.3. Experiment (III): quaternary classification

In the last series of classification experiments, the number of movements was extended by separating each task: grasp, spread, pronation, and supination. Fig. 5 presents the quaternary classification accuracy of feature extraction–classification combinations. In general, performance degradation was observed for all combinations of feature extraction and classification methods. The best classification performance for these highly diverse classes was achieved by the TDP and SRLDA (an accuracy of 58.3 ± 8.7%); this combination achieved the best performance in the binary and ternary classification experiments. The CSP had a tendency similar to those of binary and ternary classification B because KSVM was the optimal classifier. For the PSD, GB exhibited the best classification accuracy compared to the other classifiers, although the accuracy was still under 50%.

3.4. Comparison of the feature extraction methods with classifiers

Mann-Whitney *U* tests were conducted to compare significant differences in classification accuracy between the feature extraction–classification combinations. The results of the Mann-Whitney *U* tests showed significant differences in accuracy between PSD and the other feature extraction methods ($p < 0.01$; Fig. 6). In binary classification, all classifiers combined with PSD had significantly lower accuracy than when combined with the CSP and TDP (Figs. 3 and 6 A). Significant differences were also observed between TDP-GB and TDP-SRLDA in binary and ternary A classifications ($p = 0.007$, Fig. 6A). Except for PSD with GB, all PSD and classifier combinations showed significant differences compared to the other two feature extraction methods and classifier combinations in ternary and quaternary classifications (Fig. 6B–D).

3.5. Execution time

The execution time of feature extraction was calculated to compare the efficiency of the three methods (Table 2). TDP achieved the shortest average execution time among all the feature extraction methods. CSP required slightly longer than did TDP for the ternary and quaternary classification tasks and showed a linear increment with the number of classes. The time required to extract the spectral features, PSD, was more than ten times as long as the times required for CSP and TDP.

4. Discussion

This study investigated whether the features from three different EEG domains (i.e., spatial, temporal and spectral) would yield different performances against complex, multiclass discrimination tasks for robotic arm MI-BCI. Based on the data derived from the experiments, the results of this study indicate that the temporal and spatial (TDP and CSP, respectively)

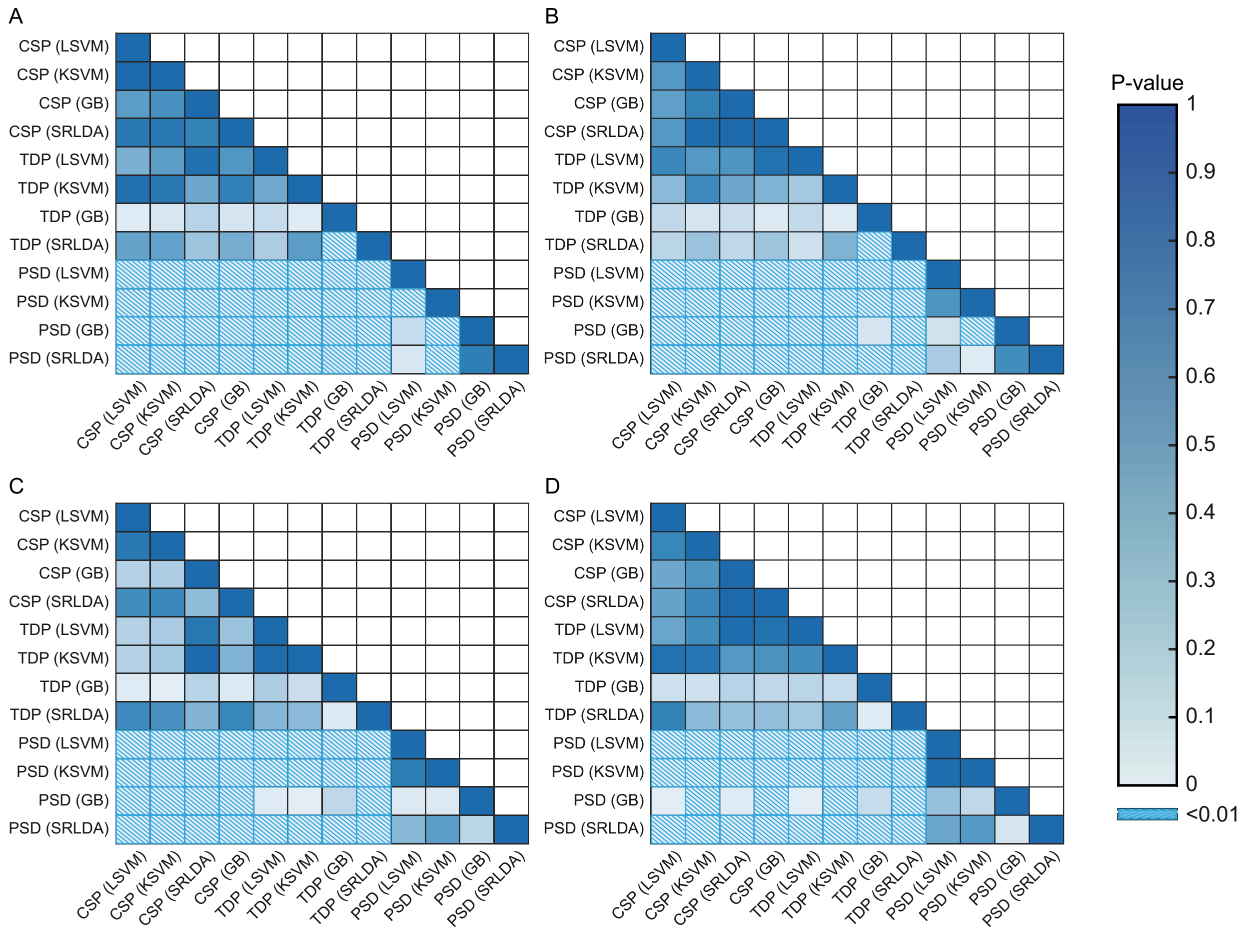

Fig. 6. The heat map for feature extraction-classifier combinations. The p values for each combination are calculated with the Mann-Whitney *U* test in (A) binary classification, (B) ternary classification A, (C) ternary classification B, and (D) quaternary classification. *P* values less than 0.01 are highlighted by slashed lines.

Table 2
Execution times for all feature extractions.

Classification class	Feature extraction time (s)		
	CSP	TDP	PSD
Binary	0.483	0.498	6.563
Ternary	0.527	0.492	6.361
Quaternary	0.624	0.487	6.524
Average	0.545	0.493	6.483

features outperform those from the spectral domain (PSD). Of the former two methods, TDP achieved slightly higher performance than CSP.

With the exception of PSD, which consistently exhibited low performance on every discrimination task, the accuracies of CSP and TDP were significantly high for binary discrimination tasks (>90%, Fig. 3). However, as the number of target classes increased, the performances of the models declined rapidly; in more diverse multiclass MI tasks (i.e., quaternary; grasp, spread, pronation and supination), only the TDP with SRLDA yielded classification accuracies of almost 60% (58.3%, Fig. 5).

For all three domain features, the use of different EEG domains and classifiers yielded only marginal changes in classification accuracy (Figs. 3–5). Notably, however, while the best discrimination performance of the CSP was achieved with various classifiers except for GB, the TDP always performed best with the SRLDA classifier. Conceptually, the TDP foregoes calculating numerous components of EEG signals; instead, the technique attempts to reflect the behavior (i.e., Activity, Mobility and Complexity) of the measured signal itself [11]. Thus, the TDP requires relatively few parameters to be selected to represent the typical elements of intricate factors. This characteristic of TDP may explain its preference toward SRLDA, which is known for its efficacy with small sample sizes [7]. In addition, TDP has the advantage of easy and fast calculation, making it computationally efficient [24]. As shown in Table 2, the time consumption for extracting the TDP feature has the shortest average time compared to the other feature extraction methods. The time consumption for CSP, which increases linearly as the number of classes increases, is the shortest when extracting features for binary classification, but it requires longer for ternary and quaternary classifications than does TDP. PSD generates thousands of features, which explains why it achieves its best performances when coupled with GB and why it requires the longest time to extract features. These results reconfirm that the characteristics of feature extraction techniques should be taken into consideration when choosing classifiers, especially for multiclass discrimination tasks.

The findings of this study suggest that the complex multiclass MI tasks may be better discriminated by utilizing relatively simple, symbolic parameters from time domain analyses rather than other more complex features from varying domains. The multiclass discrimination problem lies at the core of BCI research. CSP, while primarily used for binary classification tasks, has been actively augmented to make it more suitable for multiclass MI discrimination tasks [6]. Another important aspect of the CSP that has been actively addressed is its dependency on a multichannel EEG setup [9,25]. However, improvement attempts have rarely been undertaken for the feature extraction techniques for the other two domains (i.e., temporal and spectral). The results of the statistical analysis in our study demonstrated that the CSP and TDP were not significantly different for every single classifier (Fig. 4); the TDP showed a comparable capacity to that of the CSP. The efforts to reduce the number of required EEG channels may be more beneficial if they were directed toward temporal feature extraction techniques. Finally, most previous studies aiming to enhance feature extraction and classification performance in multiclass MI discrimination tasks are based on similar datasets [21], which may have affected the reported performances in these studies. In this context, the efficacy of temporal feature extraction methods (i.e., TDP, as demonstrated in this study) deserves more attention.

Several limitations of this study should be noted. First, the comparison of classification performance was derived from our own dataset, which could have yielded data-oriented results. Second, detailed statistical analyses were not available due to the small sample size of the experimental data. Thus, testing with more data is needed to validate the findings of this study. Finally, this study employed only well-established and widely available feature extraction and classification methods to improve the objectivity of the analyses and subsequent results; thus, recent advancements in feature extraction techniques and classifiers that may be more suitable for multiclass discrimination were deliberately not included in this study. Future studies that aim to validate the findings of this study with similar designs could benefit from including enhanced variants of feature extraction techniques and classifiers for multiple EEG domains, preferably with larger cohorts from prospective experiments.

5. Conclusions

This study investigated whether the features extracted from three different EEG domains (spatial, temporal and spectral) had different effects on the classification performances on different levels of complex, multiclass MI tasks. The conventional feature extraction methods of each domain (CSP, TDP and PSD) were applied to classify binary, ternary and quaternary MI hand grasping and wrist twisting tasks. TDP was found to be superior to the other two features (CSP and PSD) for all multiclass classifications. The multiclass MI-BCI system, which included complicated MI tasks, could be improved by analyzing the simple temporal features of EEG rather than the more intricate spatial and spectral features.

Declaration of Competing Interest

None.

CRediT authorship contribution statement

Seung-Bo Lee: Conceptualization, Methodology, Software, Writing - review & editing. **Hyun-Ji Kim:** Formal analysis, Writing - original draft, Visualization. **Hakseung Kim:** Formal analysis, Methodology, Validation, Investigation. **Ji-Hoon Jeong:** Data curation, Writing - review & editing. **Seong-Whan Lee:** Data curation, Writing - review & editing. **Dong-Joo Kim:** Conceptualization, Project administration, Resources, Supervision, Writing - review & editing, Funding acquisition.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ins.2019.06.008.

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Seung-Bo Lee received his BE in Computer and Communications Engineering (College of Information and Communication) from Korea University, South Korea (2015). He is an integrated master-PhD student in brain and cognitive engineering at Korea University, Seoul, Korea. His research interests include brain-computer interfaces, bio-signal processing and machine learning, especially artificial neural networks.

Hyun-Ji Kim received her BE in Biomedical Engineering from Korea University, South Korea (2017). She is an integrated master-PhD student in brain and cognitive engineering at Korea University, Seoul, Korea. Her research interests include brain-computer interfaces, bio-signal processing and medical image analysis.

Hakseung Kim received his BS in brain and cognitive sciences (2013), BA in Korean language and literature (2013) and PhD in brain and cognitive engineering from Korea University, South Korea (2018). His specific areas of research include quantitative medical image analysis, patient monitoring in the critical care environment, cerebrospinal fluid dynamics, brain-computer interfaces, and patient-specific finite element modeling of neurological disorders associated with space-occupying lesions. He has been a research professor in Departmen of Brain and Cognitive Engineering at Korea University, South Korea since 2018.

Ji-Hoon Jeong received his BS degree in computer information science from Korea University, Seoul, Korea, in 2015. He is an integrated master-PhD student in brain and cognitive engineering at Korea University, Seoul, Korea. His research interests include machine learning, deep learning and brain-machine interfaces.

Seong-Whan Lee received the BS degree in computer science and statistics from Seoul National University, Seoul, in 1984, and the MS and PhD degrees in computer science from the Korea Advanced Institute of Science and Technology, Seoul, Korea, in 1986 and 1989, respectively. Currently, he is the Hyundai-Kia Motor chair professor and the head of the Department of Brain and Cognitive Engineering, Korea University. He is a fellow of the IAPR, and the Korea Academy of Science and Technology. His research interests include pattern recognition, artificial intelligence and brain engineering. He is a fellow of the IEEE.

Dong-Joo Kim received his PhD in Engineering from the University of Cambridge, UK, where his time was split between clinical research (in the Neurosurgery unit at Addenbrooke's Hospital) and brain modeling (in the Engineering Department). Afterwards, he spent two years as a research fellow in the Neuroscience Mental Health Program of the Department of Critical Care Medicine at the Hospital for Sick Children (University of Toronto), Canada. Since 2017, he has been an Associate Professor in the Department of Brain and Cognitive Engineering at Korea University, South Korea. His research activity has been in brain mechanics, neuromonitoring, and numerical neuro-modeling.