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Spatial Component-wise Convolutional Network (SCCNet) for Motor-Imagery EEG Classification

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Abstract— **We study brain-computer interfaces (BCI) based on the decoding of motor imagery (MI) from electroencephalography (EEG) neuromonitoring. The robustness of MI-BCI is a major concern in practical applications, and hence various efforts in the literature have been made to enhance the MI classification accuracy from EEG signals. Recently, classifiers based on convolutional neural networks (CNN) have achieved state-of-the-art performance. In further exploration of applying CNNs to EEG data, we propose a spatial component-wise convolutional network (SCCNet), featuring an initial convolutional layer for spatial filtering, a common processing in EEG analysis for signal enhancement and noise reduction. Through a series of optimization and validation, we show the superiority of SCCNet in MI EEG classification, outperforming other existing CNNs.**

I. Introduction

A brain-computer interface (BCI) can translate observed brain activities into meaningful information to enable communications between the brain and external environments [1], [2]. The brain activity related to motor functions can be acquired from the motor-related electrophysiological patterns in the cortical electrical field using a non-invasive neuromonitoring modality, electroencephalogram (EEG). With a motor-imagery-based BCI, a user is able to send out commands through imagining different types of movements, such as left- and right-hand moving. EEG features that differentiate different motor-imagery (MI) patterns can be extracted by signal processing techniques and discriminated by machine learning-based classifiers [3], [4]. MI-BCIs have been applied to motor control, computer interaction, and post-stroke rehabilitation.

In the past two decades, continuous effort in the field has been made to improve the classification accuracy of MI-BCIs. Since the MI-BCIs are often equipped with multi-channel EEG recordings, spatial filtering methods to weight and combine multiple EEG time series recorded from different channels are exploited to accentuate the signal and/or to attenuate the noise in the data [5], [6]. Referencing is the most basic spatial filter that subtracts a reference signal (e.g., the signal at a specific channel or averaged across multiple channels) from each of the EEG channels [5]. Laplacian filters are commonly applied to reduce non-EEG artifacts or noises through differentiating an EEG channel with its neighboring channels. In addition, a number of spatial filtering methods are based on eigen decomposition, such as principal component analysis (PCA), canonical correlation analysis (CCA), task-related component analysis (TRCA), common spatial pattern (CSP), and xDAWN algorithm [5], [6]. Depending on the type of the eigenproblem, these eigen-decomposition-based methods aim to enhance or suppress certain characteristics in the data, which is usually used to maximize the signal of interest. Independent component analysis (ICA) is another computational approach that finds a linear transformation to decompose the multi-channel EEG data in order to minimize the mutual information or to maximize the non-Gaussianity among channels. The spatial filtering techniques mentioned above have been widely used on subband-passed filtered EEG to facilitate a variety of BCIs, e.g. MI-BCI [7], steady-state evoked potential (SSVEP)-BCI [8], and motion-sickness-estimation BCI [9].

Recently, convolutional neural networks (CNN) have been employed as a state-of-the-art classification approach to classify EEG data [10], [11]. A CNN model can transform multi-channel EEG data and automatically extract informative spatial and temporal features that improve the classification performance. The kernels in the CNN serve as the spatial and temporal filters for the multi-channel EEG data, and are able to implement or approximate the data processing mechanism that conventional spatial and temporal filtering methods utilize. Without the restriction of the predefined settings such as the type of spatial filtering and the frequency subband selection, a CNN has the flexibility to automatically optimize the data transformation through training.

We propose and develop a novel CNN model, spatial-component-wise convolutional network (SCCNet) that features an initial convolution layer that functions as spatial filters to extract spatial components from the multi-channel EEG time series. The SCCNet has a lightened structure to avoid over-fitting to the highly variant EEG data. To validate the performance of SCCNet, we employed an open MI-EEG dataset [12] to test its accuracy on a four-class classification task across various settings of model structures, training schemes, and data sizes.

II. MI-BCI Methods

A. EEG Data and Preprocessing

In this paper, we use an open dataset, the BCI competition IV dataset 2a [12]. This dataset has been widely used in previous studies [7], [11], enabling a fair comparison among different approaches. The dataset contains the EEG data from 9 subjects, where each subject went through two sessions of MI experiments on different days. In each session, 72 trials for each of the 4 MI classes (left hand, right hand, both feet,

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*Part of this work was completed while C.-S. Wei was an intern at MERL.

and tongue motions) were collected. A total of 5,184 trials are available in the dataset.

The preprocessing of the EEG data involves three steps: resampling, bandpass filtering, and epoching. First, the multichannel EEG data were downsampled from 250 Hz to 125 Hz since high-frequency components in the data were not used in further analysis. For each channel, the EEG time series were then bandpass filtered at 0.5–38 Hz [11]. Next, the data of each epoch is segmented from 0.5–4 seconds of the MI cue.

B. SCCNet

This section presents the design of the proposed SCCNet and its architecture. A major part of SCCNet consists of convolutional kernels that capture the spatial and temporal characteristics of the EEG data. The design of SCCNet focuses on leveraging the benefits from applying spatial filtering to EEG data for purposes such as feature extraction and noise suppression [5], [6]. The architecture of SCCNet is illustrated in Fig. 1. The input to SCCNet is multi-channel EEG data arranged in 2-dimensions, with N_c channels and T time points. The architecture of SCCNet consists of four blocks: the first convolution block, the second convolution block, the pooling block, and the softmax block. The SCCNet herein is implemented using the Keras platform [13].

In the first and second blocks, the SCCNet performs two-step 2-dimensional convolution procedures. The initial convolution extracts EEG features, mimicking a spatial component analysis that decomposes the original EEG data from the channel domain to a component domain, where N_u filters with a kernel size of (N_c, N_t). When $N_t = 1$, this convolution step essentially performs a linear combination of EEG signals across all channels. This procedure is referred to conventional spatial filtering or component analysis technique that is commonly used for signal augmentation, noise reduction, and/or artifact removal [5]. Since the multi-channel EEG data are transferred into multiple EEG spatial components, the size of channel domain becomes 1 and the size of component domain becomes the number of convolutional kernels, N_u. Thus, the tensor dimension is permuted in an order of $(2, 1, 3)$ to switch the second dimension to the first for the second convolutional block.

The second convolution uses N_c convolutional kernels with a size of (N_u, 12), where the number 12 corresponds to 0.1 seconds along time domain. At this step, the convolution procedure applies to both the temporal and spatial component domains. The spatial-temporal convolution is expected to perform spectral filtering, inter-component correlation and other spatial-temporal analysis on the EEG spatial components. Zero-padding and batch normalization were applied to both the first and second convolutions, as well as ℓ_2 regularization with a coefficient of 0.0001. We use square activation to extract the power from the data, as spectral power change is the most prominent marker in MI EEG. Next, we applied dropout with a rate of 0.5 to prevent overfitting.

Following the two convolutional blocks, we apply an average pooling layer of size $(1, 62)$ to perform smoothing in the temporal domain and reduce the dimension, where the number 62 corresponds to 0.5 seconds along time domain. The final block performs a softmax classification with 4 units corresponding to the 4 classes in the MI task: left hand, right hand, feet, and tongue.

C. Model Training

We evaluate the SCCNet using different training methods to explore its learning behavior. These training schemes use different sets of training data and training procedures, named as Individual (Ind.), Subject-Independent (SI), Subject-Dependent (SD), and Subject-Independent+Fine-Tuning (SI+FT) as follows.

1) Ind.: A model is trained and tested within a single subject. The training data is from the first session, and the test data is from the second session.

2) SI: The 9 subjects in the dataset are separated into 1 test subject providing test data and 8 training subjects providing training data. In a leave-one-subject-out cross validation, the subject-independent model is trained by the training data from all 16 sessions from the 8 training subjects and then tested on the second session of the test subject.

3) SD: While subject-independent training excludes the data from the test subject, the subject-dependent model training includes the first session of the test subject with all the 16 sessions from other subjects as the training data. In line with above-mentioned training methods, the model is tested on the second session of the test subject.

4) SI+FT: The SI+FT training is an alternative way to train an SD model that divides its training process into two phases. For a given test subject, an SI model is trained using all of the data from other 8 subjects in phase 1. Next, in phase 2, the data of the first session of the test subject are used in the FT process to tune the parameters of the pretrained SI model. Unlike the SD training, which pools all training data together, the SI+FT training may better leverage individualized traits by fine-tuning on the test subject.

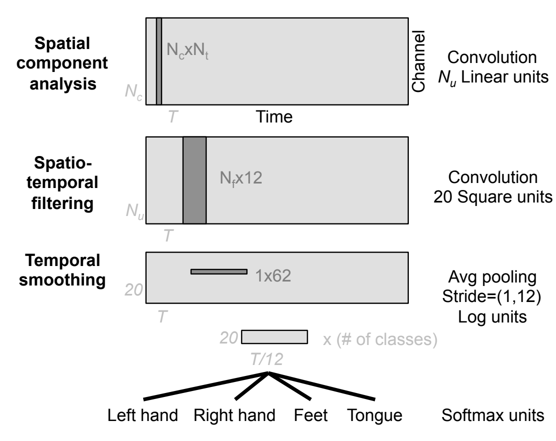

Fig. 1. The example architecture of SCCNet.

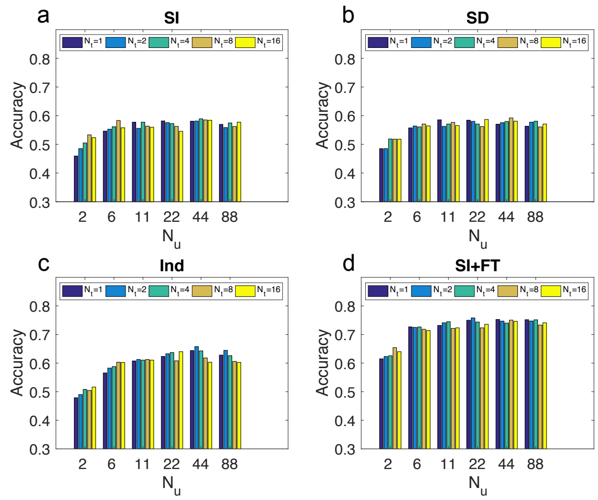

Fig. 2. The overall performance of SCCNet across subjects with different training types: (a) SI; (b) SD; (c) Ind.; (d) SI+FT. Each subfigure presents the performance across different settings of N_{u} and N_{t}.

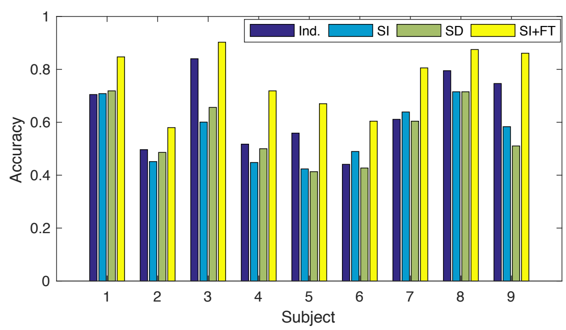

Fig. 3. The predictive performance of SCCNet for each subject using Ind., SI, SD, and SI+FT training scheme.

III. Results

Fig. 2 presents the averaged classification accuracy using SCCNet across 9 subjects with different training schemes (Ind, SI, SD, and SI+FT) and (N_{u}, N_{t}) settings. Two-way ANOVA was performed to test the significant difference in averaged classification accuracy across N_{u} and N_{t}. The p-values show no significant difference in averaged accuracy contributed by N_{t} ($p > 0.05$) regardless the training scheme. In contrast, N_{u} appears to significantly affect the accuracy ($p < 0.05$ for Ind., SI, and SI+FT; $p = 0.06$ for SD). As shown in Fig. 2, the accuracy is higher when $N_{\mathrm{u}} = 6$ or larger. We chose a proper setting of (N_{u}, N_{t}) for further simulation and analysis. As large N_{u} supports high accuracy, we heuristically select $N_{\mathrm{u}} = 22$ which is the number of EEG channels in the data. On the other hand, as N_{t} has no significant influence on the accuracy, we use $N_{\mathrm{t}} = 1$ to minimize the number of parameters in SCCNet. The setting of (N_{u}, N_{t}) essentially shapes the first layer of SCCNet into a 22×22 transforming matrix as in those conventional spatial filtering methods.

Fig. 3 presents the classification accuracy of each subject with different training schemes using $N_{\mathrm{u}} = 22$ and $N_{\mathrm{t}} = 1$. The SI+FT scheme results in the best accuracy for all subjects, and the Ind. scheme achieves the second best performance for most subjects. On the other hand, the SI and SD schemes provided lower performances. Meanwhile, the individual differences in the MI task performance is exhibited, where Subject 1, 3, 7, 8, 9 have higher accuracies than the rest of subjects. The inevitable cross-subject variability in performing BCI tasks has been investigated in previous studies.

TABLE I
Performance evaluation on SCCNet using SI+FT training scheme with (N_{u}, N_{t})=(22, 1) and with the optimal setting.

Subject	SCCNet (22, 1)	SCCNet (optimal)	N_{u}	N_{t}
1	0.7882	0.8368	6	3
2	0.5938	0.6181	4	2
3	0.8993	0.9375	5	1
4	0.6840	0.7500	4	1
5	0.6771	0.7188	3	5
6	0.6493	0.6736	4	5
7	0.8056	0.8264	3	2
8	0.8056	0.8646	6	3
9	0.7674	0.8542	4	2
(Mean, S.E.)	(0.7411, 0.032)	(0.7867, 0.034)		

Table I summarizes the classification accuracy of SCCNet using the SI+FT scheme with a heuristic setting of $N_{\mathrm{u}} = 22$ and $N_{\mathrm{t}} = 1$. As the performance of SCCNet varies across different settings of N_{u} and N_{t}, the optimal classification accuracy for the individual optimal setting of (N_{u}, N_{t}) is listed for comparison.

We further investigated the difference between the SD and SI+FT training schemes since they both use the same training data. Both SD and SI+FT schemes incorporate the data from all other subjects and from the first session of the test subject. We manipulated the portion of data from the first session of the test subject (denoted as P_{i}) to explore how the amount of calibration data from a new user affects on the decoding performance. As shown in Fig. 4, the overall accuracy of the SI+FT schemes increases with P_{i} from less than 0.6 to over 0.7. On the other hand, the SD scheme fails to improve the accuracy even with feeding data from a new user.

IV. Discussion

In a convolutional neural network, the first convolutional layer is known to extract the fundamental features in the data [14]. We tested different settings of (N_{u}, N_{t}) and found that N_{t} does not contribute to the classification accuracy. On the other hand, N_{u}, which stands for the number of subspaces in spatial filtering, can determine the amount of information extracted from the EEG data. An adequate setting of N_{u} is considered imperative to avoid over- and under-fitting, and thus should be cautiously assessed according to the type of EEG data. We tested the performance of SCCNet using 4 different training schemes (Ind., SI, SD, and SI+FT), which differ in data partitioning and learning procedure. Note that EEG data have strong variability across subjects, and even within a single subject [15]. As shown in Table I, only 5

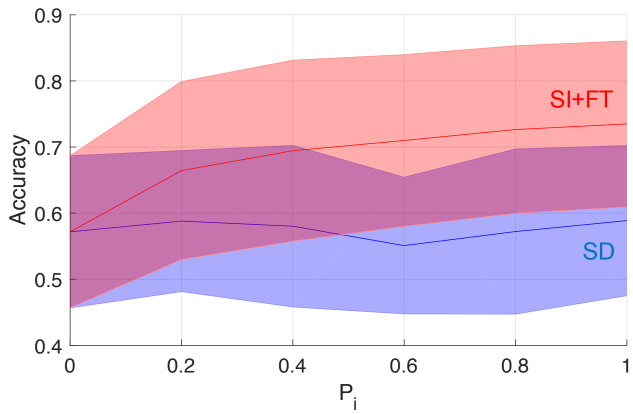

Fig. 4. A comparison between the SD and SI+FT training schemes in the SCCNet performance against the portion of new user data, P_i. The shaded area represents the standard error of the accuracy across subjects.

out of 9 subjects present more than 70% accuracy, showing the individual difference in MI-BCI task performance [16]. Previous EEG-BCI studies have concluded the importance of using individual data for training an individualized BCI model. Thus, expanding the training data size by pooling data from different subjects together might not benefit the model performance and could be destructive. This may be the underlying reason why the Ind. scheme had a higher performance than the SI or SD schemes, suggesting that, without an adequate training scheme, increasing data does not always improve model performance.

The SI model, although does not perform well for a new user, might be able to learn typical EEG processing that generally applies to most subjects. The SI+FT schemes worked successfully using a two-phase transfer-learning training strategy, while the SD scheme did not enhance the performance of SCCNet by integrating data from other subjects and the test subject. Intriguingly, as shown in Fig. 4, the fine-tuning approach is able to impact on the performance even with a small amount of new data. When the data from the new user are pooled together with other users, the model seems unable to capture the characteristics of the specific individual. Learning from the new data in a separate fine-tuning phase seems to be crucial for SCCNet to adapt itself for a single user. In comparison with other approaches, SCCNet slightly outperforms existing EEG-specific CNNs [10], [11]. The effect of transfer learning for CNN models requires further investigation, particular for physiological data with high variability.

V. Conclusions

In this study, we developed SCCNet, which features spatial-component-wise convolution at the initial layer that aims to extract spatial components of EEG and reduce noise. Combining cross-subject training with fine-tuning using new user's data, SCCNet was able to outperform existing CNN-based approaches in motor-imagery EEG classification. An in-depth evaluation on the behavior of SCCNet was presented, with emphasis on the use of training data and a variety of training schemes. We also discussed the role of training schemes in tackling pervasive subject variability that pose challenges in EEG-based applications in real-world contexts. Lastly, this work offers a preliminary guidance for further exploration towards robust CNN approach for real-world applications of EEG-based BCIs.

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