A Subject-Independent Brain-Computer Interface Framework Based on Supervised Autoencoder

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Abstract—A calibration procedure is required in motor imagery-based brain-computer interface (MI-BCI) to tune the system for new users. This procedure is time-consuming and prevents naive users from using the system immediately. Developing a subject-independent MI-BCI system to reduce the calibration phase is still challenging due to the subject-dependent characteristics of the MI signals. Many algorithms based on machine learning and deep learning have been developed to extract high-level features from the MI signals to improve the subject-to-subject generalization of a BCI system. However, these methods are based on supervised learning and extract features useful for discriminating various MI signals. Hence, these approaches cannot find the common underlying patterns in the MI signals and their generalization level is limited. This paper proposes a subject-independent MI-BCI based on a supervised autoencoder (SAE) to circumvent the calibration phase. The suggested framework is validated on dataset 2a from BCI competition IV. The simulation results show that our SISAE model outperforms the conventional and widely used BCI algorithms, common spatial and filter bank common spatial patterns, in terms of the mean Kappa value, in eight out of nine subjects.

I. INTRODUCTION

A brain-computer interface (BCI) is a system that directly links brain activities to external devices in order to enable people with movement disabilities [1], [2]. Motor imagery electroencephalography (MI-EEG) is a non-invasive technique used in BCI to acquire brain activities after rehearsing a motor act. Generally, an MI-BCI system is ready to use after a calibration procedure. The calibration includes acquiring MI-EEG signals from a subject and training a model on collected data. It takes approximately 20–30 minutes to complete this procedure [3]. Since some characteristics of EEG signals, for example the spatial origin of the signals, vary from one subject to another, a new calibration procedure is required for each new user. As a result, the instant use of a BCI system is not possible for each new user. Nevertheless, most conventional BCI studies are dedicated to designing a system based on subject-dependent approaches [4], [5]. These approaches still need calibration to be generalized to a new subject.

To alleviate the subject-dependency issue, BCI researchers aim to reduce the time or the number of training samples required for the calibration phase by leveraging data collected from other individuals [6]–[8]: Jayaram et al. [6] propose a framework based on transfer learning to reduce the training time needed in a subject-to-subject or session-to-session transfer in an MI paradigm. In order to decrease the required training samples for one subject, Jiao et al. [7] establish a sparse group representation model to find the most compact representation of a test sample based on a linear combination of the common spatial pattern (CSP) features extracted from training samples of all available subjects. However, minimum data must still be acquired from new subjects in these approaches. Therefore, a naive user is still unable to utilize the designed BCI system immediately. On the other hand, zero-calibration approaches attempt to eliminate the calibration phase in order to ready a BCI system for instant usage by inexperienced users [9], [10]: Lotte et al. [9] develop a subject-independent (SI) method utilizing a multi-resolution frequency decomposition algorithm for finding the most generalizable frequency ranges in filter bank CSP (FBCSP). Joadder et al. [10] find common discriminating patterns among different subjects by exploiting four different feature extraction methods. These features were then fed to a linear discriminant analysis (LDA) classifier in their proposed SI-BCI method. Nevertheless, most of the above zero-calibration methods rely only on the linear characteristics of the EEG signals.

In recent years, machine learning and deep learning have shown promising results in automatically extracting distinguishable features from EEG signals through non-linear processes [11], [12]: Kwon et al. [11] construct a large MI-EEG dataset and introduce an SI-BCI framework based on the deep convolutional neural network (CNN). However, current methods use supervised learning and extract features that accurately map the input data onto labels. Hence, the trained model cannot find the common underlying representation of different subjects. This fact results in a poor generalization to other datasets.

In this paper, we propose a zero-calibration method to develop a BCI system for immediate use. We utilize a large filter bank to extract features from MI-EEG signals and feed them to our subject-independent supervised autoencoder (SISAE). The autoencoder within the SISAE extracts non-linear features representing the underlying patterns of the EEG signals. The classifier of the SISAE forces the autoencoder to extract those underlying features that are suitable for discriminating the desired MI signals. Therefore, the SISAE makes a trade-off between finding the common underlying patterns and the features suited for classification.

To evaluate the generalization performance of the proposed SISAE, we utilize dataset 2a from the BCI competition IV, which consists of nine subjects. For each subject, we train the SISAE using the other eight subjects. The simulation
results show that the suggested method can extract the common underlying patterns of MI-EEG signals among different subjects and provide a promising generalization performance. The SISAE outperforms the CSP and FBCSP algorithm in eight out of nine subjects in terms of the mean kappa value.

The remainder of this article is organized as follows. In section II, we describe the dataset. The proposed method is elaborated in section III. The results are presented and discussed in section IV. Section V concludes the article.

II. DATASET

We use dataset 2a from the BCI competition IV [13]. In this dataset, 22 electrodes are used to collect EEG signals from nine subjects. The subjects performed four motor imageries: the left hand, the right hand, the feet and the tongue. The training and testing datasets are recorded on different days. Each dataset contains 72 trials for each class. No feedback is provided during the recording. The recording procedure for each trial starts with a warning tone and a fixation cross on the screen. At $t=2s$, an arrow appears on the screen for 1.25s to ask the subject to perform the motor imagery until $t=6s$. For this paper, we only use the signals of the left and right hands for our binary classification. We also extract the interval from second 0.5 to the second 2.5 of the recorded trials for our processing, similar to the procedure in [5].

III. METHODS

The spectral and spatial information in the MI signals are subject-dependent. In a subject-specific method, the most discriminative frequency bands and spatial regions are identified for each subject to enhance the system performance. However, in designing a subject-independent framework, the challenge is to extract features that can be better generalized to other subjects. To this end, we employ a large filter bank and apply CSP algorithm [4] to extract the spatial patterns of each bandpass filtered signal. The obtained features in different frequency bands are fused to feed the proposed subject-independent supervised autoencoder (SISAE) network explained in III-B.

A. Feature extraction

We define a large set of frequency bands in $\mathcal{F}$ to form our filter bank. The set $\mathcal{F}$ covers the frequencies between 4 Hz to 40 Hz and includes the frequency bands with bandwidth changing from 1 Hz to 36 Hz according to

$$\mathcal{F} = \{[4,5], [5,6], ..., [5,40], [4,40] \}.$$  

(1)

Each EEG signal is accordingly bandpass filtered with a sixth-order Butterworth filter with cutoff frequencies given in the $i$-th frequency band $\mathcal{F}_i$ in the set $\mathcal{F}$. The signals filtered with $\mathcal{F}_i$ are fed to the CSP algorithm with $m$ pairs of spatial filters to produce a feature vector $V_i$. The obtained vectors in different frequency bands are concatenated to form a larger feature vector $V$ with a size of $2mk$ where $K$ is the number of frequency bands represented in $\mathcal{F}$. This procedure is illustrated in Fig. 1.

B. Subject-independent supervised autoencoder (SISAE)

In supervised learning, the neural network does not necessarily learn the underlying patterns in the data so that it suffers from the generalization issue [14]. On the other hand, unsupervised learning strategies may not be effective in classifying different MI tasks. In this article, we propose a network that jointly learns the supervised tasks, here, the classification of the left versus right hand, and the underlying patterns for better generalization.

The proposed SISAE architecture is depicted in Fig. 2. It is composed of an autoencoder network and a fully connected feed-forward binary classifier. The AE learns the underlying representation of the data by reconstructing the input. The encoder maps the input onto a code vector $C=Enc(X)$.
Fig. 2: Proposed subject-independent supervised autoencoder (SISAE).

The decoder takes the code vector and reconstructs the input \( \mathbf{X} = \text{Dec}(\mathbf{C}) \). To prevent the AE from copying the input, the latent layer's dimensionality is set to a number smaller than the input dimensionality. The classifier is then fed with \( \mathbf{C} \). Both networks are trained simultaneously to minimize a composite loss function \( Q \). The \( Q \) comprises a reconstruction loss \( Q_r \) and a loss for classification task \( Q_c \) as follows

\[
Q = \frac{1}{N} \sum_{n=1}^{N} \left( \alpha Q_c(W_c W_c x_i, y_i) + \beta Q_r(W_d W_c x_i, x_i) \right),
\]

where \( N, W_c, W_d, W_c, x_i \) and \( y_i \) are the number of trials in the training set, the weights of the encoder, the weights of the decoder, the weights of the classifier, the \( i \)-th input and its corresponding label, respectively. The hyperparameters \( \alpha \) and \( \beta \) are the loss weights that are tuned in cross validation. We define the reconstruction loss \( Q_r \) as the mean squared error

\[
Q_r(W_d W_c x_i, x_i) = \frac{1}{|x_i|} ||W_d W_c x_i - x_i||^2,
\]

where \( |x_i| \) is the input dimensionality. The classification loss \( Q_c \) is defined as a binary cross entropy loss

\[
Q_c(W_c W_c x_i, y_i) = -\left( y_i P(y_i) + (1 - y_i) P(1 - y_i) \right),
\]

where \( P(.) \) is the predicted probability calculated by a sigmoid function as the activation function of the last layer in the classifier network.

**IV. RESULTS AND DISCUSSION**

A. Cross validation and parameter setting

For training the SISAE network, we use eight training sets corresponding to eight out of nine subjects, excluding one subject for testing. To avoid overfitting, we add an \( L_1 \) and an \( L_2 \) regularization terms to the loss function. Here, we set the regularization factors, learning rate, and the mini batch to 0.0001, 0.01, and 32 for all the experiments. In order to prevent AE from overfitting, we divided the total number of epochs into 50 and 150 epochs, and simultaneously trained both the AE and the classifier during the first 50 epochs, leaving the last 150 epochs to only train the classifier while the AE weights are frozen.

To obtain the proper model parameters, we utilize the leave-one-subject-out (LOSO) strategy for cross validation [15]. For example, assume that the test subject is subject 9. We perform the cross validation on the remaining eight subjects. We choose the training set of one of the eight subjects as the validation set and train the SISAE network on the remaining seven subjects. This way, we train the SISAE network eight times for each specific test subject.

Table I shows different settings for LOSO cross-validation.

| Setting | AE nodes | Classifier nodes |
|---------|----------|------------------|
| 1       | [5,3,5]  | [3,3,3,1]        |
| 2       | [10,5,10]| [5,5,5,1]        |
| 3       | [20,10,20]| [10,5,5,1]     |
| 4       | [30,15,30]| [15,10,5,1]   |
| 5       | [40,20,40]| [15,10,5,1]   |

Table II: Cross validation results in terms of mean Kappa value

| Subj. | 1   | 2   | 3   | 4   | 5   | Mean | Std |
|-------|-----|-----|-----|-----|-----|------|-----|
| 1     | 0.3534 | 0.3839 | 0.3765 | 0.3584 | 0.3596 | 0.3664 | 0.0131 |
| 2     | 0.4615 | 0.4658 | 0.4856 | 0.4733 | 0.4715 | 0.4715 | 0.0091 |
| 3     | 0.4411 | 0.4384 | 0.4385 | 0.4429 | 0.4392 | 0.4400 | 0.0019 |
| 4     | 0.4901 | 0.4855 | 0.4882 | 0.4697 | 0.4666 | 0.4800 | 0.0110 |
| 5     | 0.4808 | 0.4886 | 0.4929 | 0.4875 | 0.4941 | 0.4888 | 0.0053 |
| 6     | 0.4355 | 0.4520 | 0.4508 | 0.4665 | 0.4676 | 0.4545 | 0.0132 |
| 7     | 0.4452 | 0.4499 | 0.4566 | 0.4447 | 0.4500 | 0.4493 | 0.0048 |
| 8     | 0.3886 | 0.3884 | 0.3799 | 0.3950 | 0.3937 | 0.3891 | 0.0059 |
| 9     | 0.5034 | 0.5046 | 0.5035 | 0.5104 | 0.5141 | 0.5072 | 0.0048 |
TABLE III: Performance comparison of CSP, FBCSP and proposed SISAE in terms of mean Kappa value

| Test subject | CSP  | FBCSP | SISAE |
|--------------|------|-------|-------|
| Subject 1    | 0.259| 0.158 | 0.717 |
| Subject 2    | 0.047| 0.062 | 0.292 |
| Subject 3    | 0.410| 0.323 | 0.756 |
| Subject 4    | 0.331| 0.342 | 0.311 |
| Subject 5    | 0.030| 0.027 | 0.293 |
| Subject 6    | 0.116| 0.059 | 0.251 |
| Subject 7    | 0.063| 0.045 | 0.388 |
| Subject 8    | 0.550| 0.535 | 0.882 |
| Subject 9    | 0.225| 0.412 | 0.614 |
| Avg.         | 0.226| 0.218 | 0.500 |

B. Comparison of SISAE with CSP and FBCSP methods

We evaluate our proposed SISAE by comparing it with the CSP [4] and FBCSP [5] algorithms. For the CSP, the EEG signals are bandpass filtered between 4 Hz and 40 Hz. For the FBCSP, nine bandpass filters, covering the frequency range of 4–40 Hz, are used and the mutual information-based best individual feature algorithm is utilized to select the spatial features. For all methods, we used $m=2$ pairs of the spatial filters to extract the features. In addition, an LDA classifier is used to classify the spatial features extracted by the CSP and FBCSP algorithms.

Table III shows the mean Kappa value obtained for each subject. We observe that the proposed method outperforms conventional methods in eight out of nine subjects. Further, we observe the superiority of the proposed method for the subjects with low performance (Kappa < 0.1) corresponding to the CSP and FBCSP methods. The reason is that in the CSP and FBCSP the classifier is trained by directly mapping the subject-dependent features onto the labels and therefore it performs poorly on the new subject. To the contrary, the autoencoder within the SISAE network extracts the underlying patterns and the classifier maps these patterns onto labels. Further, we observe that the conventional methods perform nearly similar to a random classifier for the subjects 2, 5, 6, and 7 where our proposed method performs notably better.

The average Kappa value across all subjects are 0.226, 0.218, and 0.500 for CSP, FBCSP, and SISAE, respectively. The Kappa value improvement by our proposed SISAE is statistically significant. The p-value of the paired t-test with a confidence interval of 95% between the proposed SISAE and the two other methods is less than 0.001. In both comparisons, the null hypothesis is that the mean difference between the mean kappa value of the proposed method and each conventional method is zero.

V. CONCLUSION

In this article, we presented a subject-independent framework based on a supervised autoencoder in order to skip the calibration procedure required for new subjects. The proposed network balanced extracting features ideal for separating MI signals and finding underlying patterns suitable for subject-to-subject generalization. We evaluated our method on dataset 2a from BCI competition IV. The simulation results showed that the suggested framework significantly outperformed conventional and widely used CSP and FBCSP algorithms with a p-value less than 0.001.

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