fNIR Signal Based Mental Arithmetic Task Classification using Deep Convolutional Neural Network

Md. Fakrul Bin Kabir, Nasrin Akhter

Abstract— Brain Computer Interface (BCI) connects human brain and computers to translate the brain signal into meaningful actions. Brain Computer Interface system based on functional Near-Infrared (fNIR) signal holds the potential of classifying different types of imagery tasks. Mental arithmetic is a prominent candidate of above mentioned application of BCI system. In this work, we use Deep Convolutional Neural Network (DCNN) to classify the fNIR signal. fNIR signal recorded while performing mental arithmetic task is use in this study. First of all, signal is filtered to eliminate the noise. After that, for training the DCNN model with limited number of trials, then a hybrid dataset is developed containing all the subjects. The modification in dataset made the system robust against any bias towards any particular subject. According to our proposed method, final classification accuracy achieved is about 97.3%. As per our knowledge this is the best classification accuracy for this particular task. Finally this improvement in classification accuracy will help BCI system to be used in a practical application such as rehabilitation technology.

Index Terms— Artificial neural network, Brain Computer Interface, Deep Convolutional Neural Network, Electroencephalography, fNIR signal, Feature extraction, Mental Arithmetic.

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1 Introduction

Brain computer interface (BCI)-based systems are used for communicating directly between brain and computer without the help of any direct limb movement. Functional Near-infrared spectroscopy (fNIRS) is gaining popularity day by day in BCI system for its safety, security, light weight and highly authenticity [1]. These systems are made by the basis of invasive and non-invasive process. Electroencephalography (EEG) and functional Near Infrared Spectroscopy (fNIRS) are used to collect the brain signals in non- invasive system [2, 3]. But fNIRS gives a highly active data than the EEG [4]. Another advantage of functional Near Infrared (fNIR) signal is that fNIR is less prone to motion artifact when compared with EEG. Different mental task such as motor movement, mental arithmetic, object moving, reading book, music listening etc. are few example of fNIR based BCI system [5]. The fMRI also apply same method as fNIRs but fMRI has so many limitations in lower spatial resolution [6]. During recording of fNIR signals no need to use any conductive gels, which provides a better signal to noise ratio. fNIR signals are composed by near-infrared (NI) ray (730 nm, 805 nm or 850 nm) wavelength and is used for measuring oxygenated hemoglobin [HbO] and deoxygenated hemoglobin [HbR].

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On the otherhand, in Mental Arithmetic (MA) task, the oxygenated hemoglobin and deoxygenated hemoglobin antagonistic patterns are taking place to show different brain region for single trial classification [7]. The frontal cortex of brain plays an important role in finding of MA tasks. Different approaches had been taken to classify MA fNIR signals. H. J. Hwang et al. achieved 75.89% and 74.08% accuracy for oxy-hemoglobin and deoxyhemoglobin respectively using LOOCV method [8]. Ebru et al. used Hilbert transform, sum of derivative and k-Nearest Neighbors to classify mental arithmetic task. They reported 82.87% accuracy for HbO and 84.94% for HbR. Another researcher group using Kartz fractal dimension for mental arithmetic task classification and they found the classification accuracy about 71.10% for HbO [9]. Naseer et al. used six commonly used features namely mean, slope, peak, variance, skewness, kurtosis to find best feature combination [10]. Using LDA, they found maximum classification accuracy of 93% for the feature combination of mean and peak. The present study used the same method as P. C. Petrantonakis and I. Kompatsiaris used in their analysis [11]. They used Graph Signal Processing (GSP) theory based feature extraction. N. Naseer and their group Using SVM, they reported 92.52% classification accuracy for oxy-Hb. ANN based classification resulted 96.3% for 3-dimensional combinations of six different features [12]. Hwang et al. used the mean hemoglobin concentration values in six different time windows for features extraction [13]. An LDA classifier was applied and the classification accuracy was over all 70%. K. S. Hong and their group gained 75.6% of average classification accuracy, For feature selection, they used the signal slope (ss) and the signal mean and classified the signal by multiclass linear discriminant analysis (LDA) classifier [14]. In this paper, we tried to improve the classification performance of fNIR based mental arithmetic classification using Deep Convolutional Neural Network (DCNN). In our study we use fNIR signal instead of

EEG signal because fNIR method is easily portable, effordable and the signal has moderate spatial resolution and low noise comparing with EEG signal. Further more, fNIR is a functional neroimaging method which can measure the human brain activity with hemodynamic response. There are different kinds of machine learning methods for neuroimaging research among them we propsosed the DCNN method for mental arithmetic task classification from fNIR signal. It is well established that convolutional neural network has covolutionaql layers and has architechtural constraints to reduce computional complexity as well as CNN ensure trantional invarience.We examined with different architecture of DCNN and found the suitable DCNN model for this task. The aim of our study is to establish a highly accurate and acceptable fNIR signal based mental arithmetic task classification using Deep Convolutional Neural Network.

2 Proposed Method

The present study explored the field to Deep Convolutional Neural Network (DCNN) for classifying fNIR signals. Because of recent development of DCNN, many classification algorithms have broken previous accuracy record. Figure 1 shows the work flow of this work. At first, the signal acquisition part where the signal was collected. These raw data contain a lot of noise. And that's why it had to release the noise from the signal so that it can be used this data for furthermore. So, in the signal processing section, fNIR signals are filtered to eliminate unwanted frequency components. These filtered signals are then fed to the DCNN model as raw input. In order to make a correlation between input and output, the DCNN have to provide the correct mathematical model. However, this relationship can be linear or non-linear and its layers calculate the output's probability. Finally, DCNN model give the desired classification output.

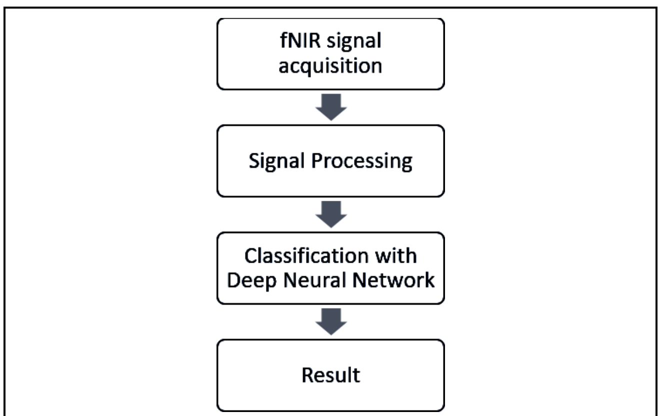

Fig. 1. Work flow of this research

3 Materials And Methods

fNIR Data Acquisition, Signal Processing, DCNN Model Architecture used in this study are explained in following subsections.

3.1 fNIR Data Acquisition

The data used in this study had collected from database [7, 15]. Total 8 subjects had included in this study that consisting of three male and five female participants. During experiment, participants were asked to perform mental arithmetic tasks. Figure 2 shows the experimental setup. The participants had to perform subtraction. Initially the participants were shown a black screen. Then for 12 seconds, they were shown numbers for subtraction on monitor. They had to do mental arithmetic as fast as possible. After trigger two, there was a resting time of 28 seconds. ETG4000, Hitachi Medical Co., Japan with 52 channels is used in the experiment.

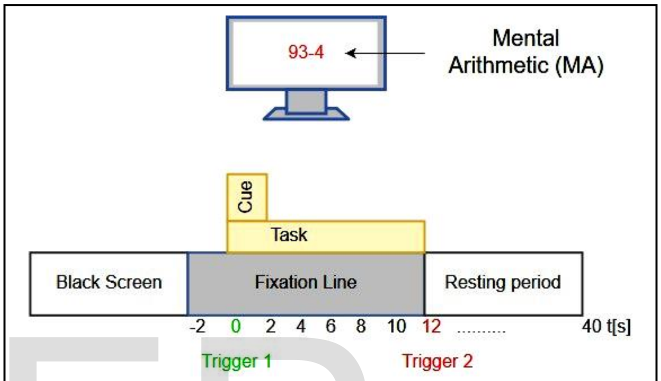

Fig. 2. Time course of one trial

The 52 channels (3 11 grid) carried 16 photo-detectors and 17 light sources (distance between them was 3cm) [7]. Sampling frequency was set to10 Hz. The channels were positioned using EEG 10-20 system. Oxy-hemoglobin [oxy-Hb], deoxy-hemoglobin [deoxy-Hb] and total-hemoglobin [total-Hb] were measured in millimolar times millimeter (mM.mm).

3.2 Signal Processing

The raw fNIR signal has a high degree of noise. This noisy fNIR data helps to find the location of brain activity and investigate the hemodynamic change of mental task. Before feeding the data into DCNN, it required to process the signal. There are many processes to remove noise from the fNIR signal by filtering. For removal of artifact, low pass filter and for base line drift removal a high pass filter is generally used [16]. Butterworth filter is one kind of signal processing filter which is used to decrease the frequency response. The n-th order butter worth filter is-

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$$\left|H_a(j\omega)\right|^2 = \frac{1}{1+\left(\omega/\omega_c{}^{2n}\right)} \quad (1)$$

Here, ωc = the frequency. From this equation, the cut-off frequency can be find. The frequency response of pass band is mathematically flatted in the cut-off frequency at 3dB.

But the low pass Butterworth Filter can response as maximally flat as the frequency response. In our work, we had used 4thorder Butterworth is band pass filter to deal with these two tasks. Lower and higher cut off frequency was set to 0.012 Hz and 0.8 Hz respectively.

3.3 DCNN Model Architecture

According to Hinton, a Deep Neural Network (DNN) is a feed forward artificial neural network that has more than one layer of hidden units between its input and output [17]. The Deep Convolutional Neural Network (DCNN) architecture used in this study is given in figure 3. The first layer of this architecture is normalization that means before feeding the data into neural networks, data is normalized. Then 1 dimensional (1D) convolutional network was used, Batch normalization and activation followed after that respectively. These three layers were then repeated two times and data was flattened then finally. Repetition of dense and activation layers were added before final batch normalization and activation.

In the present work, batch normalization was used as the first layer of model. Batch normalization is generally used to reduce the amount of hidden layer such as covariance shift process, which gives priority to the possible use of higher learning rates. By adding batch normalization at the top of the model, the input data does not required to be normalized explicitly.

In 1D CNN, layers are used for learning high level features. The number of filters on this layer will be associated with the same number of features. Rectified Linear Unit (ReLU) is an activation function which is used in CNN. ReLU is defined as:

$$\mathrm{Re}LU(x) = \max(0,\ x) \quad (2)$$

Another activation function used in this architecture is sigmoid function. Sigmoid function is defined as:

$$h\ (x) = \frac{1}{1+e^{-x}} \quad (3)$$

Flatten function is used to convert a matrix of input into a single column. It helps to connect the output of previous layer to next dense layer. At the last layer, another activation layer is added. After this layer, finally get the classification output.

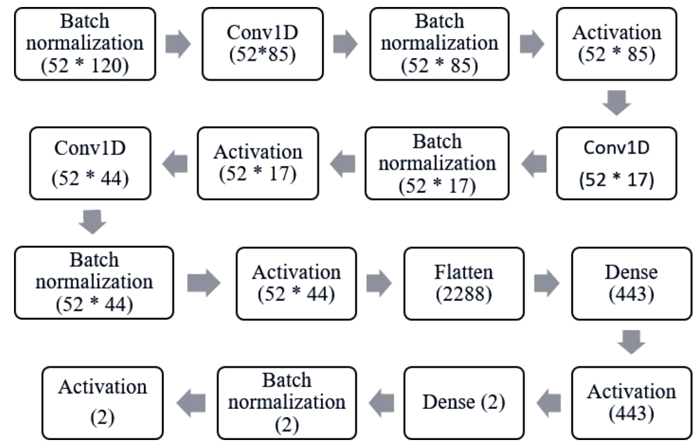

Fig. 3. Proposed DCNN Architecture for fNIR Signal Classification

4 Result and Discussion

The recorded fNIR activity of participants is first filtered with a forth order Butterworth band pass filter. The outputs of these filters are used for classification. Raw fNIR data is plotted in figure 4.

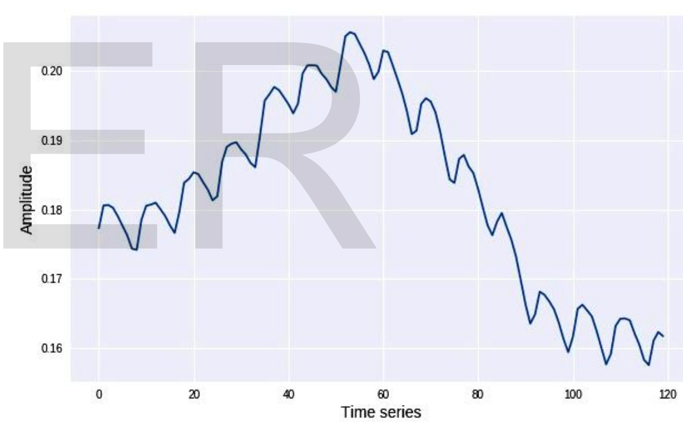

Fig. 4. Raw fNIR data

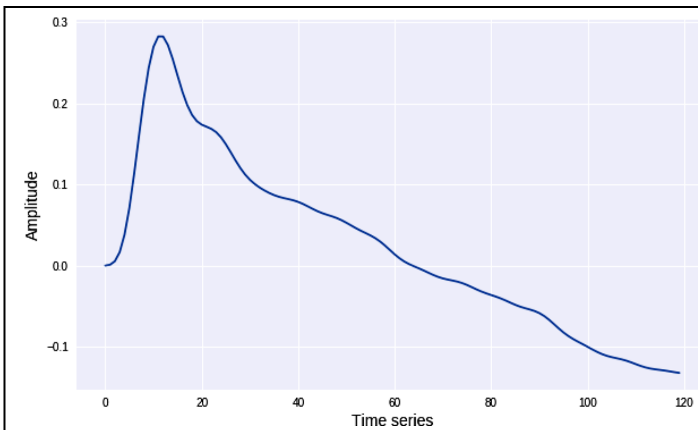

Fig. 5. Filtered fNIR data

Here it shown that the excitation is maximum at the middle of trail and then the excitation decreased rapidly. In case of classification, all 8 subjects were concatenated to make a larger dataset. By doing so, we get two major advantages. First one is, for any DCNN model, the larger the dataset the better the classification results as it is required to avoid over-fitting. As number of training set increases, robustness of model against new data is also increased. Secondly, by concatenating all subject and train the model on this hybrid dataset we do not need to extensive training of the model separately for any individual. This is also a merit of the present work. Because it is well known that for BCI system, some classification models performs better on some particular subject and on some subject, models performance degrades.

The concatenated dataset is divided into three classes. Train validation and test each having 281, 32 and 35 trials respectively. Current experiment is performed on oxy Hb. Total parameters in this architecture is 1, 053, 312, trainable parameters: 1, 052, 776 and non-trainable parameters: 536, learning rate: 0.08360, regularization rate: 0.0022. This model is selected on the basis of the performance on train and validation and test data set.

The present study achieved 97.3% classification accuracy for tested dataset. Table I shows performance evaluation of our proposed method and comparing with previous work. Here it is observed that our proposed method had outperformed all previous works. Because, DCNN model architecture was selected on the basis of trail and test method. Along with this DCNN model with best classification accuracy on train and validation dataset was chosen and then tested on test dataset. H. J. Hwang et.al. achieved 75.89% classification accuracy which is better than the work done by E. Ergu¨n and O¨. Aydemir. But N. Naseer et. al. had achieved 96.30% classification accuracy by using ANN. Current works with neural networks, state of the art classification accuracy can be obtained. Among the previous work studied by us, our CNN based classification model has achieved best classification accuracy. Another advantage of present work need very little signal processing to filter the signal.

TABLE 1
COMPARISON BETWEEN PROPOSED METHOD AND PREVIOUS WORKS

Author	Year	Classification Method	Classification Accuracy
H. J. Hwang et. al.	2016	LOOCV method	75.89%
E. Ergu¨n and O¨	2018	knn method	71.10%
P. C.Petrantonakis et. al	2018	SVM	92.52%
N. Naseer et. al	2016	LDA	93.00%
N. Naseer et. al	2016	ANN	96.30%
Proposed Method	2019	DCNN	97.3%

Furthermore, our work tested on hybrid dataset, which is all trail data of every subject are combined to form a large dataset. Large dataset is required for a satisfactory performance of DCNN. Also, to avoid over- fitting the model, we need a large dataset. Therefore, using our contribution to fNIR signal based mental arithmetic task classification may improve the Brain Computer Interface (BCI) system as higher classification accuracy.

5 CONCLUSION

The present work proposed a Deep Convolutional Neural Network (DCNN) based fNIR signal classification of mental arithmetic task. Till now there are many studies have been done on measurement of human brain activity by using various types of learning algorithm in BCI system. The classification accuracy is show a discrepancy on the previous work. Our aim of this study is to establish a better classification method .Our proposed method has achieved classification accuracy of 97.3% which is better than any other work done on mental arithmetic based on fNIR signal according to our knowledge. This improvement in classification accuracy will improve the existing BCI system which will help to move one step forward for accomplish a practical BCI system.

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