Transfer Learning based Motor Imagery Classification using Convolutional Neural Networks

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***Abstract*—Nowadays, classification of signals is considered as the crucial role of motor imagery brain computer interface. Moreover, deep learning approaches show acceptable performance in image recognition applications as well as speech recognition. However, practicality of the aforementioned technique is not generally deployed on motor imagery tasks. Hence, the goal of this paper is to apply convolutional neural networks to classify the motor imagery EEG signals. In addition, data augmentation along with excusive transfer learning strategy are used to overcome the problem of few trials in motor imagery tasks. On the other hand, analytical regression assessments are also applied to the raw data for mitigating the stress of EOG on EEG. Consequently, the simulation results clearly convey the contribution of the proposed algorithm via testing on BCI competition IV dataset 2b. Applying EOG artifact removal and data augmentation methods resulted in 0.07 improvement in kappa coefficient. Furthermore, using our proposed transfer learning method led to 0.06 improvement in terms of kappa coefficient.**

Keywords—deep learning, brain computer interface, motor imagery, transfer learning

I. Introduction

It is known that, the rehabilitation application of motor imagery brain computer interface (MI-BCI) improves the quality of life in patients. Hence, EEG implementation in such cases, because of being noninvasive has been considered as a beneficial method [1]. In addition, deep learning tactics have been revolutionized computer vision as well as natural language processing fields [2]. Parallel to this point, the methods benefiting from deep learning approaches for MI-EEG classification have been reached results which can be compared to filter bank common spatial patterns (FB-CSP). It has to be noted that the expectations have been satisfied through tolerable accuracies by means of many deep learning based strategies like deep neural network (DNN), convolutional neural network (CNN), long short-term memory (LSTM), recurrent neural network (RNN) and auto encoders. In this regard, restricted Boltzmann machines (RBM) along with frequency domain representation which considers FFT as the input of RBMs instead of raw data, have been used [3]. Authors in [4] have proposed to classify MI-EEG through LSTM network using one dimension-aggregate approximation (1D-AX) as an effective input signal representation. In [5] three types of models including LSTM, CNN and RCNN are used without any stage of feature extraction. Cropped training strategy, batch normalization and exponential linear unit (ELU) are utilized in [6] to gain an acceptable performance. Deep stacking network is used in [7] to update the input set of weights by particle swarm optimization (PSO) technique which leads to feature extraction as well as classification of MI-EEG signals. Moreover, spatio-temporal characteristics of EEG are applied to CNN in order to extract features and classify a single-trial EEG signal for which the results are compared with power+SVM, CSP+SVM and AR+SVM [8]. Features extracted by discriminative filter bank common spatial pattern (DFBCSP) are used as input to one or several CNNs and optimized by a Bayesian optimization as in [9]. In [10] CNN is applied to categorize the MI task by knowledge transferring from four subjects to other subjects. Linear discriminant analysis (LDA) is considered in [11] as the classifier by applying an active transfer learning for knowledge transferring from specific subjects to other subjects.

One of the vital problems in classification of MI-EEG through deep learning methods is the low size of data caused by exhausting subjects while performing experiments. Therefore, this paper proposes a reliable classification path based on data augmentation, transfer learning and CNN which:

- removes EOG effects from EEG signal
- increases trials of data 2 times
- uses a 5-layer CNN to classify EEG
- transfers knowledge from many subjects to one subject

The block-diagram of the methodology and the proposed transfer learning method can be seen in Figs. 1 and 2, respectively. The remaining of the paper is organized as follows: Section II explains the dataset description. Section III describes the methodology including our proposed transfer

978-1-7281-1508-5/19/$31.00 ©2019 IEEE

learning methods. The results and discussions are demonstrated in Section IV. Finally, Section V concludes the research study.

II. DATASET DESCRIPTION

To verify the performance of our method, public BCI competition IV dataset 2b has been used. The dataset consists of EEG data from nine subjects in five sessions. The two first sessions are without feedback and the three last sessions are with smiley feedback. Sessions four and five are for testing and the rest of sessions are for training. Data are recorded with sampling frequency of 250Hz containing 3 EEG and 3 EOG channels. The data are filtered between 0.5Hz and 100Hz and a notch filter on 50Hz to remove the influence of power line. It has to be noted that only third session is used as training set and that is because it was more similar to test set than the first two sessions.

III. METHODOLOGY

A. EOG artifact removal

The accuracy of EEG signals classification which is needed to be high, is a considerable factor in a BCI system. Thereby, EOG artifact removal method is applied in the methodology to purify the EEG data as shown in (1) and (2) [12].

$$b = < U^T U >^{-1} < U^T Y > = C_{NN}^{-1} C_{NY} \quad (1)$$

$$S = Y - U.b \quad (2)$$

where U, Y, $C_{NN} = < U^T U >$, $C_{NY} = < U^T Y >$, b and S are EOG signal, EEG signal, EOG channels covariance matrix, EEG and EOG cross-covariance matrix, correction coefficients and purified EEG, respectively.

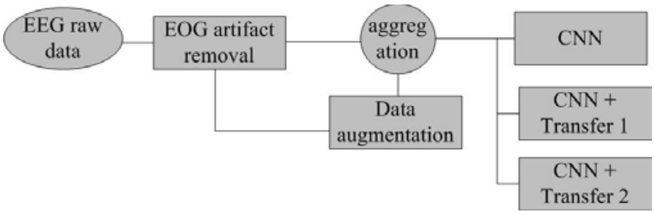

Fig. 1. Block-diagram of the proposed algorithm

B. Data augmentation

Data augmentation which enlarges the number of trials 2 times is used to increase the size of dataset accompanied by avoiding the overfitting challenge. It has to be noticed that, a Gaussian distribution with zero mean value is multiplied by 0.15 to allocate as the noise. Furthermore, this value is then uniformly summed with the above mentioned primary set. After generating new set of input, the combination of the former route set with the new generated data, increases the size of data which is equal to 2 times.

C. Convolutional neural network

The proposed CNN architecture is composed of four convolutional and pooling layers along with one softmax layer to classify MI tasks. In this regard, ELU is taken as the activation function of each layer. Adam and cross entropy are brought within the study as an efficient optimizer and error criterion, respectively. To avoid overfitting, L2 regularization is applied in this case study. The proposed CNN structure is modeled as in Table I.

TABLE I. Details of the proposed CNN structure

Layer	Size	Output Statue
Temporal Convolution	16 linear units	(1125,16,3)
Spatial Convolution	16 exponential linear units	(1125,16,1)
Max Pooling	Pool size=4 Stride=4	(281,16,1)
Convolution	32 exponential linear units	(281,32,1)
Max Pooling	Pool size=4 Stride=4	(70,32,1)
Convolution	64 exponential linear units	(70,64,1)
Max Pooling	Pool size=4 Stride=4	(17,64,1)
Convolution	128 exponential linear units	(17,128,1)
Max Pooling	Pool size=4 Stride=4	(4,128,1)
Fully Connected	----------	(512,1)
Dense	2 Softmax unit	---------

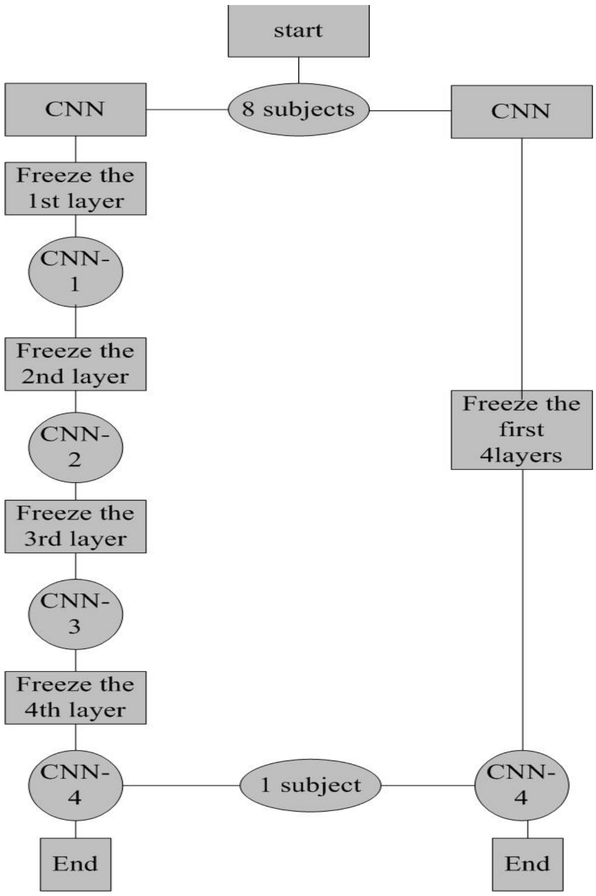

Fig. 2. The proposed transfer learning 1 and 2 structures

D. Transfer learning

After EOG removal steps and CNN construction are performed in a symmetric framework, the transferring process is deployed for training purpose. Assuming so, two types of transfer learning are described as follows:

1) The foregoing debate is initiated with eight subjects which are inserted to train the network, then the freezing operation is conducted on the primary four layers. In this regard, for the last subject, the proposed strategy is permitted to let the last layer remains immutable. Doing so, the same procedure is repeated for the rest of the subjects.

2) In this step, eight primary subjects are inserted to the architecture as the input for the training purpose. Then, the weights of first layer will be frozen. Now, the aforementioned primary subjects are considered as the input for one more time and the weights of the second layer will be frozen, too. The procedure will be repeated for the third and fourth layers. Actually, layers will be frozen one by one. Then the last layer will be tuned for the last subject. For the rest of subjects, the same procedure is repeated.

For summarizing the methodology, Fig. 1 is presented to illustrate the steps of proposed algorithm. It is noted that, Fig. 2 is plotted to demonstrate the architectures of CNN+transfer1 and CNN+transfer2.

IV. RESULTS AND DISCUSSION

As it is known, EEG signals are nonstationary and convey noise, e.g., EOG and heartbeat. Therefore, removing artifact from EEG is one of the necessary parts of EEG signal classification. Moreover, because of recording EEG signals using few channels, independent component analysis (ICA) algorithm is unable to remove EOG effects. Hence, regression based correction method is deployed to purify EEG signals from the impacts of EOG through the equations (1) and (2). It has to be noted that, deep learning architectures need high amount of input data for training. Therefore, data augmentation is utilized to increase the size of data. Furthermore, because of adding noise to generate data from primary set, the overfitting problem is resolved. In addition, the batch normalization technique is brought into account of the CNN modeling because it has a little regularization effect and can reduce training time. In order to dampening overfitting obstacle, the reasonable performance is gained by considering large amount of dropout in the last layers along with taking into account the L2 regularization. According to the above mentioned concept of transfer learning, the size of data can be increased vastly by inserting transfer learning approach. On the other hand, applying low size of data to an extra deep network will lead to overfitting problem. In this regard, the large amount of data will be fed to deep network by exerting transfer learning. Also the few amount of data will be used in shallow network by freezing the first four layers and tuning the last layer.

The evaluation of EOG artifact removal and data augmentation methods are carried out based on kappa coefficient that shows how much the accuracy gained is reliable than the random accuracy in the case study. In this matter, the results are gathered in Table II. The simulation results demonstrate the improvement rate of kappa coefficient which is 0.07 using two above mentioned techniques. Therefore, transfer learning methods are constructed using data augmentation and EOG artifact removal steps before CNN. Assuming so, two versions of transfer learning methods are introduced to classify the signals. The results show that the improvement of kappa value in version 1 (0.03) is more than CNN + EOG removal + data augmentation. Similarly, kappa value of the second version of transfer learning is improved to 0.06. It has to be noted that, the loss of train and validation processes are shown in Fig. 3 to illuminate the best number of epochs. Moreover, the accuracy of conducted architecture is mapped through Fig. 4 to demonstrate the best number of epochs for high accuracy.

TABLE II. THE KAPPA VALUE FOR EACH SUBJECT

Subject	CNN	CNN+EOG removal+data augmentation	CNN+EOG Removal+data augmentation +transfer learning 1	CNN+EOG Removal+data augmentation +transfer learning 2
1	0.20	0.40	0.46	0.49
2	0.36	0.42	0.50	0.49
3	0.66	0.67	0.75	0.77
4	0.51	0.69	0.65	0.64
5	0.58	0.77	0.78	0.80
6	0.30	0.29	0.31	0.31
7	0.52	0.68	0.70	0.78
8	0.55	0.45	0.46	0.48
9	0.35	0.29	0.33	0.33
mean	0.45	0.52	0.55	0.57

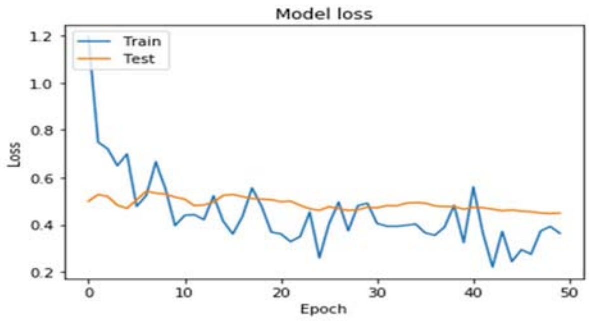

Fig. 3. Training and validation loss for each epoch

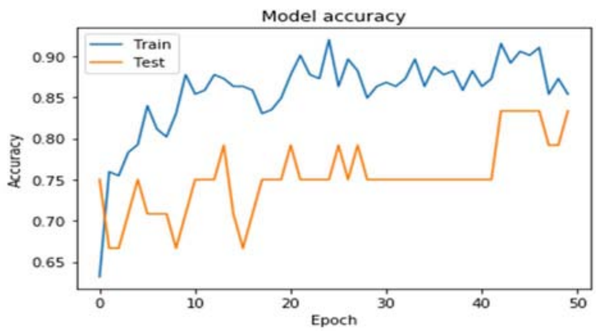

Fig. 4. Training and validation accuracies for each epoch

V. CONCLUSION

In this paper, classification of MI-EEG signals is proposed using CNN and three smart algorithms are implemented to test the resiliency of algorithm. In this regard, the combination of EEG signals with EOG removal method and data augmentation improves the efficiency of the classification. After conducting two feasible transfer learning methods, results clearly prove that such methods have a positive impact on the performance of classifier. The simulation results demonstrate that the proposed architecture is a reliable tool which compensate the flaws of sole implementing of CNN. Furthermore, the best case of CNN has a kappa coefficient of 0.66 compared to the above mentioned combined proposed method which leads to 0.67. In addition, deployment of second transfer learning technique is in favor of classification, which leads to even more improved kappa coefficient of 0.8.

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