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PERFORMANCE EVALUATION OF CONVOLUTIONAL NEURAL NETWORK IN CLASSIFICATION OF EEG SIGNALS BASED ON ATTENTION TASK

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ABSTRACT

This paper aims to present the Convolutional Neural Network (CNN) model to differentiate attention from non-attention conditions using spontaneous electroencephalogram (EEG) signals. The CNN model was constructed to acquire a general concept to classify attention conditions. A total of 30 subjects were recruited voluntarily for the data acquisition purpose. The experimental performance was benchmarked with the commonly used non-convolution learning algorithms, the support vector machine (SVM). The coherence feature extraction method was used to generate the training data for non-convolution model. The experimental results show that the proposed CNN model has accurately classify 63.89% of the test cases. It has outperformed the SVM model with 4.45% of improvement. In summary, the CNN model is able to create a decent attention classification model using spontaneous EEG signals.

Keywords: convolutional neural network, electroencephalogram, attention.

1. INTRODUCTION

Noninvasive surface electroencephalogram (EEG) is the main modality for investigating brain dynamics and performance in real-life interaction of humans with their external environment. One emerging area in EEG research is the attention regulation and monitoring with the aim to enhance human (cognitive) performance. The common way to analyze EEG signals for attention estimation is based on event-related potential (ERP). ERP is derived from presenting time-locked stimulation and the average of the time and phase-locked responses due to the stimulation. In recent time, spontaneous EEG signals is catching researchers' attention. As compared to ERP, the spontaneous EEG signals are more applicable in real-world application. One major advantage is the spontaneous EEG signals recording does not need external trigger. Spontaneous thoughts can arise from past memories, environmental cues and future tasks [1]. However, the research on spontaneous EEG signals is still lacking.

Machine learning techniques may be used to classify different levels of attention engagement of a person using EEG for the purpose to monitor the attention paid to a particular task. In the non-convolution learning approach, the input feature must be extracted first prior to the use of machine learning algorithm. However, the two separation modules (feature extraction and classification) may result in information loss during the feature extraction process [2]. To address this issue, a method that performs feature extraction and classification in one scheme, i.e., Convolutional Neural Network (CNN) is proposed.

CNN is an artificial neural network that can effectively learn spatial and temporal patterns available in the data by using convolutions as their key components [3], [4]. It is widely applied in pattern recognition and image classification recently. CNN has been used in various machine learning applications such as ImageNet [5]-[7], image segmentation [8], object detection [7], [9] and face recognition [10]-[12]. CNN had been used in handwritten digit recognition and achieved promising accuracy with 95.7% [13]. From the literature, there are only a few number of research on EEG signals using CNN. In a recent study [2], a five layers of CNN model is built to perform feature extraction and classification for single-trial motor imagery. The proposed CNN model was compared with three non-convolution learning methods, i.e. power + SVM, CSP (Common Spatial Pattern) + SVM and AR (AutoRegression) + SVM. The accuracy of the CNN model achieved 86.41%, which is 9.24%, 3.80% and 5.16% higher than the power + SVM, CSP + SVM and AR + SVM respectively.

The rest of this paper is organized as follows: Section 2 presents the materials and methods, which describe data acquisition and data preprocessing, feature extraction and classification. Section 3 describes the proposed Convolutional Neural Network (CNN) architecture used to exploit the spatial and temporal. Section 4 presents and discusses the results, while section 5 draws conclusion and suggests the direction of future work.

2. MATERIALS AND METHODS

2.1 Data acquisition, preprocessing and preparation

We developed a paradigm to collect the spontaneous EEG signals. A group of 30 healthy subjects (17 males and 13 females) ages from 20 to 30 years old were recruited voluntarily to assist in developing the case study. Only one female subject is left handed and the others are right handed. Informed written consent was

obtained from all volunteered subjects before the experiment was conducted.

EEG data were recorded from 21 active electrodes (FPZ, FP1, FP2, F7, F3, AFZ, FZ, F4, F8, T3, C3, CZ, T4, OZ, T5, P3, PZ, P4, T6, O2, O1) by using Twente Medical Systems International (TMSi) Porti system. The electrodes used were based on the International 10-20 electrodes placement. All the scalp electrodes were referred to right earlobe and grounded on right hand in the experiment. EEG was sampled at 512Hz.

The subject was seated on a back-rested chair. Two tasks were designed: attention task and non-attention task. An English audio text was played for the duration of three minutes and fifty seconds. In the attention task, the subject was asked to click the mouse whenever the word "and" is heard. This is to make sure that the subject is paying attention during the experiment. In the case of non-attention task, the subject only needs to be relax and do nothing.

Raw data were pre-processed, i.e. filtered and segmented. The purpose of filtering is to improve the signal quality by minimizing the background noise or interference. Second order Butterworth bandpass filter was used (cut off frequencies is 8-12Hz). The filtered EEG signals were segmented into a 1-second epoch and the total number of epoch is divided to 80% training and 20% testing for each subject and each channel.

2.2 Feature extraction

Coherence (CH)

Coherence is used to measure the degree of linear correlation between two signals. The correlation between two signals at different frequencies can be uncovered by coherence. Coherence has been applied in several cognitive and clinical conditions in the study of EEG signals. Coherence reflects the degree of synchrony between frequency components of two signals and provides the estimation of functional connectivity in the brain [14]. The range value for the magnitude of the squared coherence estimate is between 0 and 1, which quantizes how well x corresponds to y at each frequency. The value of 0 for the coherence function means the independence between two signals while the value of 1 for the coherence function means the complete linear dependence. The expression of coherence given as follow:

$$C_{xy}(f) = \frac{\left|P_{xy}(f)\right|^2}{P_{xx}(f)P_{yy}(f)}$$

where,$C_{xy}(f)$ is a function of the power spectral density, (P_{xx}andP_{yy}) of x and y and the cross-power spectral density (P_{xy}) of x and y.

2.3 Classification

Support vector machine (SVM)

Support Vector Machine (SVM) is widely used in EEG signals classification, bioinformatics and other disciplines due to its high accuracy. SVM is introduced by Vapnik in 1963 and act as supervised learning algorithm to analyze data, recognize pattern, classification and regression analysis. SVM is a discriminative classifier by constructing hyperplane. The constructed hyperplane can be used for classification and regression. For a given two-class linearly separable classification problem, SVM tries to find a hyperplane to separate the input space with a maximum margin.

The optimum hyperplane can be found by using the formula as follows [15]:

$$w \cdot x_i + b \geq +1, if\ y_i = +1$$
$$w \cdot x_i + b \leq +1, if\ y_i = -1$$

Where, x_i is the ith input vector ($x \in R^N$), y_i is the ith input ($y \in \{-1, +1\}$), w is the weight vector which normal to the hyperplane, and the b is the bias. The optimal hyperplane is found when the two margins are parallel to the optimal hyperplane. The margins can be calculated by using:

$$w \cdot x_i + b \leq \pm 1$$

The input vectors that determine the margins are called as support vectors. The architecture of SVM is shown in Figure-1.

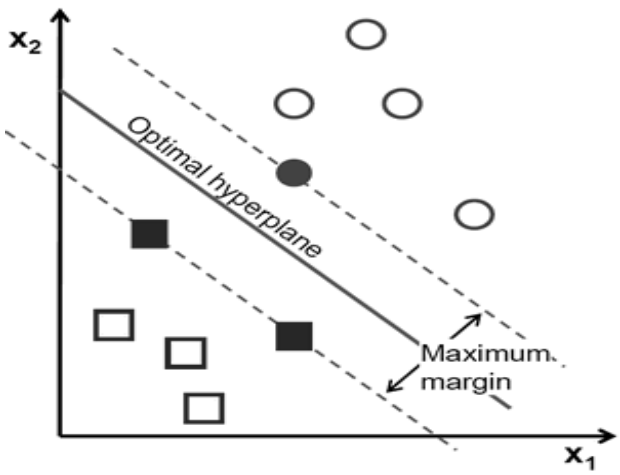

Figure-1. Illustration of the support vector machine (SVM)[15].

3. CONVOLUTIONAL NEURAL NETWORK (CNN)

The CNN model (as shown in Figure-2) was constructed to train all the 30 subjects. Based on the spatio-temporal characteristics of EEG, seven layers of CNN model is constructed to classify attention and non-attention states. The first layer is the input layer, there are five convolutional layers, which compose the feature extraction and classification; and the last layer is output layer. Max-pooling is applied to second to forth layers to reduce the size of features. We used Adaptive Moment Estimation (Adam) optimizer to update the network weights iteratively in the training data. It is an efficient method which computes individual learning rates for

different parameters from estimates the gradients. We used hyperbolic tangent function as activation function for all the convolutional layers and the learning rate is set as 0.002. The hyperbolic tangent function is described as:

$$f(x) = a\tanh(bx)$$

where $a = 1.7159$ and $b = 2/3$ (a constant value).

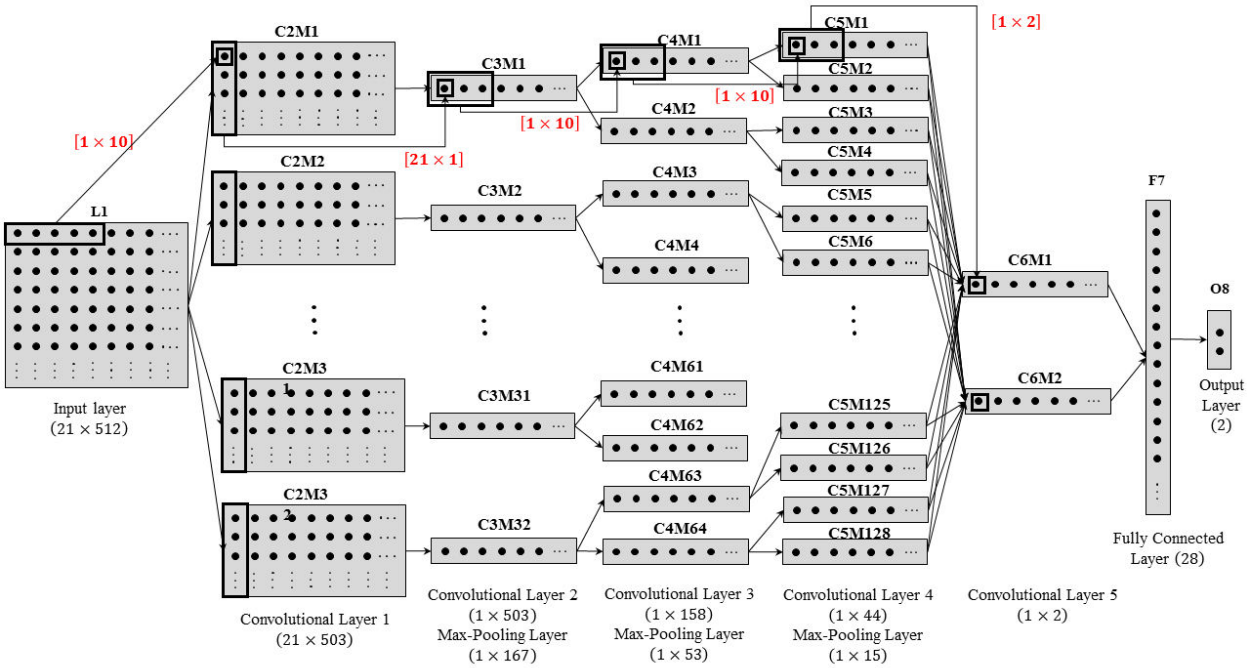

Figure-2. Convolutional Neural Network Architecture for Attentional EEG classification (30 subjects).

a) **L1:** The input layer. The input is arranged into $[21 \times 512]$ matrix.
b) **C2:** The convolutional layer (first hidden layer). 32 filters with size of kernel $[1 \times 10]$are used in this layer, convolute individual channel across the time, and feature maps with the size of $[21 \times 503 \times 32]$ is obtained after the convolution.
c) **C3:** The convolutional layer (second hidden layer). This layer aims to filter the EEG signals in the space domain. 32 spatial filters are used in this layer and 32 feature maps are obtained after the convolution operation. The size of convolution kernel is $[21 \times 1]$. A max-pooling with stride $[3 \times 1]$ is used and feature map with size of $[1 \times 167 \times 32]$ is produced.
d) **C4:** The convolutional layer (third hidden layer). This layer aims to further convolute and subsampling the EEG signals. For each feature map in C3, 2 filters are used and resulting 64 feature maps in total. The size of convolution kernel is $[1 \times 10]$. A max-pooling with stride $[3 \times 1]$ is used and feature map with size of $[1 \times 53 \times 64]$is produced.
e) **C5:** The convolutional layer (forth hidden layer). This layer aims to transform feature map of $[1 \times 53 \times 64]$ into size of $[1 \times 53 \times 128]$. For each feature map in C4, 2 filters, each with size of $[1 \times 10]$ are used and resulting in feature map with size of$[1 \times 44 \times 128]$. A max-pooling with stride $[3 \times 1]$ is used and the feature map is pooled down to size of $[1 \times 15 \times 128]$.
f) **C6:** The convolutional layer (fifth hidden layer). This layer aims to transform feature map of $[1 \times 15 \times 128]$ into size of $[1 \times 14 \times 2]$. A filter with size of $[1 \times 2]$ is used.
g) **F7:** The fully connected layer. Each neuron of F6 is connected to each neuron of C5. C5 and F6 are fully connected. This layer composed 28 neurons.
h) **O8:** The output layer. This layer has only two neurons, which represents the two classes of the problem (attention and non-attention state). A softmax operation is applied to the two values to provide the final classification result.

4. RESULTS AND DISCUSSIONS

Here, a comparison between CNN model and non-convolution learning model, SVM is carried out. The experimental results are evaluated based on classification accuracy. Figure-3 shows the experimental results of CNN model and SVM model.

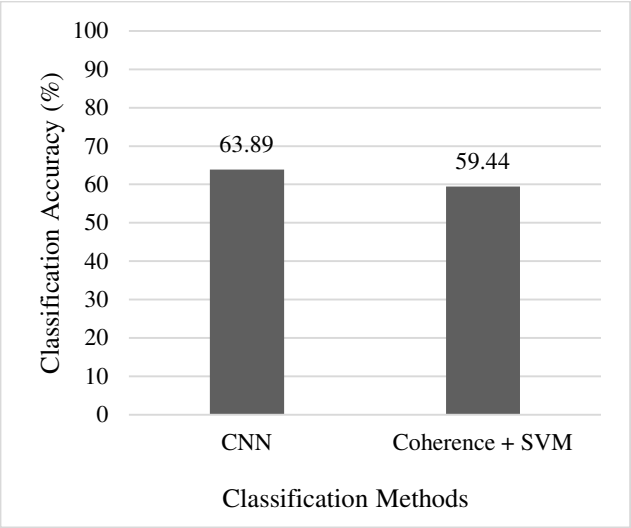

Figure-3. Accuracy measure for testing set.

Based on the figure above, both the models yielded moderate experimental results in terms of accuracy. The accuracy of CNN model achieved 63.89%, which performed better than the SVM model. With the coherence feature extraction, the accuracy of SVM obtained 59.44% only. The possible reason is due to the individual difference of EEG signals. Many researches claimed that the EEG signals are small intra-individual and large inter-individual [16]-[19]. Thus, further work can be done by classifying according to subject to improve the classification performance.

5. CONCLUSIONS

In this paper, we have investigated the use of spontaneous EEG signals for attention monitoring. From the classification results obtained in this experiment, the CNN model was outperformed as compared to other non-convolution learning model with the separation of feature extraction and machine learning method. In overall, the CNN model is able to differentiate attention condition by using the spontaneous EEG signals. However, the accuracy can be further improved by performing the classification according to subject due to the individual difference in EEG signals.

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REFERENCES

[1] C. A. Godwin, E. Morsella and M. W. Geisler. 2016. The Origins of a Spontaneous Thought: EEG Correlates and Thinkers' Source Attributions. AIMS Neurosci. 3(2): 203-231.

[2] Z. Tang, C. Li and S. Sun. 2017. Single-trial EEG classification of motor imagery using deep convolutional neural networks. Optik (Stuttg). 130: 11-18.

[3] H. Cecotti and A. Gra. 2011. Convolutional Neural Networks for P300 Detection with Application to Brain-Computer Interfaces. IEEE Trans. Pattern Anal. Mach. Intell. 33(3): 433-445.

[4] R. T. Schirrmeister *et al*. 2017. Deep learning with convolutional neural networks for brain mapping and decoding of movement-related information from the human. pp. 1-56.

[5] F. Lauer, C. Y. Suen and G. Bloch. 2007. A trainable feature extractor for handwritten digit recognition. Pattern Recognit. 40(6): 1816-1824.

[6] A. Krizhevsky, I. Sutskever and H. Geoffrey E. 2012. ImageNet Classification with Deep Convolutional Neural Networks. in Advances in Neural Information Processing Systems. pp. 1097-1105.

[7] H. M. Albeahdili, H. A. Alwzwazy and N. E. Islam. 2015. Robust Convolutional Neural Networks for Image Recognition. Int. J. Adv. Comput. Sci. Appl. 6(11): 105-111.

[8] C. Couprie, C. Farabet, L. Najman and Y. LeCun. 2013. Indoor Semantic Segmentation using depth information. pp. 1-8.

[9] K. He, X. Zhang, S. Ren and J. Sun. 2015. Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition. IEEE Trans. Pattern Anal. Mach. Intell. 37(9): 1904-1916.

[10] R. Hadsell, S. Chopra and Y. Lecun. 2006. Dimensionality Reduction by Learning an Invariant Mapping.pdf. in Proceedings of the 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. pp. 1735-1742.

[11] O. Russakovsky *et al.* 2015. ImageNet Large Scale Visual Recognition Challenge. Int. J. Comput. Vis. 115(3): 211-252.

[12] O. M. Parkhi, A. Vedaldi, and A. Zisserman. 2015. Deep Face Recognition. in Procedings of the British Machine Vision Conference 2015.

[13] B. Sivakumar and K. Srilatha. 2016. Handwritten Digit Recognition using Convolutional Neural

Networks. Int. J. Innov. Res. Comput. Commun. Eng. 4(2): 1101-1106.

[14] S. Motamedi-Fakhr, M. Moshrefi-Torbati, M. Hill, C. M. Hill and P. R. White. 2014. Signal Processing Techniques Applied to Human Sleep EEG Signals-A Review. Biomed. Signal Process. Control. 10: 21-33.

[15] K. S. Bayram and M. K. Ayyüce. 2013. Classification of EEG Signals by using Support Vector Machines. in 2013 IEEE International Symposium on Innovations in Intelligent Systems and Applications (INISTA). pp. 1-3.

[16] A. Riera, A. Soria-Frisch, M. Caparrini, C. Grau and G. Ruffini. 2008. Unobtrusive Biometric System Based on Electroencephalogram Analysis. EURASIP J. Adv. Signal Process. 2008(1): 1-8.

[17] A. Riera, J. Llobera and G. Ruffini. 2008. Multimodal Physiological Biometric Authentication. in Biometrics: Theory, Methods, and Applications. pp. 461-482.

[18] A. Zuquete, B. Quintela and J. P. Silva Cunha. 2010. Biometric Authentication using Brain Responses to Visual Stimuli. in International Conference on Bio-inspired Systems and Signal Processing. pp. 103-112.

[19] M. M. Hasan, M. H. A. Sohag and M. Ahmad. 2016. EEG Biometrics based on Small Intra-Individual and Large Inter-Individual Difference of Extracted Features. in 2nd International Conference on Electrical, Computer and Telecommunication Engineering. pp. 1-4.