Image-based Motor Imagery EEG Classification using Convolutional Neural Network

Tao Yang
Neural & Biomedical Technology
Institute for Infocomm Research
Singapore 138632
tyang@i2r.a-star.edu.sg

Kok Soon Phua
Neural & Biomedical Technology
Institute for Infocomm Research
Singapore 138632
ksphua@i2r.a-star.edu.sg

Juanhong Yu
Neural & Biomedical Technology
Institute for Infocomm Research
Singapore 138632
jyu@i2r.a-star.edu.sg

Thevapriya Selvaratnam
National Neuroscience Institute
Singapore 308433
thevapriya_selvaratnam@singheath.com.sg

Valerie Toh
National Neuroscience Institute
Singapore 308433
valerie_xl_toh@nni.com

Wai Hoe Ng
National Neuroscience Institute
Singapore 308433
ng.wai.hoe@singhealth.com.sg

Kai Keng Ang
Neural & Biomedical Technology
Institute for Infocomm Research
Singapore 138632
kkang@i2r.a-star.edu.sg

Rosa Q. So
Neural & Biomedical Technology
Institue for Infocomm Research
Singapore 138632
rosa-so@i2r.a-star.edu.sg

Abstract*— Motor Imagery (MI) based Brain Computer Interface (BCI) has clinical applications such as rehabilitation or communication for patients who have lost motor functions. Accurate classification of motor-imagery based electroencephalography (EEG) is important in developing such BCI applications. We propose an image-based approach to design a convolutional neural network (CNN) to classify EEG signals. In the proposed method, EEG signals were converted into images based on the locations of scalp electrodes, such that spatial correlation between neighbouring EEG channels was taken into consideration. We tested the proposed CNN architecture with both 2D and 3D kernels. EEG data were collected from a locked-in ALS patient over 5 weeks, when the subject was instructed to perform motor-imagery of right hand movement and idle state. Cross-day decoding showed that CNN was able to achieve a 2-class (right vs. idle) classification accuracy of 68.38±7.29% and 65.94±8.52% with 2D and 3D kernels respectively, compared to 55.09±5.74 % for the traditionally used filter bank common spatial pattern (FBCSP) method. We also observed changes in the correlation coefficient of spectral entropy in the EEG data across weeks, and these coefficients reveal frequency bands that are important for decoding. In particular, the CNN architecture with Delta band included performed 6.96% higher than that excluding the Delta band. This study shows that the image-based CNN method improves the classification performance, and the inclusion of Delta band improves classification performance for the current dataset.

Keywords*— Electroencephalography, MI-BCI, Convolutional Neural Network, EEG-as-image.

I. Introduction

Motor imagery (MI) based Brain Computer Interface (BCI) has clinical applications in both rehabilitation and communication [1-3]. It can provide a channel of communication for patients who have lost their motor function due to injury or neurodegenerative disease such as amyotrophic lateral sclerosis (ALS). However, studies have shown that the classification accuracy of MI in completely locked-in ALS patients does not differ from chance level [4]. Therefore, effective classification of electroencephalography (EEG) signals remains a challenging task.

Recently, several groups have applied deep learning algorithms in the classification of EEG signals and have shown that such algorithms can outperform traditional machine learning methods [6, 7]. One approach in fitting EEG data to a deep convolutional network is taking EEG data in the form of an image [8, 9], i.e. "EEG-as-image", each EEG channel is been taken as a pixel of an image. Such an image approach preserves the spatial features that may be significant in classifying MI. In addition, temporal information is preserved when the entire EEG signal is represented as a series of images from consecutive time steps. C. Tan et al. [8] combined EEG video and optical flow method to extract multimodal information from EEG data for classification. D. Zhang et al. [9] proposed a convolutional recurrent neural network model with cascade and parallel structure for the recognition of intention from EEG signal. In R. T. Schirrmeister et al.'s work [10], 44 channels of EEG data went through temporal convolution with 25 linear filters. The outputs of the temporal convolution were then formed as a 44 x 25 array for the subsequent convolution neural network (CNN). This layer of 1D convolutional filter increased the EEG data from a vector of 44 elements to a 44 x 25 array, and hence a large number of neurons are required to construct the network.

Using a similar method to the above described approach, we applied a CNN architecture to classify motor imagery EEG data that is regarded as a series of images. The proposed method takes into consideration of the spatial correlations among neighbouring EEG channels by accounting for the arrangement of electrodes on the scalp.

EEG signal was traditionally divided in several bands, and signal in each band associates with certain brain activities. K.K. Ang et al. [12] developed a Filter Bank common spatial pattern (FBCSP) algorithm to extract features for 4 classes motor imagery classification in BCI competition IV. In the work [12], band pass filters were applied to the data, and the

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common spatial pattern (CSP) were extracted from each frequency band. Often, Delta band in EEG signal (<4Hz) is not considered in classification [13], as this band usually represents information in lesions, deep sleep or motion artefacts. However, we show that important differences between the motor imagery states are contained within Delta band in our dataset, and investigate the impacts of the Delta band to classification accuracy in the proposed method.

II. METHOD

A. Experimental Design

Motor imagery experiments were conducted on an ALS patient (aged 29, female) over 5 consecutive weeks (1 day per week). This subject has been diagnosed with ALS for the past 5 years, and she was in a complete locked-in state during the data collection period. The experiments were conducted in compliance with the SingHealth IRB (CIRS 2016/3092).

Neuroscan amplifier and Quik-cap with 40 electrodes were used for EEG data acquisition. All channels were referenced to the A1 and A2 electrodes, which were placed at the left and right ear lobes respectively. The impedance of each channel was maintained below 10 kΩ throughout the experiments. EEG data were acquired at 250 Hz and filtered by a band pass filter of 0.5 to 40 Hz and a notch filter of 50 Hz in data acquisition software (Scan 4.5).

During each experimental trial, real-time feedback of the motor imagery decoding results was shown to the subject on a monitor. In each trial, the subject was instructed to either move a cursor into a box on the right by performing right hand motor imagery (right trial), or maintain the cursor within a box by remaining in the idle state (idle trial). Decoding was performed every 0.1s using 2 s of prior data. A total of 7 to 13 sessions were conducted on each day, with 5-10 trials in each session.

Thirty channels of EEG signal were used in the analysis. They were arranged in a 6 x 5 array as shown in Fig. 1. Data from each trial was converted into a $6 \times 5 \times N$ array, where N is the number of frames in the trial. In the offline analysis, a sliding window with a width of 500 frames (2 s) and a step size of 25 frames (0.1 s) was applied to each trial, as illustrated in Figure 2, to form training samples for the proposed CNN architecture.

F7	F3	FZ	F4	F8
FT7	FC3	FCZ	FC4	FT8
T7	C3	CZ	C4	T8
TP7	CP3	CPZ	CP4	TP8
T5	P3	PZ	P4	T6
PO1	O1	OZ	O2	PO2

Figure 1. 30 channels of EEG data were rearranged as a 6 × 5 array according to its location on the scalp; Name of the EEG channels follow the 10-20 system.

B. Preprocess of Data

Deep CNN architecture extracts features by training kernels in its filters. These kernels are initialized by Glorot normal distribution [15] in Keras. Kernels in each CNN layer are updated during the training, and become data specific kernels upon completion of training. These kernels at each layer extract different features from data presented to the CNN. Multiple layers of CNN are usually applied. The optimal feature could lie at an intermediate layer of the network [16]. However, there is only one layer of CNN in the proposed architecture. Pre-process of training data become necessary.

Raw EEG signals acquired in our experiment were first filtered with 10 band pass filters (FIR). The band pass filter was set from 0.5 Hz to 4 Hz, and further to 40 Hz with a step size of 4 Hz. After band pass filtering, the data was then converted into 6 x 5 x 10 array, where 10 is the number of frequency bands which corresponds to the RGB channels in a coloured image. Training samples are then cropped from each trail as illustrated in Figure 2.

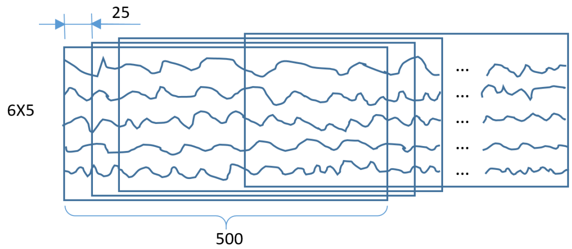


Figure 2. Cropping training samples using a sliding window of 500 frames on a $6 \times 5 \times N$ EEG data. Each training sample was down sampled from 500 frames to 250 frames during training, i.e. 6 x 5 x 250, where 250 is along the temporal dimension

C. Convolutional Neural Network

A convolutional neural network with one convolutional layer was constructed using Keras, as shown in Figure 3. It was used for the offline analysis of the acquired EEG data.

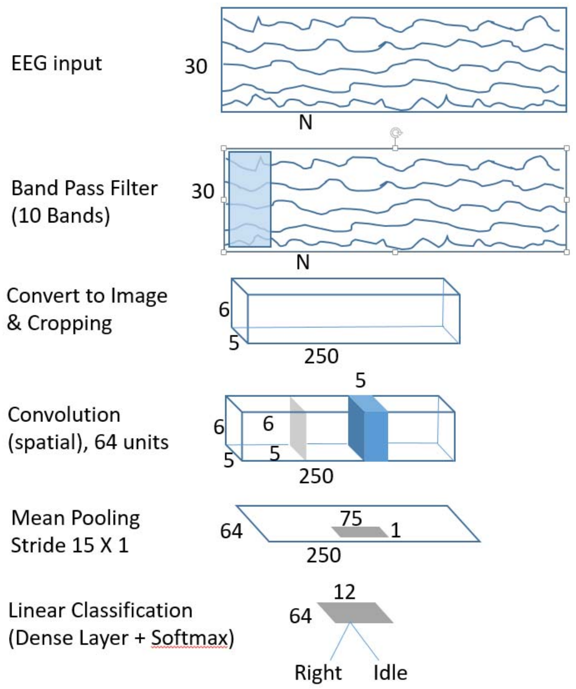
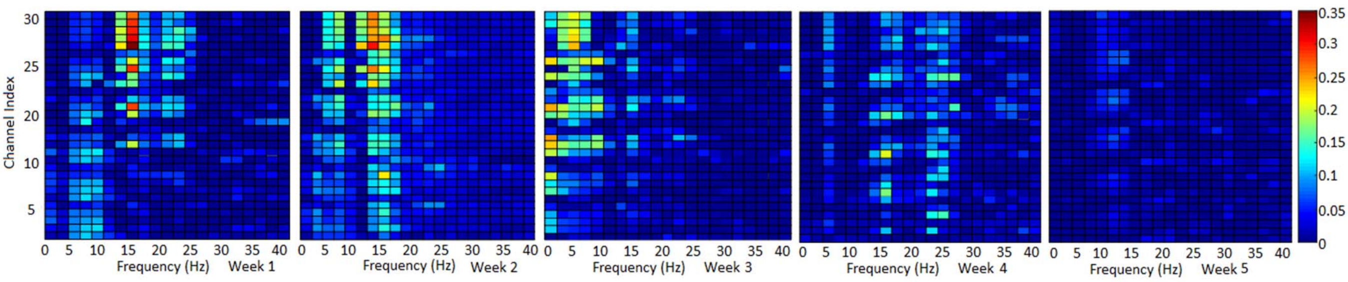


Figure 3. Convolutional neural network architecture with a 2D/ 3D kernel for motor imagery classification.



(a) (b) (c) (d) (e)

Figure 4. The correlation coefficient of spectral entropy between 'right' and 'idle' in 5 weeks. Chanel index from 1 to 30 corresponds to F7, F3, Fz, F4, F8, Ft7, Fc3, Fcz, Fc4, Ft8, T7, C3, Cz, C4, T8, Tp7, Cp3, Cpz, Cp4, Tp8, P7, P3, Pz, P4, P8, O1, Oz, O2, Po1 and Po2. Theta waves are found in week 1 to 4 [14]. Delta wave is found in week 1to 3. Week 5 has a very low contrast between 'right' and 'idle' in terms of the correlation coefficient.

64 filters were used in the convolutional layer, with a 2D kernel size of 6 × 5 or a 3D kernel size of 6 × 5 × 5. The activation function for the convolutional layers was the Leaky Rectified Linear Unit (LeakyReLU) with leak coefficient of 0.05. A dropout rate of 0.5 was used to prevent overfitting. Mean pooling with a kernel of 75 and stride of 15 were applied to the filtered data from CNN to reduce the number of features extracted. The Softmax function was applied to normalize the probability for classification.

Cross-day tests on the 5 week's data were performed using the proposed CNN architecture to understand the performance of such CNN model in adapting signal variation among experimental days. In the cross-day tests, EEG data from one of the week were used to test on the CNN model trained by data from the rest of 4 weeks, i.e. model used to decode EEG data in Week 1 were trained using data from Week 2 to 5.

III. Results

A. EEG *Variation over Experimental Period*

EEG signal varies across experimental sessions. Such variations lead to inconsistencies in selected features among experimental sessions which would affect the performance of classifier. Performance of BCI applications often deteriorates due to such non-stationarity. Spectral entropy is a measure of signal disorganization, and its correlation coefficient of two variables is an indicator of how close these two variables are linearly related [17]. Figure 4 shows the correlation coefficient of spectral entropy between 'right' and 'idle' trials for the data collected over 5 weeks. High correlation coefficients were present in data from all weeks except Week 5. The magnitude of the correlation coefficient varies across the experimental sessions. On average, the correlation coefficient in Week 4 and 5 are lower compared to the previous 3 weeks. Week 1, 2 and 3 were found with high correlation coefficient in Delta band.

B. Performance *of CNN*

Cross-day tests were performed using the CNN architecture shown in Figure 3. The CNN was configured with 2D kernel, size of 6 × 5 × 1, and 3D kernel, size of 6 × 5 × 5 separately for the tests. Figure *5* shows the classification accuracies from the cross-day tests. The average accuracies over the 5 cross-day tests are 68.38±7.29% and 65.94±8.52% for 2D and 3D kernel respectively.

Performance of the proposed CNN architecture was compared to the FBCSP algorithm (Fig. 5). The CNN architecture performed better than FBCSP in all 5 cross-day tests, by 13.29% and 10. 85% on average for 2D and 3D kernel respectively.

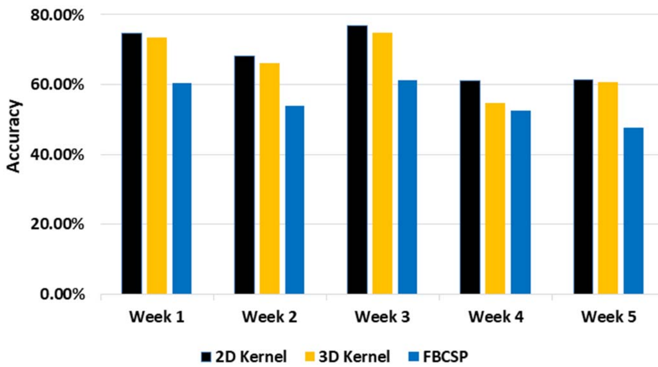


Figure 5. Cross-day validation of CNN. Black, yellow and blue bars are accuracies obtained using 2D, 3D kernel and FBCSP respectively.

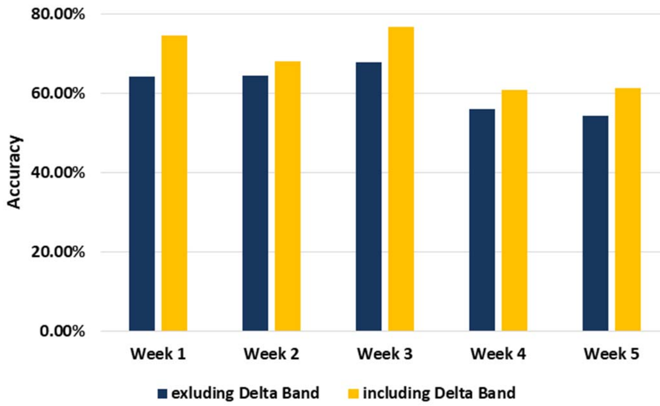


Figure 6. Classification accuracy of CNN model (2D Kernel) trained with data including and excluding Delta band in cross-day tests.

The correlation coefficients in Delta band were significant in Weeks 1, 2 and 3 (see Figure 4 a, b and c). Cross-day tests were conducted using the EEG data including and excluding Delta band. These tests were performed on the CNN architecture with 2D Kernel. The average classification accuracies of the 5 cross-day tests are 68.38±7.29% and 61.42±5.90% for CNN trained with Delta band included and excluded respectively, showing an improvement in decoding accuracy when Delta band was included (Fig. 6).

IV. Discussions and Conclusions

In this study, we tested the performance of a CNN with both 2D and 3D kernel in decoding EEG data and compared with the traditionally used FBCSP method. The average classification accuracies of both 2D and 3D kernel CNN outperforms FBCSP. No significant difference in classification accuracy was found between 2D and 3D kernels. The 3D kernel is an extension of the 2D kernel in temporal dimension of training samples. Since the subject was performing motor imagery consistently during the trial period, it is not surprising that the 3D kernel would not capture additional distinctive features compared to the 2D kernel.

The correlation coefficient of spectral entropy of the two classes of trials ('right' and 'idle') showed inconsistency in distribution in frequency bands and magnitude of correlation coefficient over the experimental period. As shown in Figure 4, (a), (b) and (c), increased correlation coefficient appeared at a frequency below 4 Hz, i.e. Delta band, in data from Weeks 1, 2 and 3. The impact of Delta band in decoding is illustrated in Figure *6*. Classification accuracy improved significantly when Delta band was included in the model training, especially for the first 3 weeks. This result shows that Delta band signals are important for motor imagery classification in the current data set.

The magnitudes of correlation coefficients in general across frequencies and channels are lower in Weeks 4 and 5 (Figure 4 d and e) compared to earlier weeks. Lower correlation coefficients indicate that the signals collected during these weeks were less distinguishable between the motor imagery tasks, and hence resulted in lower classification accuracy as shown in Figure *5* Week 4 and 5. This difference might be due to lower engagement of the ALS subject during the BCI sessions in the later weeks.

In conclusion, an image-based CNN architecture was used for classification of motor imagery EEG signals. We showed that CNN performs significantly better than FBCSP method on average using both the 2D and 3D kernels. However, no significant difference in performance was found between 2D and 3D kernel in the cross-day tests. As well, future work will include using data collected over longer periods of time to statistically validate the significance of these observations.

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