An Effective Fusing Approach by Combining Connectivity Network Pattern and Temporal-Spatial Analysis for EEG-Based BCI Rehabilitation

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***Abstract*— Motor-modality-based brain computer interface (BCI) could promote the neural rehabilitation for stroke patients. Temporal-spatial analysis was commonly used for pattern recognition in this task. This paper introduced a novel connectivity network analysis for EEG-based feature selection. The network features of connectivity pattern not only captured the spatial activities responding to motor task, but also mined the interactive pattern among these cerebral regions. Furthermore, the effective combination between temporal-spatial analysis and network analysis was evaluated for improving the performance of BCI classification (81.7%). And the results demonstrated that it could raise the classification accuracies for most of patients (6 of 7 patients). This proposed method was meaningful for developing the effective BCI training program for stroke rehabilitation.**

***Index Terms*— BCI, connectivity network analysis, rehabilitation, stroke, temporal-spatial analysis.**

I. Introduction

MILLIONS of people worldwide suffered from stroke, a chronic disorder characterized by the affections of limb movement [1], [2], [3], [4]. Various types of rehabilitation interventions were applied for improving the life quality of stroke patients [5], [6], [7]. Commonly, all patients performed physical recovery for several months. In the training, some assistive devices, such as robot arm, virtual reality technology and sensor capture equipment, were designed to assist with users at hospital [8], [9]. However, it remained unclear what neurophysiological mechanism was facilitating the functional rehabilitation.

Meanwhile, neuromodulation approaches were employed in the recovery [10]. This technology could provide quantitative indicators by translating sampled bio-signals into numerical values [11], [12]. In this field, Electroencephalogram (EEG)-based BCIs were widely used for repairing upper limb motor function [13], [14], [15]. The neural pathway was reconstructed by this technology for stroke patients. And visual/auditory feedbacks of BCI systems were designed for arousing a sense of embodiment for patients [16]. It played a positive role on facilitating the recovery training for the paralyzed [17], [18].

Feedback performances of BCI were dependent on feature selecting of electroencephalogram (EEG) signal [19], [20]. The motor-modality BCI was commonly decoded by spatiotemporal analysis. The experimental performance was satisfactory for healthy subjects with this method [21], [22]. Representatively, event-related desynchronization/synchronization (ERD/ERS) pattern was proposed for detecting the dynamics of brain oscillations in the training [23]. This qualification indicator was used for validating the effectiveness of BCI rehabilitation.

Moreover, some spatial filter algorithms were employed to extract features of EEG signals. Among them, common spatial pattern (CSP) was a popular method for classifying 2-class mental tasks with motor functions [24], [25]. Recently, numerous studies focused on improving the effect of this CSP method by feature selection in the spatial and spectral domains [21], [26], [27], [28], [29], [30]. Jin *et al.* proposed bispectrum analysis for eliminating noise and redundant information from EEG signals [31]. This algorithm achieved the better performance for motor imagery classification. Besides, spectral features were also extracted for improving the performance against these state-of-art methods in the multi-class

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tasks [32], [33]. Nevertheless, the feasibly of these algorithms had not been verified for stroke patients.

Hence, CSP had been commonly applied to decode EEG signals in the BCI-based rehabilitation [34], [35], [36]. In these studies, classification accuracies were considered as a supplementary indicator resulting from the poor performance in the recognition. Furthermore, the deep learning methods were performed for lifting the effect of BCI classifying [37], [38], [39]. These mathematical approaches were helpful for data analysis. However, the neurofeedback efforts were still confusing owing to the unexplainability of neural networks.

In essence, the works mentioned above introduced the difference of power-spectral distributions among multi-class motor tasks. The neuroscience research showed that, the cognitive state was also reflected by functional interactions between various brain regions. The previous study verified that the neural plasticity of the injured brain was related to the connection activity of cerebral regions for stroke patients [17], [40]. In another work conducted by Stem *et al.*, the significant quantitative difference of resting-state brain network was investigated between Alzheimerś patients and the healthy [41]. The connection analysis of brain networks had been widely used for clinical diagnosis [42], [43], [44], [45].

Compared with widespread applications of network analysis for pattern recognition in other fields of bio-signal process, this technology was used for classifying in the minority of studies reported for motor-modality BCI. Ma *et al.* proposed a channel-correlation network for feature extraction from motor tasks of the same limb [46]. The result demonstrated that the accuracy was higher than those of other common approaches. As we know, none of researches proposed connection analysis for BCI rehabilitation.

To address the challenges of feature selection for BCI rehabilitation, a novel approach combining connectivity network pattern and temporal-spatial analysis was proposed for constructing BCI rehabilitation systems. Connection patterns were calculated by three indices, phase-locking value (PLV), Pearson correlation coefficient (PCC), and transfer entropy (TE). CSP features were used for extracting temporal-spatial features. The fusing structure containing the above two algorithms was established for improving the prediction performance.

II. Materials

A. Subjects

Seven male stroke patients (25-75 years old) participated in this experiments, who were recruited from the Department of Rehabilitation Medicine of Huashan Hospital, Shanghai. None of them had the experience of controlling motor-modality BCI. All of them gave written consent and were informed about the procedure in our study. The inclusion criteria were listed in Table I.

TABLE I
THE INCLUSION CRITERIA IN OUR STUDY

No.	Inclusion Criteria
1	Unilateral motor dysfunction diagnosed by computer tomography or magnetic resonance imaging (MRI).
2	First onset stroke patient.
3	The time since stroke onset was more than 4 weeks and less than 6 months.
4	The assessment of cognitive functions: Mini-Mental State Examination score > 25.
5	Stable medical conditions.
6	No severe vision problems (i.e., poor sight, diplopia, hemianopia, visual field defects and total blindness).
7	Intervention treatment by non-invasive brain stimulation did not be performed for these patients.

B. Experimental Paradigm

In this study, BCI experiments contained 12 sessions. And it was performed three sessions one week for each patient. One session consisted of three runs. Each run had 30 trials for two motor tasks (motor attempt or resting state). The sequence of two tasks was randomized.

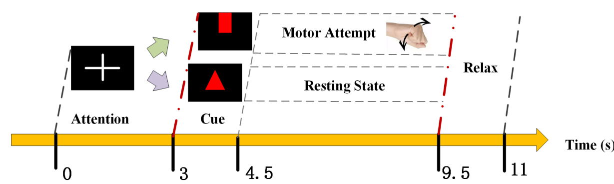


Fig. 1. The experimental procedure of two-class BCI tasks. The red circle was used for indicating the motor task and the red rectangle was used for indicating the resting task. After the red circle disappeared, the subject was instructed to image rotating his/her wrist extension with affect hand as far as possible while avoiding compensatory movements. In the other task of resting, the subject did not do any thing for a rest.

In a trial, the patient sat in a comfortable chair, and a computer display was placed at a 1-meter distance in front. As shown in Fig. 1, a white arrow was presented for 3 seconds firstly. Then, a red circle indicating the motor task or a red rectangle indicating the resting state appeared for 1.5 s. After the circle disappeared, the subject was instructed to image rotating his/her wrist extension as far as possible while avoiding compensatory movements (e.g., moving heads and shoulders). Correspondingly, the subject was required to have a rest when the rectangle cue disappeared in the screen. The duration of the mental task lasted 5 seconds. At last, the relaxing was performed for 1.5 s before the next trial began. In this experiment, the task could be interpreted as the mental work. During this period of resting task, the subject needed to keep eyes open without any thought. The subject controlled resting task with very light work load instead of normal resting state because a pure resting state was not possible to achieve in practice.

C. EEG Recording and Signal Preprocessing

The recording was made using a cap consisting of Ag/AgCl electrodes (actiCAP, Brain Products, Germany). The 31 electrodes were placed according to the 10C20 international standards on FP1, FZ, F3, F7, FT9, FC5, FC1, C3, T7, TP9, CP5, CP1, PZ, P3, P7, O1, O2, P4, P8, TP10, CP6, CP2, CZ, C4, T8, FT10, FC6, FC2, F4, F8, FP2. The reference electrode was located in the right mastoid. Electrode impedances were kept below 5 kΩ, and the sampling rate was set to 200 Hz. The fifth-order Butterworth band-pass filter of 5-30 Hz was used for filtering out components unrelated to sensorimotor rhythms.

III. Method

A. Temporal-Spatial Analysis for Motor Task Classification

As mentioned above, CSP was always used as the common approach for the comparison with proposed methods. It optimized a set of spatial filters to maximize the variance of one class j while minimizing the variance of the other class k. The average spatial covariance matrix R could be computed as

$$R_j = \frac{1}{N_j}\sum_{i=1}^{N_j}\frac{E_{i,j}E_T^{i,j}}{tr(E_{i,j}E_T^{i,j})} \tag{1}$$

where N was the number of all trials and $E_{i,j}$ denoted EEG matrix of i-th trial in class j. And the problem could be solved by

$$argmax\frac{w^T R_j w}{w^T R_k w} \tag{2}$$

where w was the generalized eigenvector. In our experiments, the first and last 3 rows from spatial covariance matrix were selected for further analysis.

Recently, it was verified that filter-bank CSP (FBCSP) was very applicable for various motor-modality BCI recognitions [34]. In particular, CSP features extracted from power-distribution bands ($5-8, 8-12, 12-16, 16-20, 20-24, 24-28, 28-30$ Hz) were investigated for spectral filtering by FBCSP. Hence, these two approaches were selected for evaluating classification performances as the benchmark.

B. Network Analysis for Motor Task Classification

In our method, three indicators (i.e., PCC, PLV, TE) computed by inter-channel relevance, were measured for network analysis. And these indicators had been widely used in neuroscientific works [47].

PCC indicator was calculated as a serial number ranging from -1 to 1, which measured the linear relationship between two signals. With the increase of the absolute value of PCC, the relevance got high. And 0 indicated that these two signals were uncorrelated. Let $X_i = \left\{X_i^1, X_i^2, \ldots, X_i^t\right\}$ denoted an EEG signal of the ith channel, where t was the time length of one trial. Thus, PCC indicators between two signals X_j and X_k was computed as

$$PCC\,(j,k) = \frac{\frac{1}{t}\sum_{t=1}^{T}(X_j-\mu_j)(X_k-\mu_k)}{\sigma_j\sigma_k} \tag{3}$$

where μ and σ represented the mean and standard deviation of the EEG signal, respectively.

PLV indicator was used for measuring the non-linear phase synchronization [48]. Supposing the instantaneous phases of two-channel signals X_j and X_k being φ_j^t, φ_k^t, then the PLV was defined as

$$PLV\,(j,k) = \frac{1}{T}\left|\sum_{t=1}^{T} exp\left\{\varphi_j^t - \varphi_k^t\right\}\right| \tag{4}$$

where t was the time point and the phase value ranged from 0 to 1.

TE [49] denoted the directed flow of information from an origin signal X_j to another target signal X_k:

$$TE\,(j\to k) = \frac{1}{T-1}\sum_{t=1}^{T-1} p\left(X_j^t, X_k^t, X_k^{t+1}\right)\Gamma \tag{5}$$

Here,Γ was defined as

$$\Gamma = \log\frac{p\left(X_k^{t+1}|X_j^t, X_k^t\right)}{p\left(X_k^{t+1}|X_k^t\right)} \tag{6}$$

Moreover, it described the gain obtained by the origin signal to predict the target signal. The value 0 meant no causal relationship between these two signals. The features of the connection network were calculated for all pairs of EEG channels. Hence, the number of obtained features was $N(N-1)/2$ for undirected connectivity (PCC or PLV) or $N(N-1)$ for directed connectivity (TE). Here N was the number of electrodes.

C. Fusing Pattern for Motor Task Classification

The cognitive states involved neural activities of cerebral regions and interactive influences between functional areas. Therefore, the fusing pattern combining temporal-spatial features and network features was proposed in our study. Firstly, EEG data were computed by CSP and network analysis, respectively. Then, the connection features ($m \times n$ samples) were pooled as an one-dimensional vector ($1 \times mn$ samples). Thus, we could combine CSP features ($1 \times r$ samples) and connection features to integrate fusing features ($1 \times (mn + r)$ samples) for model classification. The detailed procedure was illustrated in Fig. 2.

D. Evaluation of Classification Performances

To solve the problem of inter-subject differences, the personalized classifier was used for training classification models. Consequently, after collecting sufficient feature information, a classical radial basis function kernel support vector machine (RBF-SVM) with personalized settings, was used for evaluating performances of three methodologies. This classifier was widely applied to find an optimal hyperplane with the largest possible margin to separate two classes for BCI tasks. In the phase of model training, the penalty factor and kernel parameter played an important role in improving the correct rate and classification efficiency of SVM. Hence, we decided against a parameter estimation by grid search for model optimization. To avoid overfitting, 3-fold cross validation was used for validating the reliability of different algorithms.

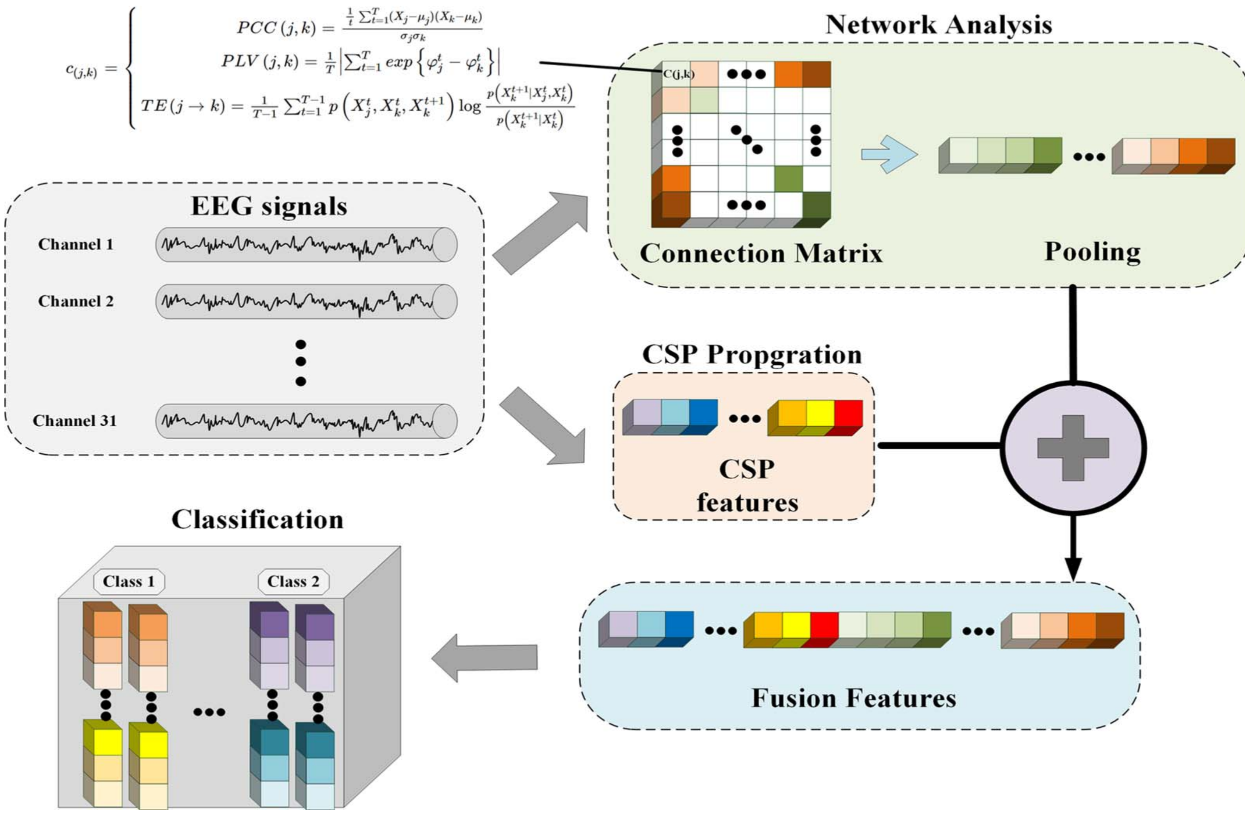


Fig. 2. Flowchart of fusing analysis. The raw data were processed by CSP method and connectivity network analysis. And these two-class features were combined for SVM classification.

TABLE II
THE MEAN ACCURACIES OF BASELINE APPROACHES, NETWORK ANALYSIS APPROACHES AND FUSING APPROACHES FOR 7 SUBJECTS

Subject	1	2	3	4	5	6	7	Mean Accuracy
CSP	0.798 ± 0.079	0.700 ± 0.064	0.771 ± 0.077	0.804 ± 0.072	0.724 ± 0.054	0.687 ± 0.040	0.707 ± 0.082	0.742
FBCSP	0.614 ± 0.096	0.578 ± 0.096	0.627 ± 0.094	0.648 ± 0.157	0.644 ± 0.057	0.630 ± 0.053	0.677 ± 0.090	0.631
PCC	0.824 ± 0.081	0.737 ± 0.072	0.893 ± 0.074	0.936 ± 0.028	**0.781 ± 0.071**	0.660 ± 0.055	0.764 ± 0.088	0.799
PLV	0.812 ± 0.095	0.684 ± 0.058	0.911 ± 0.054	0.918 ± 0.046	0.755 ± 0.063	0.671 ± 0.054	0.728 ± 0.106	0.782
TE	0.849 ± 0.065	0.659 ± 0.058	0.861 ± 0.073	0.836 ± 0.075	0.653 ± 0.074	0.674 ± 0.067	0.746 ± 0.072	0.814
CSP+PCC	0.849 ± 0.067	0.759 ± 0.085	0.902 ± 0.063	0.940 ± 0.029	0.775 ± 0.072	**0.694 ± 0.056**	**0.780 ± 0.081**	**0.817**
CSP+PLV	**0.859 ± 0.075**	**0.756 ± 0.071**	**0.919 ± 0.047**	**0.944 ± 0.022**	0.773 ± 0.071	0.693 ± 0.062	0.764 ± 0.105	0.780
CSP+TE	0.842 ± 0.071	0.722 ± 0.070	0.876 ± 0.058	0.865 ± 0.051	0.720 ± 0.057	0.688 ± 0.038	0.745 ± 0.091	0.742

IV. RESULTS

A. Experimental Performances for Each Patients

Table II reported the classification results of baseline approaches and proposed algorithms for 12 sessions of each patient. Furthermore, mean performances in terms of the sensitivity (Se) and specifically (Sp) were calculated for various algorithms (Table. III). The performances of network analysis outperformed those of conventional temporal-spatial analysis. And the statistical analysis assessed with a Wilcoxon signed-rank test verified the priority of network analysis (PCC with CSP: $p < 0.05$, PLV with CSP: $p < 0.05$, TE with CSP: $p < 0.05$, PCC with FBCSP: $p < 0.05$, PLV with FBCSP: $p < 0.05$, TE with FBCSP: $p < 0.05$).

Furthermore, fusing patterns were investigated to improve the efficiency of classification tasks. FBCSP was not combined with network pattern analysis because of its poor performances in the temporal-spatial analysis. And the result implied that the

TABLE III
ASSESSING THE MEAN ACCURACIES OF BCI REHABILITATION BY ALL PROPOSED ALGORITHMS

Subjects	1		2		3		4		5		6		7	
Parameters	Sp.	Se.	Sp.	Se.	Sp.	Se.	Sp.	Se.	Sp.	Se.	Sp.	Se.	Sp.	Se.
CSP	0.830	0.763	0.723	0.705	0.744	0.807	0.831	0.772	0.748	0.700	0.685	0.687	0.770	0.694
FBCSP	0.357	0.904	0.432	0.706	0.402	0.874	0.409	0.883	0.628	0.656	0.538	0.712	0.655	0.699
PCC	0.843	0.817	0.778	0.767	0.865	0.920	0.928	0.944	0.806	0.756	0.654	0.702	0.794	0.750
PLV	0.832	0.802	0.698	0.687	0.883	0.939	0.908	0.928	0.761	0.698	0.696	0.654	0.741	0.735
TE	0.858	0.869	0.633	0.698	0.807	0.915	0.825	0.848	0.668	0.615	0.655	0.686	0.761	0.700
CSP+PCC	0.861	0.835	0.810	0.764	0.878	0.920	0.932	0.946	0.756	0.761	0.685	0.698	0.796	0.770
CSP+PLV	0.872	0.818	0.783	0.729	0.891	0.933	0.906	0.952	0.739	0.758	0.676	0.719	0.787	0.761
CSP+TE	0.889	0.817	0.731	0.715	0.869	0.896	0.883	0.857	0.709	0.724	0.709	0.665	0.761	0.768

[1] Se = sensitivity, Sp = specificity.

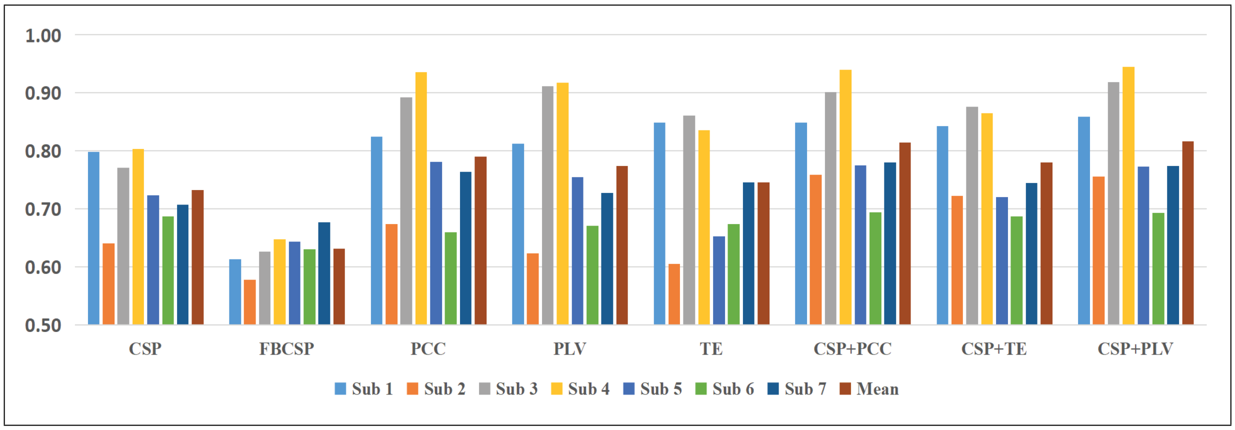


Fig. 3. The comparison of mean accuracies for all subjects among these algorithms.

accuracies of fusing patterns were higher than those of network analysis for most of the subjects (6 of 7). However, we did not observe the statistical significance between the representative algorithm, which achieved the highest accuracies among fusing patterns for all subjects ($p > 0.05$).

All patients had participated in FuglĺCMeyer Assessment of Upper Extremity (FMA-UE) at the beginning of BCI training (Table IV). It was considered one of the most gold standards in the field of stroke rehabilitation. And this criteria was clinically well-established for evaluating the impairment degree of stroke patients. Obviously, Sub. 1, Sub. 3 and Sub. 4 performed better performances in the evaluation (FMA-UE score $>$ 30). And we found that the accuracies of BCI tasks for these 3 patients were higher than those for other subjects for all approaches. It was confirmed that the subjects who had higher FMA-UE scores performed better performances in this task. The results implied that the level of motor impairment affected the efforts of neurophysiological rehabilitation.

B. Performance Comparison of These Algorithms

In this experiment, the mean accuracies of the comparison among these algorithms were listed in Fig. 3. It was suggested that classification effects of fusing analysis were better than those of temporal-spatial analysis for all patients. Moreover, the significant improvement of the combination between network analysis and temporal-spatial analysis was not reflected in this result. It was indicated that the connectivity of several brain regions was important for the rehabilitation of affected brain tissue and cognitive activity.

TABLE IV
FUGLĹCMEYER ASSESSMENT OF UPPER EXTREMITY (FMA-UE) AT THE BEGINNING OF BCI TRAINING

No.	FMA-UE Score
1	36
2	30
3	50
4	37
5	28
6	25
7	13

Meanwhile, ROC curves and AUC scores of the proposed algorithms were reported in Fig. 4. The observation implied that fusing patterns (CSP and PLV, CSP and TE) achieved the best performance compared to other approaches for all subjects. This result demonstrated that fusing analysis was more effective for pattern recognitions of IoT-enabled BCI rehabilitation.

C. Time Consuming Analysis

For assessing the practical performances of BCI systems, which were based on the proposed approaches, the training time and testing time of various patterns were investigated in Fig. 5. The result was evaluated with 3-fold cross validation

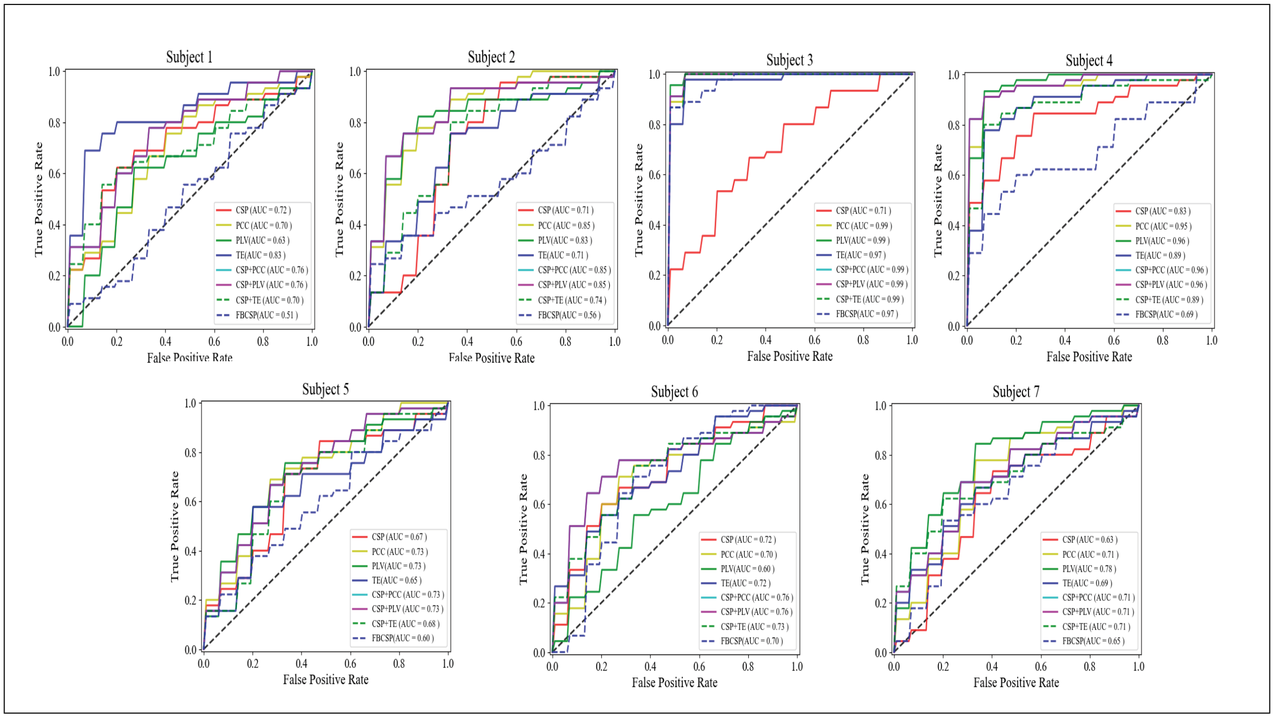
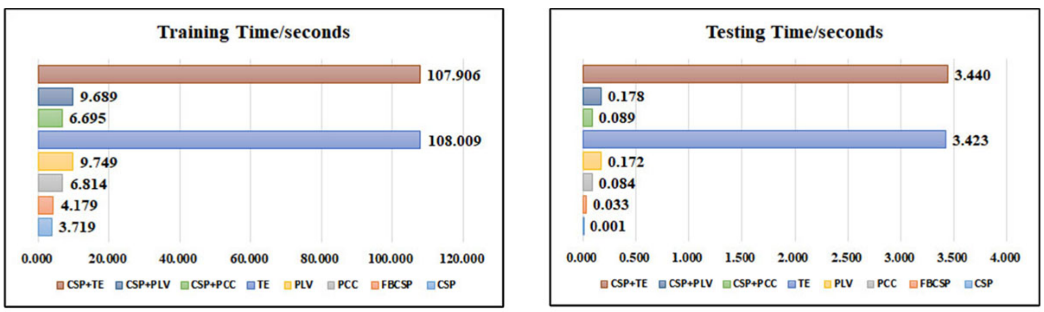


Fig. 4. ROC curves with AUC scores for all algorithms. The features with higher ROC and AUC are deemed more salient.



(a) (b)

Fig. 5. (a) The training time of SVM classifiers for temporal-spatial analysis, connectivity approaches and fusion algorithms. (b) The testing time of SVM classifiers for temporal-spatial analysis, connectivity approaches and fusion algorithms.

using Python 3.8.5 on a PC with an i5-6500K 3.2GHz CPU and 8GB of RAM. Commonly, BCI models should be retrained for each session per subject. This process was unavoidable for all BCI systems as a result of the limitation of subject-dependent mechanism. In detail, the time consuming of thirty trials on one subject was reported as the training time of one session. Furthermore, the time consuming of predicting motor classes on one subject was reported as the testing time of one trial.

As shown in Fig. 5, the time consumption of the fusing pattern combining CSP and TE was the longest one. However, we think about 107 s training time and nearly 3.44 s testing time per trial were both in an acceptable range for BCI rehabilitation. Moreover, standard physical recovery would last 20-30 minutes and spent about 5 minutes doing some preparatory work. Considering the requirement of classification accuracy, the above pattern was the optimal choice. For the requirement of quick setup, real-time performances, and relatively loose classification precision, the fusing pattern combining CSP and PLV was another excellent choice.

It was worth noting that performing TE method was more time consuming than performing PCC and PLV methods. It was due to TE method performed the discretization process to reconstruct the conditional probability during the pre-processing. Finally the entropy value was calculated based on the conditional probability, which produced a great increase in computational cost. In terms of the programming calculation, the time complexity of PCC and PLV methods were $O(nmlogm)$, while the time complexity of TE method was $O(nmxlogm)$. Here, n was the number of trials, m was the number of leads, and x was the length of data in a trial. Hence, the time consuming difference between TE method and other approaches depended on the value of x. In this experiment, the value of x was 1250.

V. Discussion

A. Comparison With State-of-Art Algorithms

In this paper, a network analysis was firstly proposed for BCI rehabilitation. Experimental performances had verified

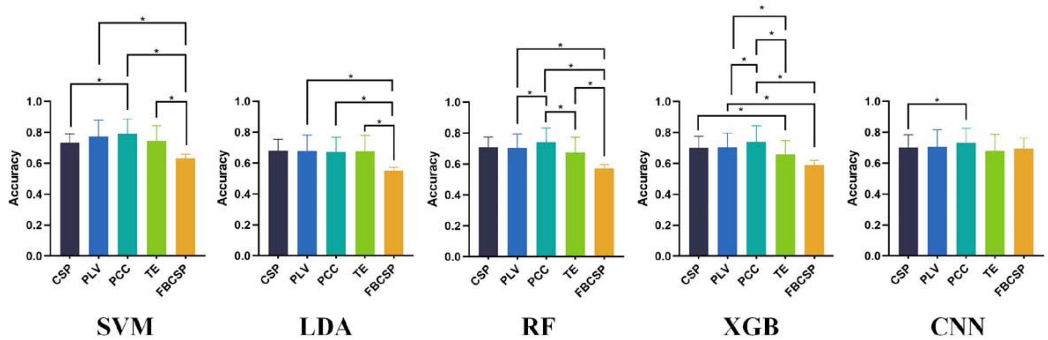


Fig. 6. The classification performance across several state-of-art classifiers. The asterisk denotes $p < 0.05$ for paired t test.

the effectiveness of network analysis and fusing patterns. The novel fusing features combining connectivity patterns and temporal-spatial patterns were not ever used in the rehabilitation of BCI systems [50]. However, the network analysis was performed for healthy subjects in the task of motor imagery (MI) -based BCI [46], [51], [52], [53], [54]. There was little difference between the performances of our work (69%-95%) and those of the above studies (73%-98%). It was implied that our approach was feasible for effective BCI communication with an accuracy threshold of 70% [55]. Whereas the temporal-spatial analysis was ineffective for BCI tasks conducted by several patients.

Meanwhile, we compared classification performance across several state-of-art classifiers (i.e., linear discriminating analysis (LDA), random forest (RF), xgboost (XGB), convolutional neural network (CNN)). The results validated that the total accuracies of network connectivity analysis were higher than those of other state-of-art approaches (Fig. 6). It was consistent with above conclusion. And the classification effects were close in all models, while classification accuracies of CNN were slightly worse. It was implied that the classification performance was dependent on feature selection for BCI rehabilitation. These findings supported the validity of our proposed methods.

Evidently, several studies of motor-modality BCI reported time consumptions of modeling computation (Table V). We could observe that the training time and testing time of our approach were the second least among those of all state-of-art algorithms. In our approach, we used 31 electrodes for data collecting. And Belwifi *et al.* proposed a classification model with two-channel (i.e., C3 and C4) inputs to take the least time consumption (i.e. 0.399 s) in a recognition. In essence, the decoding time of BCI model could be reduced by limiting the number of electrodes. However, the time consumption of experimental preparing and cognitive task were greatly longer than that of model classifying. Hence, the significant increase of decoding time (about 4 s) was affordable for BCI rehabilitation. Moreover, our computational resources were low-price and it was affordable for all users. This verified that our approach was high performance-price for BCI-enabled healthcare systems. Furthermore, we compared the qualities of our models with these baseline models in Table V. It could be seen that our models were the most lightweight among them. It was useful for BCI-enabled devices with limited storage resources.

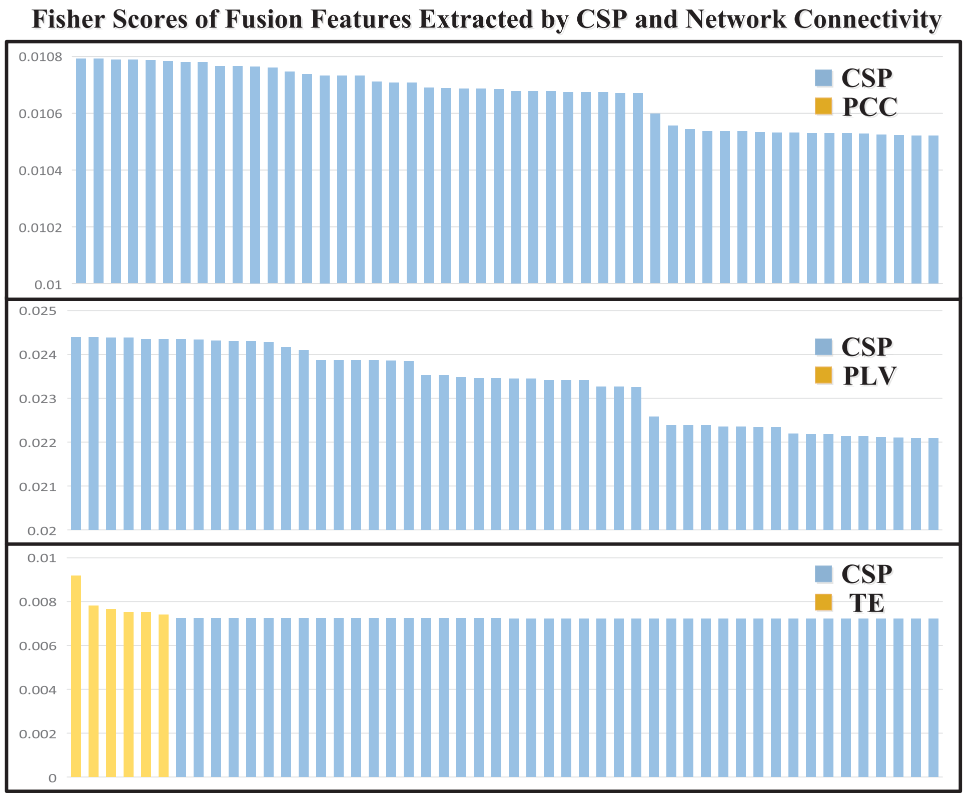
TABLE V
THE COMPARISON OF TIME CONSUMPTIONS BETWEEN OUR APPROACH AND PREVIOUS STUDIES

Studies	Training time (s)	Testing time (s)	The size of parameters (M)
Our approach	108.9	3.44	0.25
Zhao et al. [56]	33.6	3.88	2.02
Miao et al. [30]	138	143.19	0.28
Belwafi et al. [57]	N/A	0.399	0.55

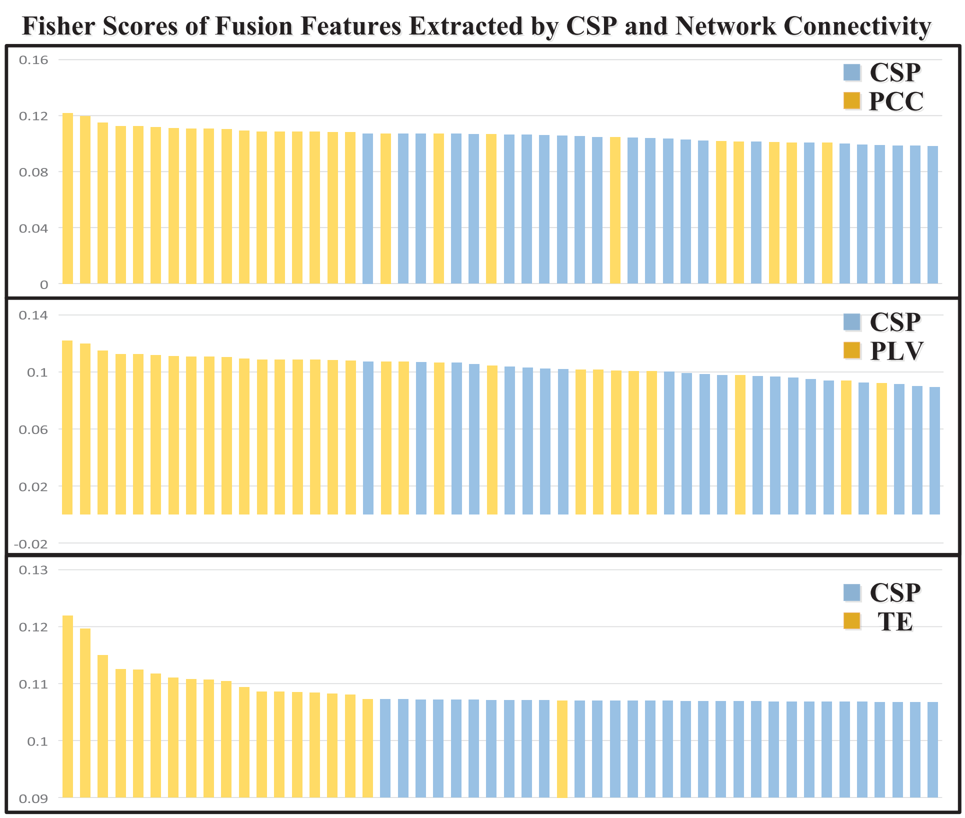
B. Neurophysiological Assessment for BCI Tasks

Previous studies reported that volume conduction effect could affect the connectivity estimates tricked by false neuronal interaction from the same underlying source at the two channels [48], [58]. Hence, we used the Mann-Whitney test, one of nonparametric permutation tests, to alleviate the adverse effects of volume conduction. The results were listed in Table VI. We found that significant differences between FBCSP and connectivity approaches were obtained for most of the subjects (6 of 7 patients). Moreover, higher significance results between CSP and connectivity approaches were obtained for 3 subjects. The results were inconsistent with the previous parametric test for several participants. However, the connectivity features of TE were still reliable as a result of its model-free type of directed measurement.

Typically, features contribution had been evaluated by fisher score algorithm for best-performing and worst-performing patients (i.e., Sub. 4 and Sub. 6). And the top scores of 50 features were ranked in descending order (Fig. 7). The results implied that connection features (i.e. PCC, PLV or TE) played a more prominent role in BCI recognitions for the best-performing patient (Sub. 4). On the other hand, we could see that opposite phenomena took place for the worst-performing patient (Sub. 6). It was presumed that ranking differences might be induced by neurophysiological function. To some extent, the functional connectivity was constructed by neural rehabilitation for best-performing patients. Nevertheless, the performance of BCI control was inefficient ($< 70\%$) compared with the criterion level for the worst-performing patient. It was probably due to the control loss of neural modulation in this task. As a result, connectivity features digitized by network connection could be effectively characterized for neural activities evoked by limb movement.



(a) The features contributes evaluated by fisher score algorithm for Sub.4.



(b) The features contributes evaluated by fisher score algorithm for Sub.6.

Fig. 7. The features contributes evaluated by fisher score algorithm for best-performing and worst-performing patients (i.e., Sub. 4 and Sub. 6). And the top scores of 50 features were ranked in descending order.

TABLE VI
THE RESULTS OF MANN-WHITNEY TEST BETWEEN BASELINE APPROACHES AND NETWORK ANALYSIS APPROACHES FOR 7 SUBJECTS

Subject	CSP v.s. PCC	CSP v.s. PLV	CSP v.s. TE	FBCSP v.s. PCC	FBCSP v.s. PLV	FBCSP v.s. TE
1	$p > 0.05$	$p > 0.05$	$p > 0.05$	$\boldsymbol{p < 0.05}$	$\boldsymbol{p < 0.05}$	$\boldsymbol{p < 0.05}$
2	$p > 0.05$	$p > 0.05$	$p > 0.05$	$\boldsymbol{p < 0.05}$	$\boldsymbol{p < 0.05}$	$\boldsymbol{p < 0.05}$
3	$\boldsymbol{p < 0.05}$	$\boldsymbol{p < 0.05}$	$\boldsymbol{p < 0.05}$	$\boldsymbol{p < 0.05}$	$\boldsymbol{p < 0.05}$	$\boldsymbol{p < 0.05}$
4	$\boldsymbol{p < 0.05}$	$\boldsymbol{p < 0.05}$	$p > 0.05$	$\boldsymbol{p < 0.05}$	$\boldsymbol{p < 0.05}$	$\boldsymbol{p < 0.05}$
5	$\boldsymbol{p < 0.05}$	$p > 0.05$	$\boldsymbol{p < 0.05}$	$\boldsymbol{p < 0.05}$	$\boldsymbol{p < 0.05}$	$p > 0.05$
6	$p > 0.05$	$p > 0.05$	$p > 0.05$	$p > 0.05$	$p > 0.05$	$p > 0.05$
7	$p > 0.05$	$p > 0.05$	$p > 0.05$	$\boldsymbol{p < 0.05}$	$p > 0.05$	$\boldsymbol{p < 0.05}$

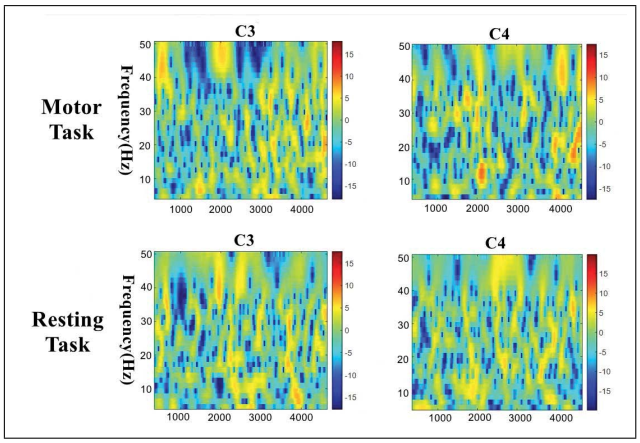


Fig. 8. Temporal features of spectral powers under conditions of motor and resting tasks for Sub.2.

Relating these changes to post-stroke neuropsychological variables and motor abilities would improve understanding of functional plasticity after stroke. However, fisher scores of all features were evenly distributed for these subjects. It was indicated that CSP and connectivity features were reliable and effective for pattern recognitions in the experiments. Hence, the combination of CSP and TE could be considered as the first option for BCI rehabilitation according to the above findings of neurophysiological reliability.

C. Comparison of Feature Distribution

In previous studies, CSP and FBCSP features were commonly applied for motor-modality BCI tasks [59]. Nevertheless, they performed poorly in our experiments for decoding bio-signals of motor attempts. This might be due to brain damage corresponding to limbs control. The typical temporal-spatial features of spectral powers had been illustrated in Fig. 8 and Fig. 9. Specifically, the ERD/ERS pattern had been observed in the alpha and beta bands. Therefore, CSP-based spatial filtering analysis was ineffective in discriminating motor-modality task and resting state.

The network linkages of Sub.2 were illustrated in Fig. 10. We observed that the network connectivity of motor tasks was denser than that of the resting task for 3 methods. The comparison of network patterns indicated that connectivity pattern was feasible for detecting the difference between these two cognitive activities.

Moreover, the network linkage of the TE indicator implied that the directions of the resting task were towards the

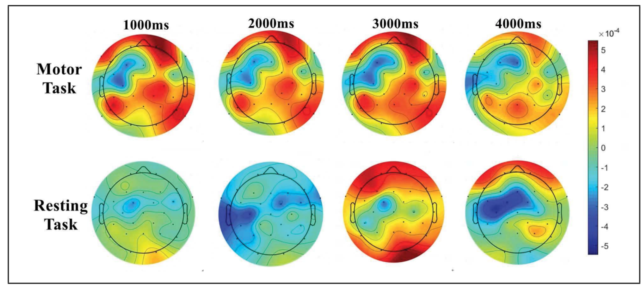


Fig. 9. Scalp spatial powers distributions between 0.1 Hz and 40 Hz at 4 time points under conditions of motor and resting tasks for Sub.3.

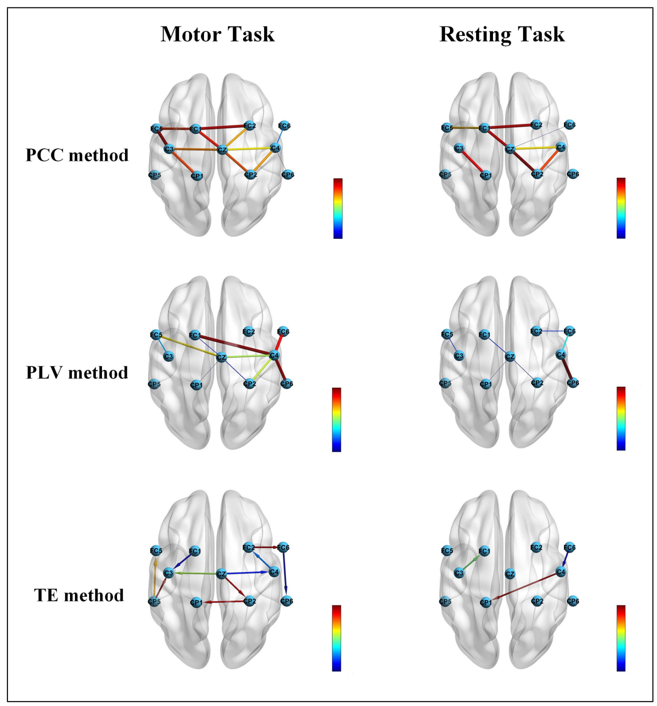


Fig. 10. The network linkages constructed by PCC, PLV, and TE methods under conditions of motor and resting tasks for Sub. 5. The straight lines depict undirected connections, and the arrow lines depict directional connections.

unilateral hemisphere. And the directions of motor tasks were disordered displayed in the network topology. The difference between two tasks was helpful for classifying these tasks. Compared with other undirected connectivity patterns, the feature of direction played a more effective role in improving the performances of classification tasks.

Besides, we reported the quantitative connectivity matrix computed by PCC under conditions of motor and resting

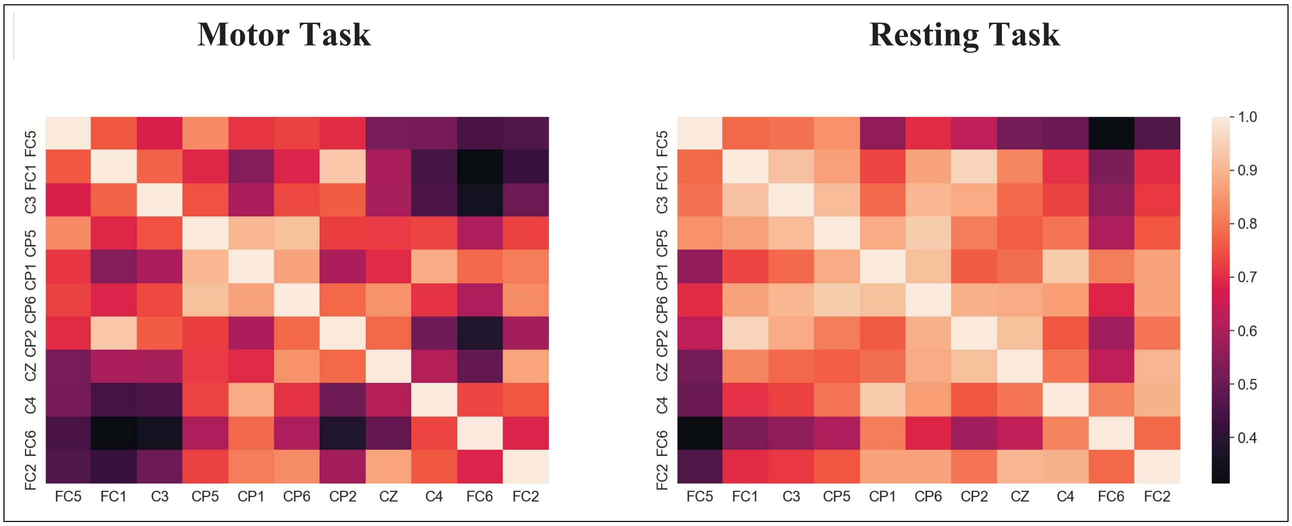


Fig. 11. The quantitative connectivity matrix computed by PCC method under conditions of motor and resting tasks for Sub.3.

tasks. (Fig. 11). It was associated with the above investigation of network analysis. The connectivity strength of motor tasks was higher than that of resting task at the motor cortex. It was implied that neural connectivity should be involved to provide related training programs in the recovery.

D. Limitation of Our Works

The possible limitation of the current study would be that we did not give a method of optimal selection for connectivity indicators (e.g., PCC, PLV and TE). In future work, we will perform BCI experiments conducted by enough patients to evaluate the effectiveness of these connectivity patterns and provide the alternative network features for motor-modality -based BCI classifications. Moreover, none of female stroke patients were recruited owing to personal willingness. However, it was reported that a significant interaction between experimenters and participantsǵender was found on the evolution of movement-related BCI [60]. Therefore, we will try to evaluate the BCI performances for female patients by their voluntary recruitment in future. The interaction between genders will be discussed to further benefit from it while preventing any bias.

VI. Conclusion

Motor-modality -based BCI can promote neural rehabilitation for stroke patients. This paper introduced a novel approach combining connectivity network pattern and temporal-spatial analysis is proposed for BCI-enabled rehabilitation. Effectiveness was evaluated by real-world experiments for improving the performance of BCI classification. Furthermore, the results demonstrated that our approach outperforms several competitive state-of-the-art baselines. This proposed method is practical for stroke patients via by BCI rehabilitation, which is demonstrated by statistical analysis of time consumption and performance comparison.

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