Motor Imagery Brain Activity Recognition through Data Augmentation using DC-GANs and Mu-Sigma

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***Abstract*—The brain-computer interface is a technology that allows a machine to connect with the human brain and work based on the commands released by thoughts and activities of the brain. Electrodes are placed on the scalp and the changes in electric waves released by the brain are recorded as Electroencephalography (EEG) signals. In this work, we propose the use of generative adversarial networks and mu-sigma methods to augment the EEG signals. Some of the existing deep learning methods such as convolutional neural network and recurrent neural network for classification of the EEG signals are implemented and their classification performance is examined with and without data augmentation. It is shown that the use of data augmentation can improve the performance of the EEG signal classification with deep learning models to a considerable extend.**

***Index Terms*—Brain computer interface, binary classification, convolutional neural network, common spatial pattern, data augmentation.**

I. Introduction

Motor task imagery in brain-computer interface (MI-BCI) comprises of detecting the motor actions such as arm, hand, leg, foot, or tongue movement without the actual limb movement [1], [2]. MI-BCI can bring a huge revolution in terms of handling any machine just by stimulating thoughts and activities of the brain. This can facilitate the lives of people who are physically handicapped, for instance, a person in a wheelchair can control the chair just with their thoughts without any limb movements.

There has been a surge of interest in designing and developing learning methods for motor task recognition in MI-BCI systems [3] . Most of the existing methods have been built on the collection of commands as data from the brain by placing electrodes on it and recording the Electroencephalography (EEG) signals. The EEG signals are known to be very noisy and thus need to be pre-processed to remove their noise and any existing artifacts [3]. A common practice in analyzing the EEG signals after the pre-processing step is to perform some spatial filtering such as principal component analysis or common spatial patterns (CSP) to not just reduce the signal dimensions but also to prepare the signals for further feature extraction procedure [4].

There exist many works in which CSP and its variants were used to spatially filter the EEG signals [4]–[8]. Some of these methods are using deep neural networks to automatically extract features from the spatially-filtered EEG signals [4], [5]. Extracting features from the EEG signals even in the absence of a large volume of data has proven deep learning an effective way of automating this process [5].

However, there is still room for improving the performance of these deep learning-based methods in motor task recognition. In view of this, in this paper, we propose the use of data augmentation based on deep convolutional generative adversarial networks (DC-GANs) and mu-sigma to improve classification accuracy of some of the existing deep neural networks in classification of the spatially-filtered EEG signals. To this end, for the motor task recognition of right foot or right hand, we formulated a binary classification problem and implemented four classifiers based on convolutional neural network (CNN), recurrent neural network (RNN), multi-layer perceptron (MLP) and long short-term memory (LSTM) network.

II. Data Preprocessing

In order to examine the performance of the various models built in this work, the EEG signals data is taken from BCI competition – III [3]. This dataset is comprised of signals from 5 subjects (persons), AA, AL, AV, AW, and AY, each having 280 trials of the right hand and right foot. Following the approach proposed in [5], we process the EEG signals using bandpass filtering using a 5th order Butterworth filter in the range of [7 - 30] Hz. The filtered EEG signal is then smoothed by a weighted moving average filter with a window size of 10 samples at a time [2]. Table I lists the subjects and training and testing splits of each subject.

To prepare data for the data augmentation and use them as input to the deep learning models, the EEG signals are spatially-filtered using a modified CSP method [2], by preserving the temporal resolution of the spatially-filtered EEG signals, i.e., 2D features in both the time and frequency domains. More specifically, after applying CSP filter on the EEG signal, we have 201×6 dimensional samples for each subject. The 2D representations are then used in data augmentation.

III. Data Augmentation

Processing EEG signal has several challenges such as low signal-to-noise (SNR) ratio, non-stationary characteristics of the signal, and small size of the dataset [9]. The low SNR ratio,

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TABLE I
DATA SET USED IN OUR EXPERIMENTS

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

as well as non-stationary characteristics, have been addressed in the [10], [11]. The small size of the EEG dataset needs to be addressed. For overcoming this small size data challenge, in this paper, two methods have been applied: DC-GANs and mu-sigma methods.

A. Data augmentation using DC-GANs

The DC-GANs are generative [12] and unsupervised learning models that allow automatic discovery and learning of patterns as well as regularities in the input data to generate new outputs based upon the original dataset provided. The DC-GANs model includes a generator model that generates an augmented dataset as well as the real dataset, which are both passed on to the discriminator which further creates a generator loss and a discriminator loss. The model tries to maximize the discriminator loss and minimize the generator loss in order to generate augmented samples [13]. The generated data obtained from DC-GANs for the two classes of right hand and right foot are visualized in Fig. 1 using the t-SNE visualization method.

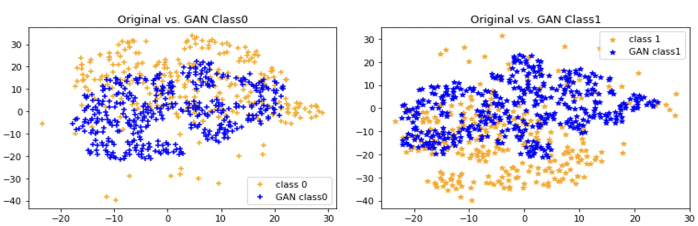

Fig. 1. Data visualization for DC-GANs method when subject AA is used.

B. Data augmentation using Mu-Sigma

The Mu-Sigma method allows adding and subtracting a noise signal to the original input signal dataset for augmenting the dataset [14]. The random noise signal is generated by calculating the zero mean and variance of the individual input signal dataset, as given in (1). Two extra samples can be generated using randomly generated noise. Adding and subtracting this generated noise creates two new signals $X_{augmented} = X \pm Noise$ dataset as shown in Fig. 2.

$$Noise \sim \mathcal{N}(0, \sigma^2) \tag{1}$$

The dataset augmented using this randomly generated noise by adding and subtracting the same from the EEG signals is visualized using t-SNE visualization in Fig. 3.

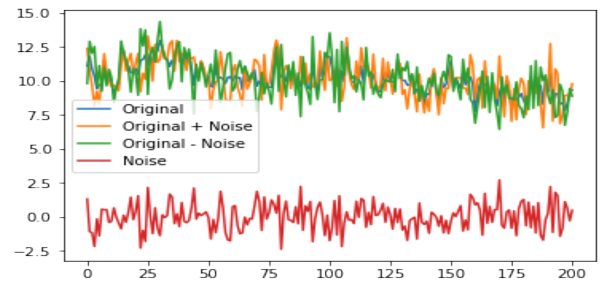

Fig. 2. Two more signal generation by adding and removing randomly generated noise from original signal

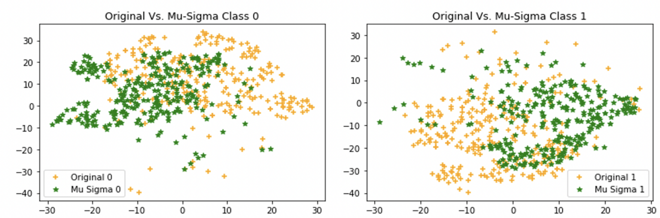

Fig. 3. Data visualization for mu-sigma method when subject AA is used.

IV. DEEP LEARNING MODELS

In this work, four deep learning models are developed to classify the motor task EEG signals into either right-hand or right-foot task, namely MLP, CNN, RNN and LSTM. The input to these models are the preprocessed EEG signals and their augmented versions. All the models architecture and hyper-parameters are tuned using keras hyperband [15] tuning method. The performance of the classification models are assessed by obtaining the confusion matrix and calculating the accuracy metric, as given in (2)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \tag{2}$$

where TP and TN are true positives and true negatives, while FP and FN denote false positives and false negatives.
We now explain the model architectures for the deep learning models used in our experiments. The MLP model is built by one input layer followed up by 3 hidden deep layers having 200, 100 and 50 neurons, respectively and a single sigmoid output, which is returning whether it is classified in a right-foot class or right-hand class. ReLU activation is used in all the hidden layers and the loss function used is binary cross-entropy. CNN blocks0 comprises of one input layer followed by deep hidden layers consisting of the max-pooling layer and batch normalization for each CNN layer. In our architecture, we use 2 CNN blocks in the hidden layers each having a Max-Pooling layer followed by a batch normalization, having 4×4 filters. The CNN blocks are followed by a fully-connected layer with 10 neurons and one output layer which is a single node sigmoid. It is noted that each hidden layer includes ReLU activation, and a binary cross-entropy is used as the loss function. The RNN model consists of an input

TABLE II
CLASSIFICATION ACCURACY OBTAINED USING DIFFERENT METHODS

	MLP			CNN		
	No-Augment	Mu-Sigma	GAN	No-Augment	Mu-Sigma	GAN
AA	93.75%	91.96%	**95.54%**	**94.64%**	93.75%	91.07%
AL	96.43%	96.43%	**96.43%**	92.86%	92.86%	**96.43%**
AV	**94.39%**	91.33%	92.86%	**92.35%**	88.27%	77.55%
AW	93.3%	91.07%	**95.54%**	89.73%	90.62%	**91.07%**
AY	95.24%	95.24%	**96.03%**	93.65%	**94.84%**	91.67%
Overall	94.62%	93.2%	**95.27%**	**92.64%**	92.06%	89.55%

	RNN			LSTM		
	No-Augment	Mu-Sigma	GAN	No-Augment	Mu-Sigma	GAN
AA	83.93%	**88.39%**	87.5%	85.71%	91.96%	**92.86%**
AL	**92.86%**	91.07%	87.5%	91.07%	91.07%	**92.86%**
AV	81.12%	**83.67%**	82.14%	87.24%	89.8%	**92.86%**
AW	80.8%	**85.71%**	82.59%	85.27%	87.5%	**89.73%**
AY	81.35%	**86.51%**	80.95%	88.49%	**92.46%**	91.27%
Overall	84.01%	**87.07%**	84.13%	87.55%	90.55%	**91.91%**

layer followed by 2 simple RNN layers containing 28 and 12 neurons,respectively, which is followed by 2 dense layers having 16 and 10 neurons. LSTM comprises of an input layer, LSTM hidden layers and an output layer. We use a stack LSTM with two layers having 24 and 20 neurons in each layer, respectively, and 2 subsequent fully-connected layers each having 16 and 6 neurons, respectively. The activation function used for the hidden deep layers in this architecture is ReLU and binary cross-entropy is used as the loss function. The output layer consists of a single sigmoid activated node.

V. EXPERIMENTAL RESULTS

As discussed in Section II, the EEG signals were spatially-filtered using CSP method and the filtered version was used to train different classification models. Data augmentation was also performed to increase the number of EEG samples.

The classification accuracy of each model is listed in Table II. Accuracy for each subject and overall accuracy for the model were given in this table. In addition, we compared the classification accuracy of different methods with and without data augmentation. It is seen from this table that the overall accuracy of the MLP model without using data augmentation is 94.62%, which is higher than current state-of-the-art. The same model was used with the augmented data using mu-sigma and DC-GANs methods. The accuracy achieved with mu-sigma and DC-GANs augmentation methods is 93.20% and 95.27%, respectively. For the CNN model, the overall classification accuracy is 92.64% without data augmentation, while using mu-sigma and DC-GANs augmentation methods, the accuracy is 92.06% and 89.55%, respectively. In case of RNN, the classification accuracy with is 84.01%, 87.07% and 84.13%, respectively without augmentation, with mu-sigma and with DC-GANs. From this table, it can be seen that using the LSTM model, the classification metric was improved with and without data augmentation.

We also compared the performance of the proposed models with data augmentation to some of the state-of-the-art methods. Table III gives the classification accuracy comparison using different methods. It is seen from this table that the proposed method with DC-GAN data augmentation achieves higher classification accuracy than the other methods.

TABLE III
CLASSIFICATION ACCURACY OF THE PROPOSED METHOD WITH THOSE YIELDED BY THE OTHER METHODS

	AA	**AL**	**AV**	**AW**	**AY**
LRDS [16]	80.4	94.6	50.0	90.6	83.3
FBRCSP [17]	84.82	96.43	63.78	74.55	73.81
EEGCAPS [5]	85.50	**97.52**	62.15	94.70	83.57
MLP_GAN	**95.54**	96.43	**92.86**	**95.54**	**96.03**

From the two tables, it was shown that the augmented dataset with DC-GANs could provide improved classification accuracy results across subjects especially when MLP and LSTM models were used. In addition, we observed that mu-sigma augmented dataset provided higher classification metrics when using RNN model. As compared to the state-of-the-art methods, better results were achieved with and without data augmentation using the MLP model.

VI. CONCLUSION

In this paper, we have proposed a a classification method for recognizing brain-wave motor imagery tasks in MI-BCI systems. The EEG signals were first pre-processed and spatially-filtered using the modified common spatial paterns method and the resulting 2D signal was used as input to some deep learning models, namely, MLP, CNN, RNN and LSTM. Since, the size of recorded EEG signal dataset from MI-BCI was small, we performed data augmentation using two methods, namely, mu-sigma and DC-GANs, to train our models with even more precision and overcome overfitting. All the implemented models were evaluated on a dataset taken from BCI competition III. We conducted several experiemnts to assess the performance of the proposed methods and to compare them against some of the state-of-the-art methods. It was shown that as compared to the other methods, better classification accuracy was achieved with and without data augmentation using the MLP model.

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