Empirical mode decomposition for improved EEG signal classification with Convolutional Neural Network in Brain-Computer interface experiments

Kahoko Takahashi (P)[1], Zhe Sun[2], Jordi Sol-Casals[3], Andrzej Cichocki[4], Anh Huy Phan[4] and Ruggero Micheletto[1]

[1] Yokohama City University, Graduate School of Nanobioscience,
22-2 Seto, Kanazawa Ward, Yokohama, Japan

[2] Computational Engineering Applications Unit, Head Office for Information Systems and Cybersecurity,
RIKEN, 2-1 Hirosawa, Wako-shi, Saitama, Japan

[3] University of Vic - Central University of Catalonia,
Data and Signal Processing Research Group, Vic, Catalonia (Spain)

[4] Skolkowo Institute of Science and Technology (SKOLTECH), Moscow, Russia

E-mail: n175224a@yokohama-cu.ac.jp

Abstract— Electroencephalogram (EEG) is generally known as a non-destructive method to examine the functioning of human brains. These days, the development of Brain Computer Interface (BCI) technology is being actively promoted. In motor imagery (MI) tests, participants were asked to think of moving the left or right arm during EEG recording. The data were classified by analyzing Wavelet Transformed EEG signals using Convolutional Neural Network (CNN). The quality of this classifier relies on the amount of data used for training. However, it is difficult and time consuming to collect enough EEG data because of the limited availability of subjects. Therefore we created new artificial frames by applying Empirical Mode Decomposition (EMD) on the EEG frames and mixing their Intrinsic Mode Function (IMFs)[1]. These artificial frames were used as training data with significantly better classification accuracy.

Keywords— Convolutional Neural Networks, CNN, EEG, Empirical Mode Decomposition, EMD, Wavelets, Classification Neural Network

1 Introduction

Brain computer interfaces (BCI) are of growing interest nowadays. These devices will provide means to send commands of various complexity to computers and this will help people with handicaps and may contribute to the realization of security devices in various fields. We are involved in experiments where subjects are requested to think about moving their left or right arm while their EEG pattern is recorded. We developed a Convolutional Neural Network (CNN) to classify these data. In this study we improved the network learning process using the so called Empirical Mode Decomposition[1] and used advanced wavelets analysis for the classification process. With this novel approach we could increase the network classification accuracy significantly.

2 Data Set

We used EEG data from motor imagery dataset[2]. These datasets are relative to left/right motor imagery (MI) movements recorded from 62 channels (with sampling frequency of 500 Hz). The duration of the recording was of 2 seconds with a 4 second break between the trials.

The dataset was recorded for 2 subjects and has 200 trials for each class (left or right thought movements). In total, 60 trials (30 trials for each class) were used for the training process and 140 trials (70 trials for each class) were used for the actual classification tests. The trials were performed in order, the first 30 trials belong to the *left* category and the remaining trials are for the *right* class.

3 Methods

3.1 Convolutional Neuronal Network

In figure 1 we show the structure of the convolutional neural network (CNN) used. The first layer in the input tensor is of dimension 23x50x62 (the signal pre-processing is done with wavelets with output dimensions 23x50, 62 is the number of EEG channels).

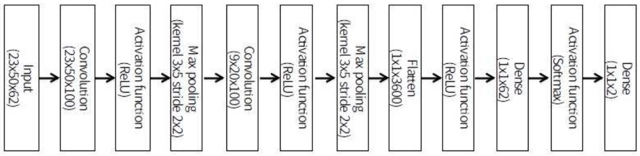

Figure 1: A schematic representation of the convolutional neuronal network used.

4 Artificial EEG

We used an Empirical Mode Decomposition (EMD) approach to create the new artificial EEG signals [1].This algorithm decomposes the original signal into a finite number of functions called IMFs (Intrinsic Mode Function). Then the new artificial EEG signals can be created by randomly combining some IMFs from different real EEG signals. We made the new artificial EEG from 60 real EEG data for each subjects and used them for the CNN training process.

5 Wavelet transform

The EEG signal is a one-dimensional time series of 2 seconds of duration for 1000 points (500Hz sampling). We used a *Morlet* wavelet, this transformation converts the time series to a two-dimensional array of dimension 23x50 [2].

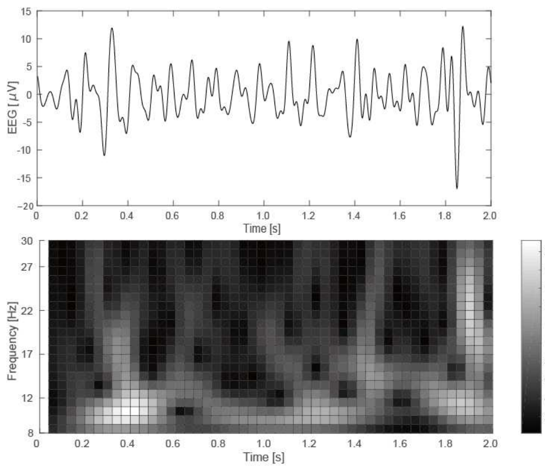

Figure 2: Example of dynamic spectra of EEG

Since we have 62 channels the imput tensor is of 23x50x62, see figure 2 for an example of the output. In the time domain EEG data of each trial can be represented as a matrix (2-D) of 62 channels 1000 samples (500Hz, 2s). The Morlet *motherwavelet* used is the following:

$$\Psi_{Morlet}(t) = \frac{1}{\sqrt{\pi f_b}} \exp(2i\pi f_c t) \exp(\frac{-t^2}{f_b}) \qquad (1)$$

where the parameter f_b and f_c are 1Hz. The transformation integral is done with equation 2, where the two scaling parameter a and b are variable.

$$W_\Psi[\chi(t)] = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} \chi(t)\Psi(\frac{t-b}{a})dt \qquad (2)$$

6 Results

We used four types of dataset to test the accuracy of our methodology. First, the 60 original dataset were used for training our CNN network.

Then, using the EMD and wavelet method described above, we constructed 120 artificial dataset *frames* that were added to the original 60, for a total of 180 frames for the training. This process was repeated in the same way for a total of 360, and 660 frames.

As a result, the validation loss (network output error) performance of the network improved and it is plotted for the two subjects in figure 3. For the three groups of new training data (180,360 and 660) we observed an increasingly faster convergence.

As a consequence, the CNN improved its accuracy significantly, it was about 84% for the first subject and 81% for the second and reached over 90% in one case. See table 1 for details the results.

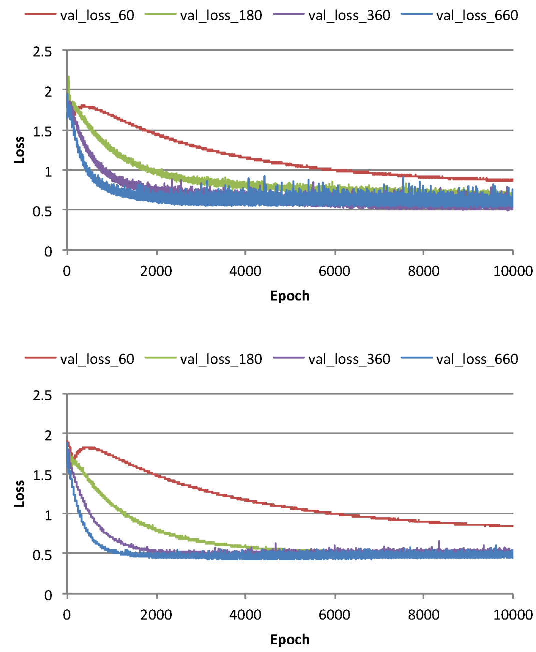

Figure 3: Validation loss output of the CNN network in case of Subject 1 (top) and 2 (bottom). The red line is done with the original 60 training frames, the colored curves are instead output done with an increasing number of artificial frames done with our original EMD method. The improvement of performance is evident.

Table 1: Classification accuracy with different number of training data.

Number of training data	Accuracy	
	Subject 1	Subject 2
60 (Original Dataset)	84.29%	81.43%
180 (120 Artificial Frames)	86.43%	85.71%
360 (300 Artificial Frames)	91.43%	87.86%
660 (600 Artificial Frames)	88.57%	87.86%

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