Motor Task Learning in Brain Computer Interfaces using Time-Dependent Regularized Common Spatial Patterns and Residual Networks

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***Abstract*—This work proposes a method for motor task recognition in brain computer interfaces (BCI). The proposed method is realized by EEG signals classification using time-dependent regularized common spatial patterns and deep residual networks. Unlike other existing methods, the proposed method relies on both the spectral and temporal features by preserving the temporal resolution of the spatially-filtered EEG signals. These features are projected onto an image representation and fed into a residual network for a hierarchical feature learning and classification. Experiments are carried out on benchmark datasets taken from BCI competitions to evaluate the performance of the proposed method and to compare it with other existing methods. The binary classification results of the proposed method demonstrate a superior performance in classification accuracy compared to other existing methods.**

***Index Terms*—Brain computer interface, EEG signal, residual network, common spatial pattern.**

I. Introduction

Imagining of hands, feet and tongue movements are motor imagery (MI) tasks investigated in several brain computer interface (BCI) studies [1], [2]. In most of these studies, electroencephalogram (EEG) signals have been used to analyze the brain activities, which are recorded using a number of electrodes and have a high temporal resolution. A common practice in analyzing the EEG signals for MI-BCI tasks recognition is to perform some spatial filtering such as principal component analysis or common spatial patterns (CSP) to not only reduce the dimensionality of these signals but to prepare them for the feature extraction procedure.

CSP and its variants have widely been applied in MI-BCI studies to take into account distinct characteristics of EEG signals by determining the directions in the pattern space through projecting EEG signals onto a subspace and optimally distinguishing between classes [3], [4]. Several variants of CSP have so far been applied to EEG signals. Many of these techniques have taken advantage of subband decomposition, spatial or spectral weighting, and regularization in order to extract highly discriminative features from the EEG signals. However, it is challenging to take into account all the complex patterns of EEG signals in designing an MI-BCI task recognition problem manually. In other words, most of the existing works rely on a limited number of features extracted from recorded EEG signals in the time, frequency or time-frequency domain, which requires domain knowledge and may lead to sub-optimal feature selection. One possible solution is to devise automated, data-driven approaches that allow discovery of the optimal discriminative features in EEG signals, which is accomplished using deep learning. It is known that deep learning has provided a different paradigm to motor task recognition, and can work independently of or in tandem with other feature selection methods.

Few attempts have so far been made to design an automated feature extraction method from EEG signals [5]. In [6]–[9], deep learning approaches were proposed for MI-BCI EEG signal classification using time or frequency domain features of EEG signals. In [10], deep belief networks were used to model EEG waveforms for exploratory analysis, pre-training and semi-supervised classification. Deep learning schemes based on restricted Boltzmann machine were proposed in [11] and [12], by obtaining frequency domain representations of the EEG signals. In [13], different feature extraction methods in frequency domain were investigated for MI tasks and a convolutional neural network was used for classification. In [14], an LSTM-based framework with a CSP-like channel-weighting strategy was employed to extract features from EEG signals.

These studies have shown the benefits of adopting deep neural networks in systematically extracting features from EEG signals and classifying them, even in the absence of a large volume of data. However, to the best of our knowledge, there is no other work in the literature distinguishing MI-BCI EEG signal characteristics related to different tasks via a spectral-temporal image representation and a deep residual network for hierarchical feature extraction. In other words, the existing works have not attempted to preserve the structure of EEG signals within both the time and frequency domains before feeding them into the neural networks. In this context, a time-dependent regularized CSP feature learning in tandem with a residual network is proposed. In the following sections, the proposed task recognition method for BCI systems using the proposed residual network is presented and its performance is compared to some of the existing methods on EEG data from different subjects taken from publicly available BCI competition data sets.

II. Data Preprocessing

In MI-BCI settings, the main goal is to discriminate brain states using a limited number of trials. Thus, feature extraction

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TABLE I
DATA SET UNDER STUDY FOR PERFORMANCE EVALUATION OF THE PROPOSED METHOD.

Subject	AA	AL	AV	AW	AY
Trials	280	280	280	280	280
Training set (T_r)	168	224	84	56	28
Testing set (T_s)	112	56	196	224	252

and classification of such data is a challenging task. To examine the performance of the proposed method, the EEG signals are taken from a publicly available dataset, where the data samples were collected from subjects performing a classical MI, i.e., imagination of limbs movements. More specifically, data set IVa from BCI competition III is selected, which is comprised of EEG signals from 5 subjects, performing 280 trials of right hand and right foot MIs, recorded using 118 electrodes. During recording, EEG signals were initially filtered between 0.5 and 100 Hz. A 50 Hz notch filter was applied to suppress the line noise. In addition, in order to remove eye blinking and muscle artefacts, the signals should be further processed using bandpass filtering and smoothing techniques. In the proposed MI-BCI task recognition method, the EEG signals were bandpass filtered using a 5th order Butterworth filter to extract contents of the signal in $[7-30]$ Hz. The signal was then smoothed using a weighted moving average filter with a window size of 10 samples at a time [2]. Table I gives information about the subjects and the number of training (T_r) and test (T_s) trials used in the experiments.

III. PROPOSED TASK RECOGNITION METHOD

In this section, the proposed motor task recognition methods based on automatic feature extraction from time-dependent regularized CSP signals using the proposed residual network is presented.

A. Time-dependent Regularized CSP

In order to extract the time-dependent regularized CSP features from the EEG signals, the optimal spatial filters are obtained by maximizing the following objective function:

$$\widehat{W} = \underbrace{\arg\max}_{W} \frac{\mathbf{W}^T \mathbf{C}_1 \mathbf{W}}{\mathbf{W}^T \left(\mathbf{C}_1 + \mathbf{C}_2\right) \mathbf{W} + \alpha P(\mathbf{W})}, \qquad (1)$$

where $\mathbf{C}_i$ is the spatial covariance matrix of class i, $P(\mathbf{W}) = \mathbf{W}^T \mathbf{L} \mathbf{W}$ is a Laplacian penalty function measuring how much the spatially smooth filter $\mathbf{W}$ satisfies a given prior, $\alpha \geq 0$ is a regularization parameter and $\mathbf{L}$ is the graph Laplacian matrix derived from the graph weighting matrix $\mathbf{K}$. A weighted graph may be constructed as a function of proximity between electrodes as given by

$$\mathbf{K} = \exp\left(-\frac{d(p,q)^2}{2\sigma_d^2}\right), \qquad (2)$$

where $\mathbf{K}$ consists of weights $[k_{pq}]_{n\times n}$, p and q are the electrode positions, $d(p,q)$ denotes the geometrical distance between the two electrodes, and σ_d specifies closeness level of the two electrodes [15]. The normalized graph Laplacian is defined as $\mathbf{L} = \mathbf{I} - \mathbf{D}^{-1/2}\mathbf{K}\mathbf{D}^{-1/2}$, where $\mathbf{I}$ is the identity matrix and $\mathbf{D}$ is the degree matrix given by $\mathbf{D} = \text{diag}\left\{\sum_q k(1,q), ..., \sum_q k(n,q)\right\}$. It is noted that the regularization function $P(\mathbf{W})$ ensures that neighboring electrodes have relatively similar weights, i.e., it enforces smoothness between the recorded signals from neighboring neural populations.

The objective function has an analytical solution through joint diagonalization of the covariance matrices and solving a generalized eigenvalue decomposition problem. Eigenvalues $\boldsymbol{\psi}$ and eigenvectors $\boldsymbol{U}$ of $\hat{\mathbf{C}} = \mathbf{C}_1 + \mathbf{C}_2$ are obtained as $\hat{C} = \boldsymbol{U}\boldsymbol{\psi}\boldsymbol{U}^T$. The class projection onto the first or last eigenvalues ensures that the largest eigenvalue in one class correspond to the lowest eigenvalue in the other class. It is noted that the discriminatory nature of this technique is promising for extracting features from the EEG signals. It is also noted that only a small number of eigenvectors $m << N_{ch}$ are selected for discrimination analysis [16], where N_{ch} is the number of EEG electrodes. The final projection matrix is defined as $\mathbf{P} = \mathbf{U}^*\mathbf{W}$. The projection matrix is further used to spatially filter EEG trials $\mathbf{X}_i$ as $\mathbf{Z}_i = \mathbf{P}\mathbf{X}_i$.

At this stage, the common approach to extract features from EEG signals is to apply a log transformation to $\mathbf{Z}_i$ in order to project the data into a normal distribution [3], [4]. However, in the proposed method, the spatially-filtered EEG signals are projected onto an image representation. This is realized by keeping the temporal resolution of $\mathbf{Z}_i$ unchanged, resulting in 2D features keeping the information with respect to both the time and frequency domains. More specifically, instead of using the log variance as measure of feature extraction, $\mathbf{Z}_i$ is constructed from the first and last m largest eigenvalues only through spatial filtering, i.e., the dimension of the trial signals is spatially reduced to $2m \times N_t$, where m is set to 3 and N_t is the number of samples collected from each electrode. The image representations are then fed into the proposed residual network for automatic feature learning.

B. Deep Residual Network

Common approaches to MI-BCI EEG signal classification include extraction of a set of features from EEG signals in the time, frequency, or time-frequency domain. Any improvement in the classification performance of such approaches is highly reliant on the type of features extracted. Automatic feature learning using neural networks has obviated the need for manual feature engineering and domain knowledge of the data.

In the proposed method, a residual network is applied to the time-dependent regularized CSP signals for automated feature extraction. It is known that residual networks preserves information across layers by providing direct gradient flow through the bottom layers. This is realized by taking shortcuts to jump over some layers in each residual block [17].

In the proposed method, the residual blocks are constructed by stacking convolutional layers. Each convolutional layer i

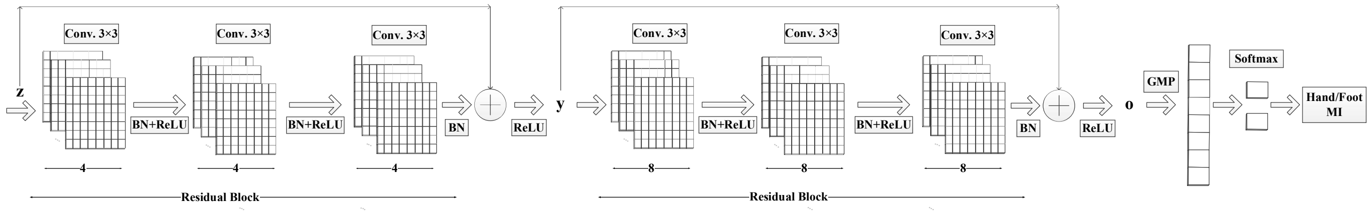

Fig. 1. Architecture of the proposed residual network for MI task recognition.

is followed by batch normalization (BN) and a rectified linear unit (ReLU) activation function, i.e., $f(x) = \max(0, x)$. The resulting feature map $\mathbf{S}$ is obtained as $\mathbf{S}^{c_i} = \mathbf{S}^{c_{i-1}} * \mathbf{K}^{c_i} + \mathbf{b}^{c_i}$, where c denotes the convolutional layer index, $*$ is the convolutional operator, $\mathbf{K}$ and $\mathbf{b}$ denote the trainable kernels and biases, respectively. It should be noted that the number of convolutional layers, number of kernels and kernel sizes are optimized via random search optimization. In particular, in the first residual block, there exist 3 convolutional layers $\{c_i\}_{i=1}^{3}$, each having 4 kernels $\left\{k_j^{c_i}\right\}_{j=1}^{4}$ of size 3×3. The relatively small kernel sizes give rise to discover the local temporal-spectral information of 2D regularized CSP more accurately. The resulting feature map from the final convolutional layer in the first block is added to the input image $\mathbf{z}$, and the result is passed through a ReLU. The output feature map $\mathbf{y}$ has a depth of 4.

In the second residual block, a similar procedure is followed with convolution layers having 8 kernels. The BN is performed after each convolutional layer to improve the network steadiness. The output of the second residual block o goes to a 2D global maximum pooling (GMP) layer. This pooling mechanism is selected to lower spatial dimensionality of the extracted features and circumvent overfitting [18]. In the output layer, the softmax activation function is used to map the final non-normalized features to a probability distribution over the predicted classes. The proposed residual network is trained using the back-propagation algorithm. The learning model minimizes the categorical cross-entropy cost function using the Adam optimizer [19]. The learning rate equals to 0.0001 and the number of epochs, i.e., training iteration, is set to 200.

IV. Experimental Results

Experiments were conducted on a set of EEG signals to evaluate the performance of the proposed task recognition method. In the proposed method, the EEG signals are first preprocessed and spatially-filtered using regularized common spatial patterns, as discussed in Sections II and III. The resulting 2D regularized CSP image representations are fed into the proposed residual network to test whether the task is right hand or right foot MI.

The classification accuracy of the proposed regularized CSP (RCSP)-based method is obtained with both the residual and convolutional neural networks (CNN). For CNN, similar to the proposed residual network, the categorical cross-entropy cost function and Adam optimizer are used in the training process. It is noted that in RCSP-CNN, only one block of the residual network is used without any skip connection with the same network structure and hyperparameters. The optimal values for α and σ_d are obtained via grid searching, when regularization parameter α is varying in $\left[0 - 10^{-5}\right]$ and σ_d is in $[0.01 - 1.5]$. Table II gives the classification accuracy obtained using the proposed method along with the performance achieved by alternative methods, namely, linear discriminant analysis (LDA), decision trees (DT), and multi-layer perceptrons (MLP). MLP is comprised of two layers having 400 and 200 neurons, respectively. The hyper-parameters are the drop out, which is set to 0.5 for each layer, and the learning rate, which is set to 0.001. It is noted that the results presented for each method are the best results obtained using the optimal parameters found for each classifier using a random search optimization technique.

It is seen from this table that the proposed method using ResNet outperforms the other methods by yielding higher classification accuracies on the test set for AA, AL and AY subjects. In particular, the proposed method achieves 100% and 86.90% accuracies for AL and AY subjects, respectively, which are higher than those yielded by the other methods. The superior performance of the proposed method using residual networks is due to the fact that the structure of the residual network can learn discriminative features of the 2D RCSP signals more accurately than the other methods. In addition, our RCSP-based method using CNN shows superior performance in detecting motor tasks for subject AW. Noticeably, the proposed method based either residual network or convolutional neural network performs better than LDA, DT and MLP-based methods in recognizing MI tasks in a binary classification problem by providing higher accuracy values.

The classification accuracy of the proposed method is also compared to those obtained using other existing methods on the MI-BCI EEG signal classification. To this end, the complete dataset for each subject is split into five partitions, i.e., 5-fold cross validation. Tables III gives the classification accuracies of the proposed method as well as those of other existing methods for various subjects. It is seen from this table that the classification accuracy obtained using the proposed method based on regularized CSP with residual network is higher than those yielded by the other methods. The superior performance of the proposed method in providing better class discrimination and higher recognition accuracies can be attributed to the fact that it takes into account both the spectral

TABLE II
CLASSIFICATION ACCURACY OBTAINED USING VARIOUS METHODS USING TIME-DEPENDENT REGULARIZED CSP.

	AA (168 T_r+ 112 T_s)	AL (224 T_r+ 56 T_s)	AV (84 T_r+ 196 T_s)	AW (56 T_r+ 224 T_s)	AY (28 T_r+ 252 T_s)
RCSP-ResNet	**93.75**	**100**	80.12	81.25	**86.90**
RCSP-CNN	93.75	96.43	83.16	**85.27**	83.33
RCSP-MLP	93.75	91.24	85.11	83.76	81.28
RCSP-DT	82.32	88.50	70.14	78.08	73.85
RCSP-LDA	55.46	86.79	**85.33**	63.19	57.91

TABLE III
CLASSIFICATION ACCURACY OBTAINED USING THE PROPOSED METHOD AS WELL AS THOSE YIELDED BY THE OTHER EXISTING METHODS BY 5-FOLD CROSS VALIDATION.

	AA	AL	AV	AW	AY
SSRCSP [3]	70.54	96.43	53.57	71.88	75.39
FBRCSP [4]	84.82	96.43	63.78	74.55	73.81
DTMKL [20]	91.07	94.64	71.94	82.59	88.89
MSRCSP [21]	69.64	96.43	59.18	71.88	52.78
SRCSP [21]	72.32	96.43	58.16	72.32	87.30
LRCSP [22]	79.46	**98.21**	72.45	87.95	87.7
Proposed	**94.64**	97.50	**83.57**	**89.64**	**93.21**

and temporal domain features simultaneously, as well as to the reliance on hierarchical feature extraction using the residual network. In particular, the proposed method outperforms its closest competitors, LRCSP [22] and DTMKL [20], with an improved classification accuracy of 7.7% and 6.8%, respectively, averaged over all the subjects.

V. CONCLUSION

A new MI-BCI task recognition method has been proposed using a time-dependent regularized CSP and supervised learning approach based on residual network. The EEG signals were spatially-filtered with regularized CSP to obtain a 2D signal keeping both the spectral and temporal resolutions. These signals were fed into a residual network for automatic feature learning. Experiments were conducted to assess the performance of the proposed method and to compare it with that of the existing works. The results have demonstrated that the proposed method outperforms the other methods in terms of providing higher classification accuracy across subjects. The superior performance of the proposed method may be attributed to the fact that, unlike the other methods, it preserves the temporal behavior of EEG signals by constructing the regularized CSP image representation and that it relies on high-level feature extraction using residual network.

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