ORIGINAL ARTICLE

Introducing a Convolutional Neural Network and Visualization of Its Filters for Classification of EEG Signal for SSVEP Task

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Abstract

Purpose: Brain-Computer Interface (BCI) systems are able to understand and execute commands through processing brain signals. It has numerous applications in the field of biomedical engineering such as rehabilitation, biometric and entertainment. A BCI system consists of four major parts: signal acquisition, signal pre-processing, feature extraction and classification. Steady State Visually Evoked Potentials (SSVEP) is one of the most common paradigms in BCI systems, which is generally a response to visual stimuli with the frequency between 5 to 60 Hz.

Materials and Methods: In this study, we suggest a Convolutional Neural Network (CNN) based model for the classification of EEG signal during SSVEP task. For the evaluation, the model was tested with different channels and electrodes.

Results: Results show that channels number 138 and 139 have the great potential to appropriately classify EEG signal.

Conclusion: Using the suggested model and the mentioned channels, the accuracy of 73.74% could be achieved in this study.

Keywords: Brain-Computer Interface; Steady State Visually Evoked Potentials; Electroencephalogram Signal Processing; Convolutional Neural Network.

1. Introduction

A Brain-Computer Interface (BCI) system establishes a connection between computer and human brain using biological signals such as Electroencephalogram (EEG). Electroencephalography, due to its non-invasive nature, is one of the most important tools for analysis of patterns generated by human brain [1].

Electroencephalography is widely used in BCI systems in which EEG signals are acquired using an electrode cap which is positioned on the user's scalp. Combination of signals, which are acquired from different electrodes, form a complex pattern which contains valuable information about brain activity [2]. Useful information such as what is happening in the brain can be extracted from these patterns. This information can further be processed to translate brain signals into machine commands. These commands can be used to control some Electromechanical vehicles for rehabilitation purposes [3].

Currently, EEG-based BCI systems use EEG paradigms such as Motor Imagery (MI) [4], Event-Related Potentials (ERPs) [5] and Steady State Visually Evoked Potential (SSVEP) [6]. In SSVEP paradigm, visual stimuli are used to evoke some patterns in the visual cortex of brain. Generally, the frequency of the evoked patterns is the same as the frequency of the flicker in the visual stimuli. In the other words, it can be observed that we have an increase in the corresponding frequency in the power spectrum of acquired EEG signal. Consequently, we can assign each frequency to a different command in which user can transfer a specified command to computer with looking at each visual stimulus.

Various machine learning algorithms have been applied for classification of EEG signals during SSVEP task [7]. In this research, the focus is on the neural network based model for EEG signal classification. In [7], the effect of various pre-processing methods and parameters for EEG signal classification is investigated in which Support Vector Machine (SVM) classifier is utilized for final classification.

Recent studies have shown that deep learning based approaches could outperform traditional methods. A variety of deep learning approaches are proposed in

[8] in which Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Long-Short Term Memory (LSTM) structures have been investigated. It was reported that CNN structure showed a better performance compared to others. In [1], a comprehensive comparison is done between traditional methods and deep learning based algorithms. It was reported that CNN structure without any pre-processing could achieve 96% accuracy while SVM achieved 86%. A comparative study is also done in [9] in which a variety of algorithms, including neural network based ones are compared together with respect to their performance. In this study, a convolutional neural network based model is investigated for EEG signal classification during SSVEP task. CNNs are a group of neural networks which can extract unique features from complex data across multiple layers. In the convolution layer, the input data is convolved via filters in order to obtain features maps [10]. These feature maps are also visualized in this study to get a better insight of what is happening in the network. Therefore, it can be stated that the contribution of the current research is to introduce a compact CNN followed by a visualization procedure in order to find out what is being learnt in the network. A simple block diagram of the whole structure of this research is depicted in Figure 1.
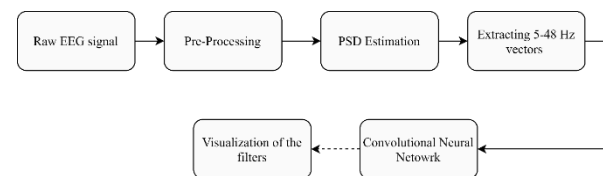

Figure 1. A simple block diagram of the whole structure

One of the most important advantages of CNNs is that they can remove the necessity for signal pre-processing [11]. In other words, CNNs can learn to do pre-processing inside the network. The performance of the proposed structure is evaluated across a five-stimuli SSVEP task using K-Fold cross validation (with K=10). This performance is also compared with different neural network based structures and some baseline studies. In section II, SSVEP dataset, pre-processing, classification and investigation of filters are described. In section III, results and discussions are proposed. Finally a summarization of this study is presented in section IV.

2. Materials and Methods

2.1. SSVEP Dataset

MAMEM SSVEP dataset Experiment II is used in this study [7], which contains 11 subjects (8 male and 3 female). Subjects' ages are in the range of 25 to 39 years old and all of the signals are recorded using GES 300 with 256 electrodes with the sampling frequency of 250 Hz. It is notable that all of the subjects were physically and mentally healthy and did not have any disability. Five flickers with the frequency of 6.66, 7.5, 8.75, 10, and 12 Hz are used in this experiment. Each of these flickers are generated on an LCD screen with purple color and can be assigned to a specific command in order to be executed in the computer.

In addition, the EGI 300 Geodesic EEG System (GES 300), using a 256-channel HydroCel Geodesic Sensor Net (HCGSN) and a sampling rate of 250 Hz has been used for capturing the signals [7].

2.2. Pre-Processing

In this study, two different approaches were taken for pre-processing. In the other words, signals are further processed with and without pre-processing. Since the visual cortex is located in the occipital lobe, the electrodes which are placed in the occipital lobe were selected for processing which contains electrode numbers 116, 117 (O1),124, 125, 126 (Oz), 137, 138, 139, 149, and 150 (O2) [7]. In the first approach, for suppressing DC component and 50 Hz noise, a bandpass filter between 5-48 Hz and a 50 Hz notch filter are applied to the signal. Then Power Spectral Density (PSD) of the signal is estimated using Welch method [12]. Frames with the length of 2.5s are used as a single input in this study. After estimating PSD, the components related to the frequencies of 5-48 Hz are chosen. Finally, we will have vectors with the length of 176 for the input of the network. In the second approach, i.e. without any pre-processing, after suppressing DC component and 50 Hz noise, raw EEG signal is fed to the network for classification. Corresponding results of each approach is reported in this study.

2.3. CNN Structure

In this study, convolutional neural network based is suggested for classification of EEG signal for SSVEP task. Traditionally, EEG signal processing was done using hand craft features and manual feature engineering [13]. With the help of CNNs, the network can learn to learn suitable features which can minimize the loss function and reach to the desired goal. The specifications of the suggested CNN structure can be seen in Table 1.

Table 1. Specifications of CNN structure

Parameter	Value
Number of convolution layers	1
Number of pooling layers	1
Number of fully connected layers	1
Number of convolution filters	16
Convolution filter size	1*8
Learning rate	0.001
Pooling window size	1*4
Dropout rate	0.5
Activation function	ReLu

Once the data is convolved with the convolutional filters, final classification is done via a Softmax function. This function takes the input vector x and computes the conditional probability as follows (Equation 1):

$$softmax(y|x) = \frac{exp\ (x)}{\sum exp\ (x)} \tag{1}$$

The loss function of the network is Categorical Cross Entropy (CCE), which measures the distance between network output distribution ($\hat{y}$) and labels (y) described as follows (Equation 2):

$$CCE(y, \hat{y}) = -\frac{1}{N}\sum_{n=1}^{N}(y_n \log(\hat{y}_n) + (1-y)\log(1-\hat{y})) \tag{2}$$

Where N is the total number of samples for training.

2.4. Experiments

In order to evaluate our suggested structure, we evaluate the model using a few experiments. In the first experiment, the effect of every single channel is investigated individually on the performance of the network. In the next experiment, the two best channels are considered together for the input of the network. In the third experiment, all of 10 channels are considered. Finally, raw EEG signal is considered for the fourth experiment.

3. Results and Discussion

In this section, the results of each experiment are presented. The performance of the suggested structure is presented in Table 2 with respect to each channel.

It can be observed that channels number 138 and 139 are the best channels for classifying EEG signal. Figure 2 shows the output of each 16 filters after 100 epochs of training for subject 1. This output corresponds to the 10 Hz flicker (as an example) and channel number 138. It can be easily observed that around 10 Hz frequency of all of the filters have a high value. In Figure 2, 10 Hz frequency and its neighbor is specified with the bounding box.

It is interesting to have a comparison between network input and the output of filters. Figure 3 shows the input of the network for the first subject. It can be seen that there is a high value near 10 Hz component in the input and the similar scenario can be observed in the output of the filters. In other words, the filters on the CNN try to learn and focus on the 10 Hz and its adjacent components.

Table 2. The performance of the network for each single channel (Experiment one)

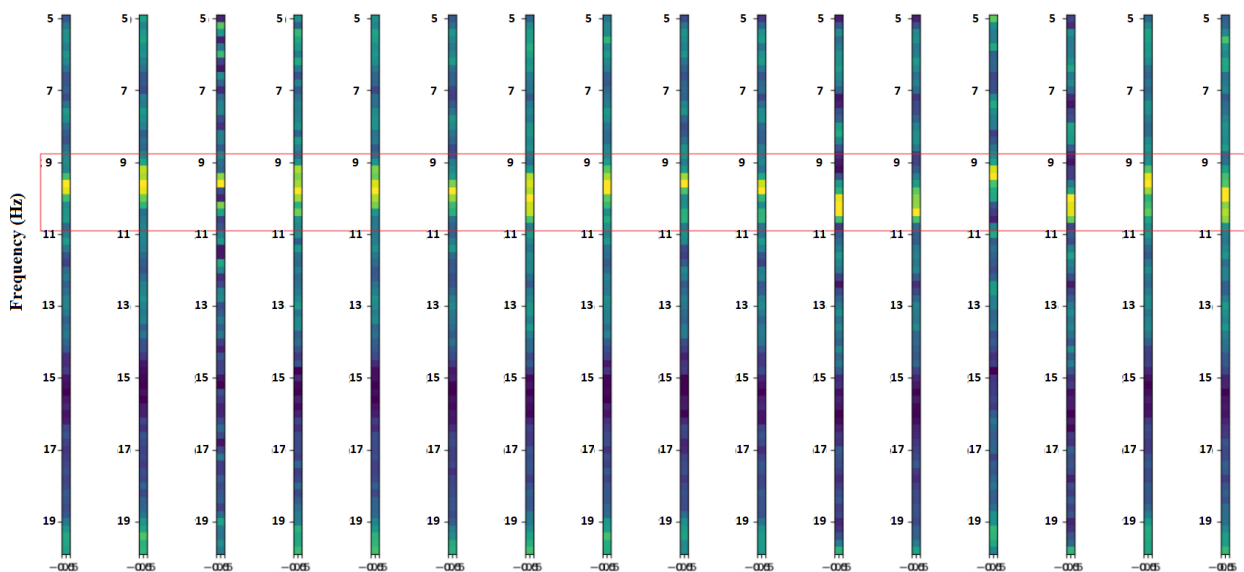| Channel Number	Average Accuracy (%)
116	58.62
117	63.21
124	61.61
125	68.17
126	66.42
137	67.39
138	72.61
139	70.08
149	67.44
150	68.17

Figure 2. Output of each 16 convolutional filter for the first experiment (subject 1). It can be seen that all filters have a high value around 10Hz component
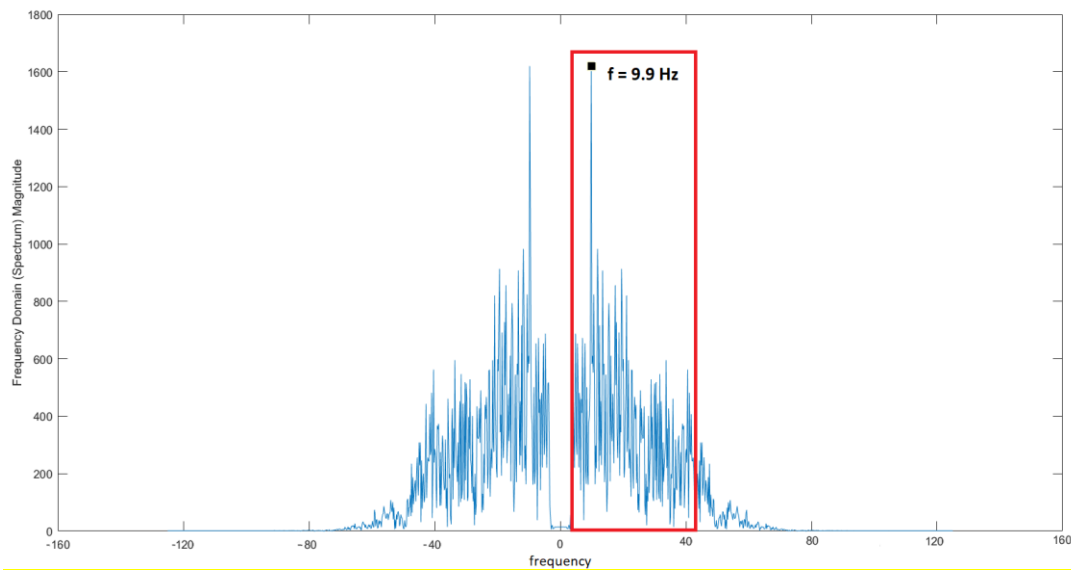
Figure 3. PSD with all of frequencies. The input of the network (5-48 Hz component) is specified with bounding box
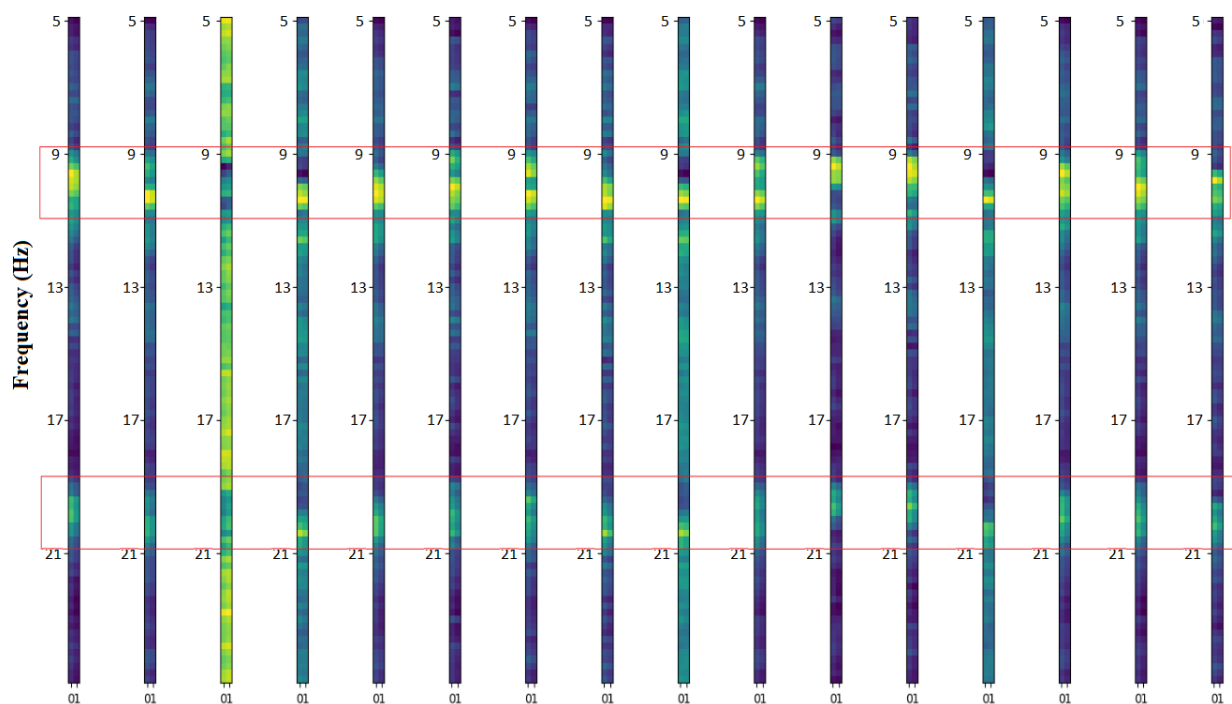

Figure 4. Output of each 16 convolutional filter for the second experiment (subject 1). It can be seen that all filters have a high value around 10Hz component and its harmonic

Since the channels 138 and 139 were the best channels, in the second experiment these two channels are considered simultaneously. This consideration leads to the 73.72% accuracy in the network.

Figure 4 shows the output of each filter for subject 1 for the second experiment. 10 Hz frequency and its harmonic can be observed in the output of the filters. In the third experiment, all of 10 channels are considered together. In this situation, the average accuracy of 72.47% could be achieved.
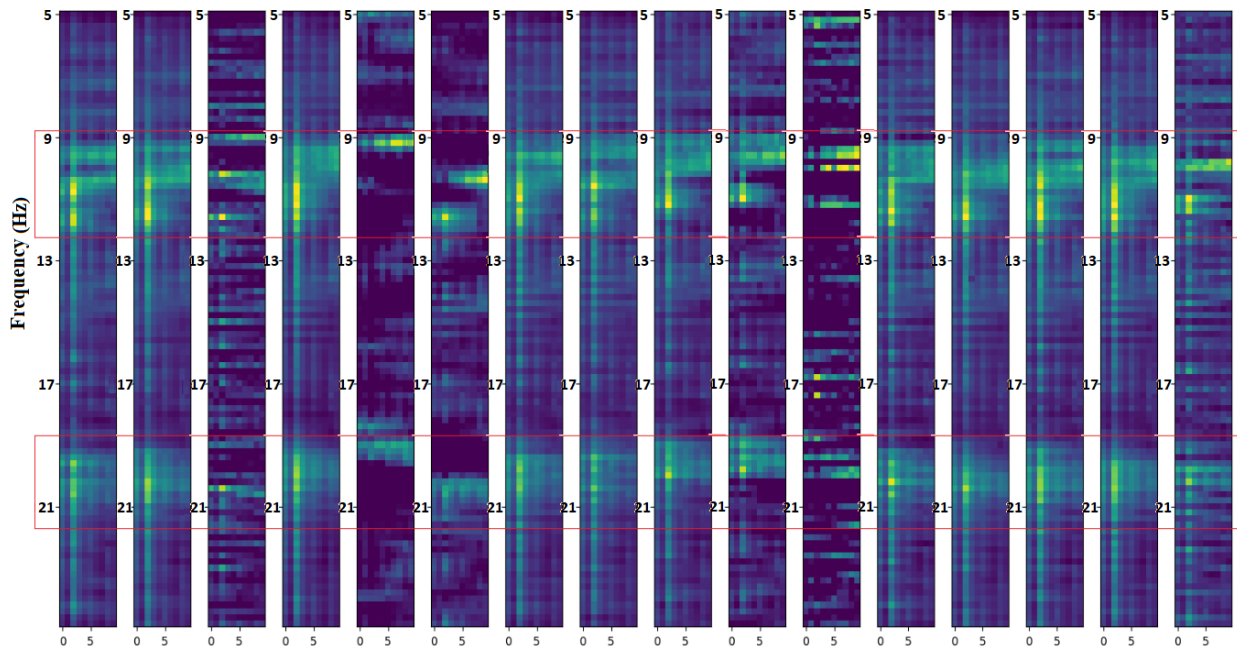
Figure 5. Output of each 16 convolutional filter for the third experiment (subject 1). It can be seen that all filters have a high value around 10Hz component
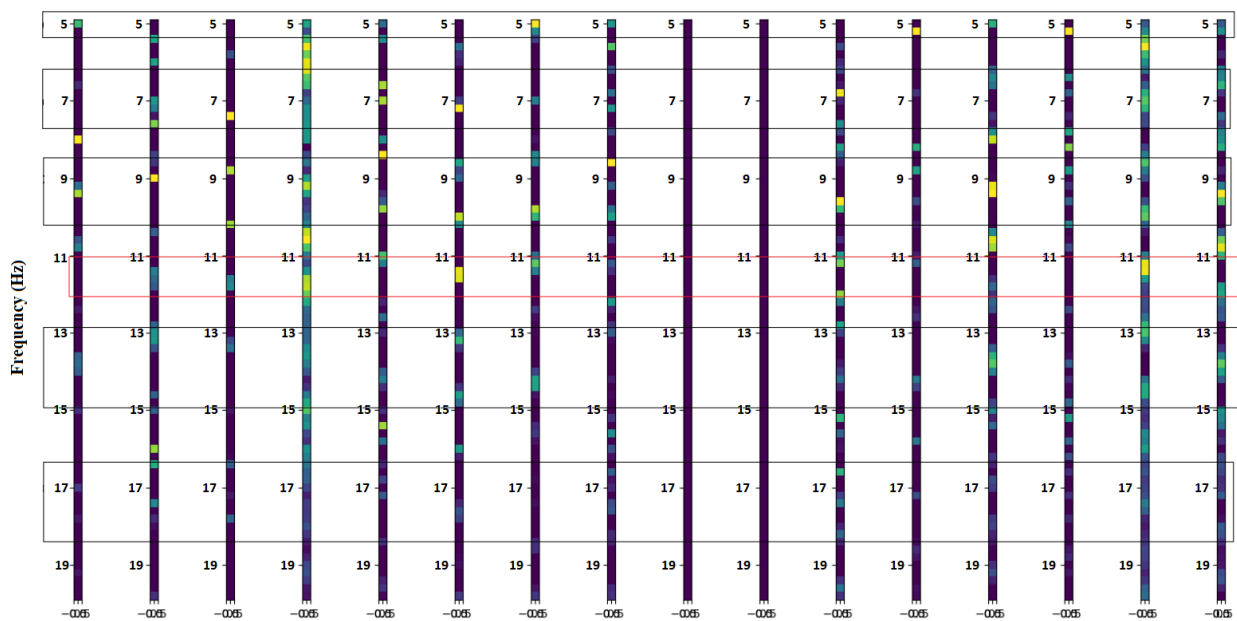

Figure 6. Output of each 16 convolutional filter for 8th subject. It can be seen that there is no specified pattern in the output of filters due to the contamination with ECG signals

Figure 5 shows the output of filters in the third experiment for the subject 1. It can be observed that we have high value in the output of the filters around 10 Hz frequency and its harmonic.

Due to the fact that reducing the preprocessing stages as much as possible and making the model end to end, may lead to less neurophysiological information loss, in some neuroscience researches like [14], the raw EEG signal was fed to the neural network as the input, which outperformed any other pre-processing methods. In order to assess the ability of the proposed method for SSVEP stimulus recognition from raw EEG signal, the preprocessing stage was omitted from experiment 4. It was observed that the

performance decreases down to 27.08% accuracy in this situation which is not favorable. One of the most probable reasons for this decrease in performance is that the introduced CNN model is so simple and compact which cannot do complicated task such as pre-processing. More complex models can do complex tasks but they need high amount of data for training, where, in our case, this condition is not satisfied.

For some subjects such as subject number 8, all of the suggested structures have a very low performance. This issue is addressed by investigating the time series signal. It was observed that the signal of the 8th subject is highly contaminated with ECG signal which made it inseparable.

Due to this contamination, the network couldn't extract the suitable features to classify the EEG signal. Figure 6 presents this issue. The output of the network is visualized in this situation and it was observed that there is no specific pattern in the output of the filters.

Figure 7 shows a small portion of time domain EEG signal for subject 8 which verifies the above statement. It seems that it is affected by an ECG-like signal which could considerably decrease the performance of the classifier for SSVEP task.

Compared to other structures in the literature [8], it was observed that the suggested model can outperform other structures. A brief comparison between different structures is presented in Table 3.

With regard to justifying the optimality of the achieved results, the introduced CNN structures were tested with different number of convolutional layers. It has been observed that with increasing the number of convolutional layers, the performance of the network considerably degrades. Table 4, justifies this statement.

It can be observed that the best result is achieved by using 1 convolutional layer which was introduced in this research. One of the main reasons for such result is that the number of trials in the dataset is not well enough compared to the number of parameters in the network.
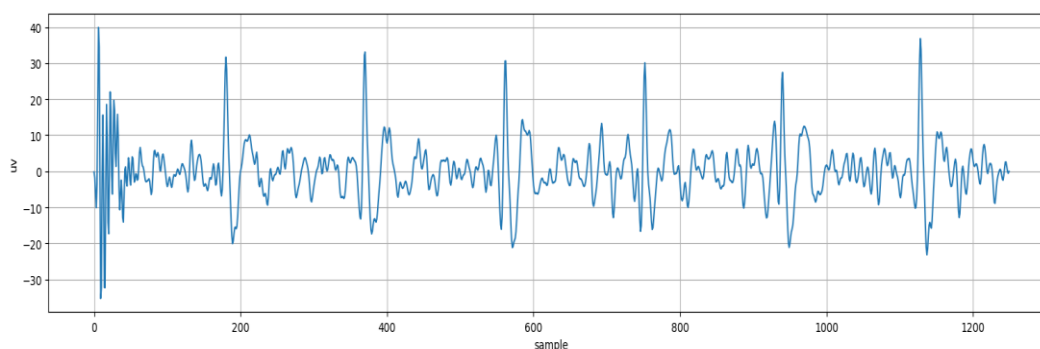

Figure 7. A small portion of time domain EEG signal for subject 8

Table3. Comparison between different structures

Method	CNN	SVM	LSTM	CNN (this study)
Average Accuracy	69.03 %	66.09 %	66.89 %	73.72 %

Table4. Performance of the network regarding to the different number of convolutional layers

Number of CNN Layers	1	2	4	8
Average Accuracy	73.72 %	73.29 %	72.6 %	64.22 %

In fact, increasing the number of convolutional layers will result in increasing the number of parameters of the network and therefore the model tends to overfit on the training data. When using deeper networks, better performance could be achieved with sufficient amount of trials in the dataset.

Due to the fact that lack of sufficient amount of data is the bottleneck in neural network based models, data augmentation methods could be a suggestion when dealing with medical problems.

4. Conclusion

Current researches in the field of BCI systems are trying to find much easier ways to translate brain signals into the machine language. It would be ideal to connect any artificial part directly to the brain. This will lead to a big leap in the rehabilitation studies. The current study is trying to take a forward step in designing models to appropriately process the brain signal to reach the desired goal. In this research, a CNN based model was suggested for the classification of EEG signal during SSVEP task. Different channel configuration was tested in order to find the best channels and electrodes for this problem. It was observed that channels number 138 and 139 have the best performance for this classification problem.

In addition, some efforts were made to visualize the CNN, which was introduced in this research. This visualization can be so important for understanding the network behavior and can also be used as a feedback to the network. Suggesting a structure, which can benefit from the visualization for training the network and achieving the best performance, could be the future work in this research field.

In our case in which the input of the network is EEG signal, this visualization can also be used as a tool for brain mapping applications.

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