Chessboard EEG Images Classification for BCI Systems Using Deep Neural Network

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Abstract. Classification of electroencephalography (EEG) signals is a fundamental issue of Brain Computer Interface (BCI) systems, and deep learning techniques are still under investigation although they are dominant in other fields like computer vision and natural language processing. In this paper, we introduce the chessboard image transformation method in which the motor imagery EEG signals were transformed into images in order to be classified using a hybrid deep learning model. The EEG motor movement/imagery Physionet dataset was used and the Motor Imagery (MI) signals for two frequency bands (Mu [8–13 Hz] and Beta [13–30 Hz]) were transformed into 2-channel images (one channel for each band). The network model consists of Deep Convolutional Neural Network (DCNN) to extract the spatial and frequency features followed by Long Short Term Memory (LSTM) to extract temporal features and then finally to be classified into 5 different classes (4 motor imagery tasks and one rest). The results were promising with 68.72% classification accuracy for the chessboard approach compared to 68.13% for the azimuthal projection with Clough-Tocher interpolation (2-bands scenario) and to 64.64% average accuracy for a baseline method, i.e., Support Vector Machine (SVM).

Keywords: Brain Computer Interface (BCI) · Electroencephalography (EEG) · Classification · Motor imagery · Convolutional Neural Networks (CNN) · Long Short Term Memory (LSTM)

1 Introduction

Recently, Brain Computer Interface (BCI) systems have been deployed to enable disabled people to control assistive devices and for rehabilitation purposes [1]. Namely, the BCI systems translate brain activity into control signals for an interactive application [2]. Due to its inexpensiveness, high time resolution, and portability, the electroencephalography (EEG) signal has been widely adopted for BCI applications [3].

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The sensorimotor rhythms (SMR) is one of the most popular Motor Imagery (MI) EEG-based BCI paradigms in which the person imagines moving body organs, e.g., hands and feet. The brain activity is modulated by the imagined movement and the Event-Related Desynchronization (ERD) and event-Related Synchronization (ERS) are produced in Mu (8–13 Hz) and beta (18–26 Hz) bands [4].

Although great efforts have been carried out to develop high quality BCI systems, however, still there are lots of challenges facing the EEG signals classification; the signal-to-noise ratio is low and non-stationarity is a key issue to handled, and furthermore, recording the EEG signals is a time consuming process and this leads to a limited amount of EEG data. Choosing the appropriate classification algorithm is a fundamental question for building the BCI systems. Adaptive classification algorithms [5–7] are still successful. Furthermore, Riemannian geometry based algorithms [8, 9], tensors [10] and deep learning based algorithms [11] are getting more and more research interest.

Deep learning revolutionizes computer vision and natural language processing but it needs more investigation when it comes to BCI systems and MI-EEG signals classification. Researchers have devoted much attention lately to transforming EEG signals into images aiming to fully exploit the advantages of deep learning.

Qiao and Bi [12] proposed a combination between inception based CNN and Bidirectional Gated Recurrent unit (BGRU) to classify 4 motor imagery tasks using the dataset 2a from the BCI competition IV. The EEG signals ranging from 1 Hz to 45 Hz were transformed into images by applying Morlet wavelet transform and cubic spline interpolation which produces distortion that affects the spatial information and this might decrease the classification accuracy.

Short time Fourier transform images were extracted regarding Mu and Beta bands and then a CNN was used to extract the features before the classification stage where a Stacked Auto Encoder was applied [13]. As discussed by Xu et al. [14], C3 and C4 electrodes were selected, and the wavelet transform was performed to extract to EEG images and finally a CNN with 2 layers was used for classification. In order to overcome the shortage of the dataset size, a previously trained deep CNN was suggested by Chaudhary et al. to classify the extracted scalogram EEG images [15]. Ha and Jeong [16] tried to overcome the limitations of CNN based methods by applying a capsule network model in which the raw EEG signals were transformed into STFT input images in order to be classified into 2 motor imagery classes, i.e., left hand and right hand using the competition IV 2b dataset, and they reached better classification accuracy compared to traditional and state of the art methods.

In order to overcome some of the drawbacks related to the above mentioned studies, a relatively large dataset was chosen and the 64 electrodes were involved in the signal-to-image transformation process because, due to the subject-to-subject and session-to-session brain activity difference, relying on a small subset of the electrodes to extract the features has potential limitations.

In this paper, we propose the chessboard motor imagery EEG signal-to-image- transformation method, and the resulted input images were classified into 5 classes using a hybrid model that consists of a CNN to extract spatial and frequency features and LSTM to extract time dependency between consecutive chessboard images.

2 Materials and Methods

2.1 The Motor Imagery Physionet Dataset

The EEG motor imagery Physionet dataset [17] is a 109 subjects data each one performing 14 runs based on the 10–10 system with 64 electrodes set. 6 badly recorded data of the subjects S043, S088, S089, S092, S100, and S104 was eliminated [18], so only 103 subjects were used. As the aim of this work is to classify the motor imagery tasks, the 2 baseline runs and the 6 real movements runs were omitted from each subject recordings, and therefore only the 'rest' tasks and the 4 motor imagery tasks, i.e., left fist, right fist, both fists, and both feet imagined movements were extracted and labeled accordingly in order to be transformed into images in the next stage. Each of the 6 remaining motor imagery runs lasts for 2 min and contains 30 tasks (trials) where each trial is 4 s long.

2.2 Chessboard EEG Signal-to-Image Transformation

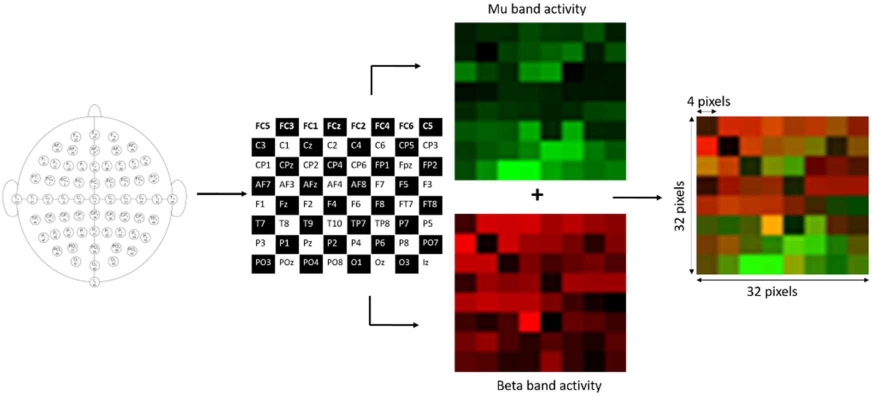
The labeled 'rest' tasks and the 4 different motor imagery tasks are first filtered into Mu [8–13 Hz] and Beta [13–30 Hz] bands which hide the most useful motor imagery information, and then Fast Fourier Transform (FFT) with 0.4 s window was applied over each trial to get 10 different measures per trial for each band and for every electrode. After that, the sum of the squared absolute values was calculated for each electrode in order to be represented as color intensity.

Chessboard EEG signal-to-image transformation is proposed in this work to transform the motor imagery EEG signals into images. The electrodes in the 3-D space are projected to a 2-D plane and each electrode position is represented as a 4×4 pixels square. The color intensity of each 4×4 pixels square represents the activity power obtained from the corresponding electrode where green grades refer to Mu band activity and red grades refer to Beta band activity, and thus we got 32×32 2-D unicolor images pairs that represent the 64 electrodes activity of Mu or Beta bands, and by adding every pair together we get the 2-channel images, and we have $30 \times 10 \times 6 = 1800$ images per subject where 30, 10, and 6 refer to the number of tasks per run, the number of measurements per task, and the number of motor imagery runs, respectively. For 103 subjects, we get 185400 2-channel images that formulate the model input. Figure 1 shows the chessboard transformation method.

We also applied the 2 bands scenario of the azimuthal projection with Clough-Tocher interpolation approach which was discussed in our previous work [19], and 32×32 pixels 2-channel images were obtained as shown in Fig. 2.

2.3 The Recurrent Convolutional Neural Network

CNN structure is inspired by the mammals visual cortex and it was introduced for the classification of handwritten numbers images by LeCun and Bengio [20], and the network consists of consecutive convolutional layers where learnable filters take place and the pooling layers to perform down sampling and the fully connected layers. The VGG model [21] is used to capture spatial and frequency features.



FC5	FC3	FC1	FCz	FC2	FC4	FC6	C5
C3	C1	Cz	C2	C4	C6	CP5	CP3
CP1	CPz	CP2	CP4	CP6	FP1	Fpz	FP2
AF7	AF3	AFz	AF4	AF8	F7	F5	F3
F1	Fz	F2	F4	F6	F8	FT7	FT8
T7	T8	T9	T10	TP7	TP8	P7	P5
P3	P1	Pz	P2	P4	P6	P8	PO7
PO3	POz	PO4	PO8	O1	Oz	O3	Iz

Fig. 1. Chessboard transformation method where Mu band activity is represented in green grades and Beta band activity is represented in red grades, and each electrode position is represented by 4 × 4 pixels to form a 32 × 32 2-channel images. (Color figure online)

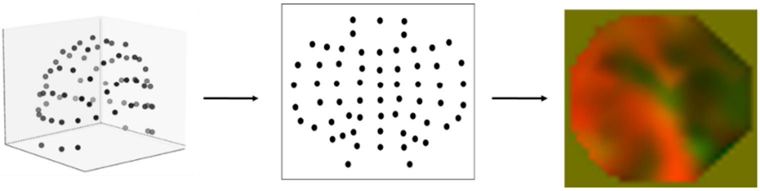


Fig. 2. The azimuthal projection and Clough-Tocher interpolation.

LSTM is a recurrent neural network that captures the dependency between data points using cells as memory units and three regulation gates, i.e., input gates, forget gates, and output gates [22]. LSTM is used in this paper to capture time dependency between EEG frames and it is followed by fully a connected layer and a softmax layer.

The network model consists of a CNN followed by LSTM (see Fig. 3), and the network configurations were selected carefully. For the Chessboard transformation approach, the best configuration were: 3 stacked Convolutional layers (3–32) followed by max pooling layer then 1 convolutional layer (3–64) then another max pooling layer followed by 2 convolutional layers (3–128) followed by ReLU layer and finally max pooling layer. Adam optimization algorithm and cross entropy loss function were used, the batch size was 16 and the number of epochs was 20, and one layer LSTM with 128 cells was used.

For the azimuthal projection approach, the best results: 3 stacked Convolutional layers (3–64) followed by max pooling layer then 2 convolutional layers (3–128) then another max pooling layer followed by 2 convolutional layers (3–256) followed by ReLU layer and finally max pooling layer. Stochastic Gradient Descent (SGD) optimization algorithm and cross entropy loss function were used, the batch size was 16 and the number of epochs was 20, and one layer LSTM with 256 cells was used.

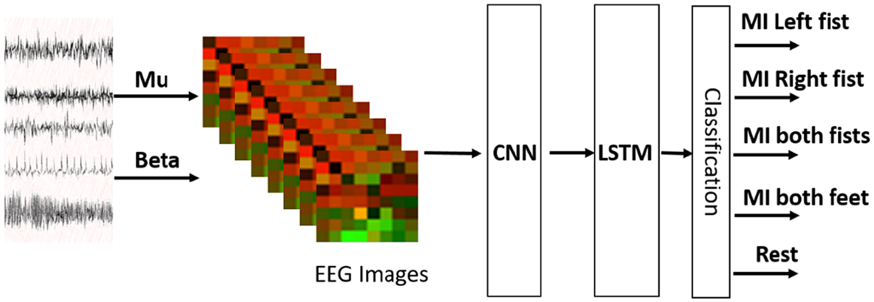


Fig. 3. The recurrent convolutional neural network classification model.

2.4 Results

The Leave-One-Out-Cross-Validation (LOOCV) was used for performance evaluation. The 1800 2-channel images (chessboard transformation approach images or azimuthal projection images) for one subject were used for testing and the images for another randomly chosen subject was used for validation and the remaining 101 subjects images were used as the training set. The average test classification accuracy for 5 classes (one 'rest' and 4 motor imagery classes) was 68.72% for the chessboard approach and 68.13% for the azimuthal projection approach, and the classification test accuracy for each subject is presented in Fig. 4. We can notice that for some subjects the classification accuracy was high for the two approaches, e.g., S004 and S098, while for other subjects the classification accuracy was high for one approach and relatively low for the other as shown in Table 1 and Table 2 and Fig. 4, and this drops the attention toward the importance of the input data representation form. Moreover, adding Delta [0.5–4 Hz] band to the analysis to form 3-channel images improved the azimuthal projection approach results but it did not when it comes to the chessboard transformation approach, and this emphasizes the idea that the input image structure is highly important.

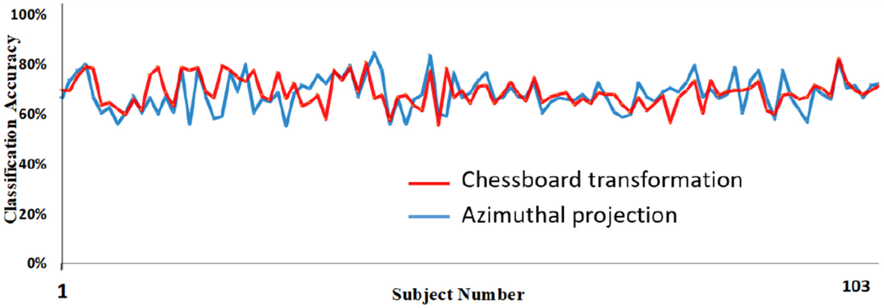


Fig. 4. Classification accuracy for each subject after applying the leave-one-out-cross-validation. Red line represents the classification accuracy of the chessboard approach and blue line represents the azimuthal projection approach results. (Color figure online)

Table 1. The highest classification accuracy values for the chessboard approach.

Subject number	Chessboard approach accuracy	Azimuthal projection accuracy
S098	**82.12%**	81.17%
S039	**80.60%**	77.33%
S021	**79.34%**	59.13%
S004	**78.80%**	80.04%
S037	**78.65%**	79.50%

Table 2. The highest classification accuracy values for the azimuthal projection approach.

Subject number	Chessboard approach accuracy	Azimuthal projection accuracy
S047	77.20%	**83.50%**
S098	82.12%	**81.17%**
S004	78.80%	**80.04%**
S024	73.13%	**80.02%**
S080	73.24%	**79.53%**

The results are better compared with those of a famous baseline method for EEG classification which is Support Vector Machine (SVM) that had 64.64% classification accuracy.

3 Conclusion and Future Work

In this paper, we introduced the chessboard signal-to-image transformation method to transform the motor imagery EEG signals into 2-channel images before the 5-class classification stage, and it showed better results, in terms of highest average classification accuracy and after investigating several network structures and configurations, compared with the azimuthal projection approach which was discussed in our previous work, and the results are also better than those of SVM. We applied CNN to extract spatial and frequency features followed by LSTM to extract time dependency between consecutive images, and no artefact elimination was used. It is important to mention that the azimuthal projection approach gave better results compared to the chessboard transformation approach for most of the network configuration varieties (but none of them reached the highest average value for the chessboard approach 68.72%), so the network structure and configuration are key issues along with the input images structure, and it is also crucial to notice that the classification accuracy for some subjects is highly dependent on the signal to image transformation method.

In the future, we are planning to transform the EEG signals into different image structures and to investigate subject dependent approaches. Furthermore, other CNN based models and channel selection methods should be investigated, and different datasets will be used.

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