ORIGINAL ARTICLE

Single-Channel Selection for Detecting Steady-State Visual Evoked Potentials in a Brain-Computer Interface Speller

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Abstract

Purpose: Brain-Computer Interface (BCI) provides a secondary communication pathway for patients with neuromuscular diseases such as amyotrophic lateral sclerosis (ALS) or brainstem stroke in which they are almost incapacitated to move or talk. BCI enacts neural oscillations to generate a command signal for machines to operate desired tasks instead of patients. Steady-State Visual Evoked Potential (SSVEP) is the brain response to a visual stimulus, with the same frequency as its eliciting signal (or its harmonics), that has been widely used in BCI environments. In order to provide a more convenient situation for BCI users, we aim to find the best single-channel EEG, which results in the highest accuracy for detecting SSVEP.

Materials and Methods: We developed a Deep Convolutional Neural Network with single-channel EEG as input to classify a 40-class SSVEP; each class represents a stimulus, which has been acquired from 35 subjects. We used 3.5 s windows of the data (Trials of 3.5 seconds length for each class) to train our model and leave-one-subject-out cross-validation for the testing.

Results: The proposed method resulted in the average classification accuracy of 74.30%±20.85 and Information Transfer Rate (ITR) of 57.51 bpm which outperforms the previous single-channel SSVEP BCIs in terms of ITR. Also, the O1 channel achieved the best performance criteria among the channels in the occipital and parietal lobes, which seems reasonable according to previous researches for finding the location of neurons, responsible for visual tasks in the brain.

Conclusion: In this study, we dedicated our efforts to reduce the number of EEG channels to a single channel while proposing a deep learning strategy for an SSVEP-based BCI speller to make it more feasible for patients whose lives are dependent on such systems. The overall results, although not ideal, open a new promising window toward a feasible BCI system.

Keywords: Brain-Computer Interface Speller; Steady-State Visual Evoked Potential; Deep Learning; Convolutional Neural Networks; Single-Channel Electroencephalogram.

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1. Introduction

Brain-Computer Interfaces (BCIs) provide a secondary pathway of communication with the help of measuring brain activity [1, 2, 3]. The main aim of these systems is to utilize the neural activity of the brain to produce command signals and send them to a machine to perform predefined tasks [4]. As such, people can communicate with their environment without almost any muscle movements [5]. Electroencephalography (EEG) is one of the most promising neuroimaging modalities to measure the neural oscillations of the brain. Recently, this technique has gain attention, especially from the BCI community, due to its high temporal resolution and inexpensiveness. We could extract the essential features from the EEG data to generate suitable command signals for the predetermined purpose of the BCI. To this end, there are numerous ways to elicit electrophysiological patterns in the neural activity of the brain such as Event-Related Potentials (ERP) and Steady-State Visual Evoked Potentials (SSVEP) which are auspicious avenues for producing these signals for further measurements and usages [2, 6, 7], with copious advantages which make them a suitable choice for many BCI applications.

SSVEPs are sensory-stimuli-based potentials [8], obtained by applying visual stimuli, generally with frequencies greater than 4 Hz [9]. The most distinctive feature of SSVEP is having the same frequency components as the stimuli or its fundamental harmonics [10], which would be advantageous for many BCI functions. For instance, decoding information in stimuli with a specific frequency and further detection and enacting it as a command signal would be less demanding in comparison with other eliciting patterns in BCIs, since the brain response would have the same frequency of that stimuli [5]. Furthermore, in comparison with other neural patterns, SSVEPs have a higher Signal-to-Noise Ratio (SNR) [5] and Information Transfer Rate (ITR) [11].

The core of any BCI system is the module that detects the essential information from the EEG signals [12]. This part aims to extract the key patterns from the EEG to generate a proper command as the output of the system [13]. In the SSVEP case, this module should extract the SSVEP from EEG signals and classify each frequency component of the SSVEP as well. Power Spectrum Density Analysis (PSDA) [14, 15], which utilizes amplitude of the signal in the frequency domain to classify SSVEPs, and Canonical Correlation Analysis (CCA) [16, 17], which uses the correlation coefficient of the stimuli and the EEG for detecting SSVEPs, are some traditional methods that have been adopted in SSVEP-based BCI. These algorithms have encountered some issues regarding SSVEP classification which convinced researchers to use some alternative approaches. For instance, PSDA could not perform properly in noisy environments [18], or CCA results in low ITR due to the time-consuming process of self-calibrating [12]. With this regard, machine learning and especially deep learning approaches would be highly advantageous in a noisy and non-stationary situation such as EEG [19].

Since the emergence of machine learning and deep learning algorithms, they have played significant roles in solving complex classification problems [20] with no priori information about the discriminative features, but generally, with the cost of requiring a considerable amount of data for training the models. Also, in order to provide a more convenient environment for BCI users, and make these systems more practical, we should reduce the number of EEG channels in use. Therefore, we aim to combine these two issues and come up with a convolutional neural network and to find the best single-channel EEG among the most probable channels, that reaches out to reasonably high classification accuracy and ITR and sound performance. By considering this fact that regularly, a deep learning model requires a huge amount of data to be well-trained, our CNN model has been designed in such a way that could outperform other deep learning models that have been trained on a multi-channel EEG. To the best of our knowledge, no other deep learning model has been proposed for a single-channel BCI, with an acceptable outcome regrading ITR. In the following parts of this article, we dive into our model and discuss it in detail, and thereafter, the analysis of each EEG channel and the conclusion of the research would be presented.

2. Materials and Methods

2.1. SSVEP BCI Speller Dataset

In this study, we train and test our proposed model with the SSVEP dataset that is freely available in [20]. In this experiment, 35 subjects with normal or correlated-to-normal vision contributed. They have been exposed to 40 class visual stimuli containing English characters and numbers. Each subject has gone through the experiment for all of the stimuli in 6 blocks, each of them contains a 6-second stimulus (0.5 seconds before onset and 0.5 seconds after the off-set). The EEG data were recorded at a 1000Hz sampling rate and then down-sampled to 250 Hz, which means that each trial consists of 1500 samples. Moreover, they have used 64 EEG channels for their recording, including nine important channels in SSVEP studies O_1, O_2, Oz, POz, Pz, PO_3, PO_4, PO_5, and PO_6. Further information about the dataset is available in [20].

2.2. Convolutional Neural Network (CNN)

Pattern recognition and machine learning methods have had tremendous effects on different fields of science, which mainly concern the classification problems, including computer vision [15], natural language processing [16], as well as studies with biological directions such as medical image processing [17] or biological signal processing [18]. Respecting this, since the performance of a BCI system hugely depends on the accuracy of the classification part, researchers have commenced gaining favor from these remarkable algorithms to boost the proceeds of their systems.

Despite the significant progress that classical machine learning methods bring about in BCI systems [19], there are remaining challenges in this field that should be taken away such as the vulnerability of EEG signals to various noise and artifacts such as heart signals and eye blinking [19] which makes it a demanding task to extract essential features from the naturally polluted EEG signals. Considering this, deep learning algorithms like CNN would become handy in this kind of situation, especially since they automatically extract the essential features [12].

CNN consists of different types of modules with specific tasks, in which they perform for the final goal of the model. Generally speaking, these models include convolution windows with activation functions, pooling layer, batch normalization, and fully connected layer. Moreover, some other techniques such as drop out have been included in these networks to avoid overfitting. Typically, the convolution window comprises some filter of specific dimension that is convolved with data, multiplies each weight with the data window, adds the bias, and uses the activation function to provide the appropriate input for the next layer. In this way, the number of trainable parameters will be significantly reduced, in comparison with a fully connected neural network which multiplies every weight with every segment of the data window. Other modules in the CNN have their own purposes like a pooling layer for reducing the dimensionality of the data and computation cost, or batch normalization for accelerating the learning procedure. Finally, the fully connected layer provides as much information for the final layer, to perform the final goal of the model, which could be a SoftMax layer in a classification problem.

2.3. Our Proposed CNN Model

In this study, we are going to decrease the number of EEG channels to a single channel to make the SSVEP-based BCI speller more practical for real applications, while proposing a deep learning strategy to make the system more powerful in exploring the discriminative features. Consequently, we proposed a deep convolutional neural network that is trained by just a single EEG channel. The scheme of our model is presented in Figure 1.

As illustrated in Figure 1, the input layer contains one EEG channel with 896-time samples (1 × 896). In fact, we utilize a 3.5-second time window of the data (with a 256 sampling rate) which adds up to 896-time samples. The first convolution layer consists of 96 kernels with 1 × 256 size. Afterward, there is a depthwise convolution for each map with the 1 × 9 kernel size. Then, the last convolution layer consists of 96 kernels with 1 × 16 size. Lastly, there is a fully connected layer to provide as much information for the classifier layer, with 40 neurons representing 40 stimuli and classes. Each convolution layer follows a batch normalization layer for boosting the training speed of the model [21]. After the second and third convolution layers, we have average pooling and dropout layer, with 0.5 dropout rates, to avoid overfitting. The Elu activation function has been adopted for each layer except for the output layer, which contains a SoftMax activation to perform

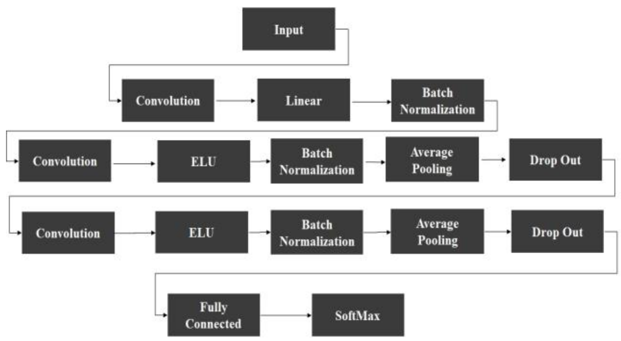

Figure 1. The block diagram of the proposed CNN model

the classification task. The Adam optimizer [22] with a 0.001 learning rate and a categorical cross-entropy loss function (Equation 1) is used.

$$Loss_i = -\sum_{j=1}^{C} t_{i,j} log\ (p_{i,j}) \quad (1)$$

Where p represents the model prediction, C denotes ground truth, i is the sample number, and j shows the class label.

3. Results and Discussion

Since it is most likely to detect SSVEP in the occipital and parietal lobes [9], we focused our analysis on just nine EEG channels (O_1, O_2, Oz, POz, Pz, PO_3, PO_4, PO_5, and PO_6) instead of all 64 available channels. We trained our CNN model with each of these nine channels to analyze our model. The leave-one-subject-out cross-validation technique was used for training and testing our model to ensure avoiding overfitting and selection bias. The model was trained for each channel in this way for 100 epochs. The learning curve of subject number 32 for the O_1 channel is represented in Figure 2, which illustrates an example of subjects that achieve the best test result (100%). As indicated in this figure, the model is well trained and had successfully reached the optima.

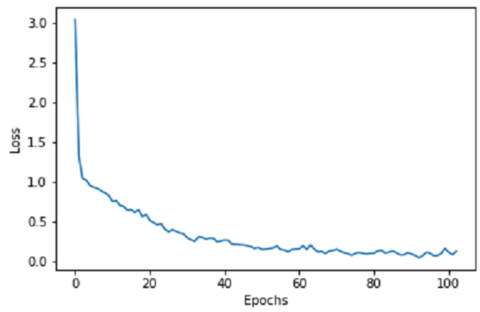

Figure 2. The Learning curve for subject 32, using O_1 channel as an input

The classification accuracy metric evaluates our CNN model, which guarantees us how accurate our model could predict the labels of the new data based on the ground truth that the model was trained on. Table 1 illustrates our analysis results in which channel O_1 achieved the best performance with 74.30±20.85 % classification accuracy on average for 35 subjects which is significantly (p-value<0.01, paired-samples t-test) higher than those of all other single channels. This result does make sense according to previous research for finding the location of neurons responsible for generating SSVEP [8, 21], in which they achieved similar results for spatial location of SSVEP sources. Afterward, another evaluation metric for measuring the performance of a BCI system, called the Information Transfer Rate (ITR), was investigated, which mainly depends on the classification accuracy. ITR shows the BCI system's speed for transferring the information with a bit per second/minute unit (Equation 2) [22], and it is a much more reliable metric than classification accuracy for a BCI system since it also considers other aspects of the data such as the number of classes and the duration of the data.

$$ITR = (log_2\, m + P\, log_2\, P + (1-P)\, log_2 \left[\frac{1-P}{m-1}\right]) \times \frac{60}{T} \quad (2)$$

Where m represents the number of classes, P denotes the accuracy of the selected channel, and T represents the selection time (in our case, 3.5 seconds). The mean ITR

Table 1. The classification accuracy (%) of our proposed CNN for each EEG channel. (S_n=nth Subject in the dataset)

EEG Channel (ordered by mean accuracy)	Max	Min	Mean	STD
$\mathbf{O_1}$	100 (S_{31})	6.75 (S_{32})	**74.30**	20.85
$\mathbf{PO_3}$	100 (S_{25})	20.5 (S_{32})	70.28	23.53
$\mathbf{O_z}$	99.16 (S_4)	5.16 (S_{32})	56.66	25.68
$\mathbf{PO_5}$	97.08 (S_{19})	4.7 (S_{16})	55.34	25.46
$\mathbf{O_2}$	100 (S_4)	4.78 (S_{32})	53.85	26.50
$\mathbf{PO_z}$	100 (S_3)	9.75 (S_1)	53.27	26.23
$\mathbf{P_z}$	87.90 (S_{25})	11.31 (S_{28})	37.20	20.60
$\mathbf{PO_4}$	82.08 (S_{25})	3.75 (S_{33})	35.81	22.21
$\mathbf{PO_6}$	79.58 (S_4)	2.08 (S_{33})	32.55	20.41

for the O_1 channel was 57.51 bpm that was significantly (p-value < 0.01, paired-samples t-test) higher than those of all other single channels. Also, the maximum ITR for the O_1 channel was 91.23 bpm higher than those of all other single-channels. A comparison among (some of) single-channel SSVEP BCI has been provided in Table 2. It should be noted that some of these methods have not been applied to the same dataset and consequently, this comparison could not be intuitive in all aspects. Since the length of time window has been different among different studies, considering ITR instead of the classification accuracy would give us a fair comparison. In terms of ITR, our proposed method significantly outperforms the previous single-channel SSVEP studies. Moreover, as it is shown in Table 2, it should be noted that other models such as [18], have been trained on a dataset with only five classes, which is a much simpler classification task compared to our problem. In addition, only some of these models like [18, 23, 24] have used single-channel EEG data, and the rest of the models (deep learning models) have used at least three channels of EEG. By considering all of these into account, our proposed model, which only uses single-channel EEG outperformed all of these methods in the case of ITR which normally, a BCI is evaluated by.

4. Conclusion

In the presented research, a CNN was developed with the aim of recognizing and classifying SSVEP in a BCI environment, with the limitation of using just a single EEG channel. For our model, we adopted time samples of EEG as inputs and got rid of transforming the data to the frequency domain and its computational cost, as opposed to several other related works [11, 18]. Moreover, the reduction of EEG channels in our study provides a more convenient and practical setting for BCI users, indeed. Lastly, the presented CNN model outperforms other classical methods for classifying SSVEP, such as Canonical Correlation Analysis and PSDA or state-of-the-art deep learning models [23, 26]. Despite this significant progress, the performance of an algorithm is highly dependent on the subjects, and its achievements extremely vary across the subjects. Hopefully, there could be other machine learning methods, such as transfer learning that may address this issue and add more generalization to these systems. Developing the proposed method using transfer learning can be the topic of future research.

Table 2. A comparison among classification methods for single-channel SSVEP BCI. (Methods with the same dataset as ours indicated by *)

References (Method)	Number of Classes	Time Window (s)	Accuracy (%)	ITR (bpm)
[18] (Deep Learning)	5	2	97.4 ± 2.1	49 ± 7.7
[23] (PSDA)*	40	2.5	52.6	42.8
[24] (FBCCA)	40	5.5	97.92	50.66
[25] (Deep Learning) *	40	5	68.63	30.18
[26] (Deep Learning) *	40	5	86.19	43.78
Proposed Method	40	3.5	74.30±20.85	57.51±15.32

References

1-Wolpaw, Jonathan R., Dennis J. McFarland, and Theresa M. Vaughan, "Brain-computer interface research at the Wadsworth Center," *IEEE Transactions on Rehabilitation Engineering*, vol. 8, no. 2, pp. 222-226, 2000.

2-N. Birbaumer, "Breaking the silence: brain–computer interfaces (BCI) for communication and motor control," *Psychophysiology*, vol. 43, no. 6, pp. 517-532, 206.

3-Nijboer, Femke, E. W. Sellers, Jürgen Mellinger, Mary Ann Jordan, Tamara Matuz, Adrian Furdea, Sebastian Halder et al, "A P300-based brain–computer interface for people with amyotrophic lateral sclerosis," *Clinical neurophysiology*, vol. 119, no. 8, pp. 1909-1916, 2008.

4-Wolpaw, Jonathan R., Herbert Ramoser, Dennis J. McFarland, and Gert Pfurtschelle, "EEG-based communication: improved accuracy by response verificatio," *IEEE transactions on Rehabilitation Engineering*, vol. 6, no. 3, pp. 326-333, 1998.

5-Wang, Yijun, Xiaorong Gao, Bo Hong, Chuan Jia, and Shangkai Gao, "Brain-computer interfaces based on visual evoked potentials," *IEEE Engineering in medicine and biology magazine*, vol. 27, no. 5, pp. 64-71, 2008.

6-Nijholt, Anton, Desney Tan, Gert Pfurtscheller, Clemens Brunner, José del R. Millán, Brendan Allison, Bernhard

Graimann, Florin Popescu, Benjamin Blankertz, and Klaus-R. Müller, "Brain-computer interfacing for intelligent systems," *IEEE intelligent systems*, vol. 23, no. 3, pp. 72-79, 2008.

7-Pfurtscheller, Gert, and FH Lopes Da Silva, "Event-related EEG/MEG synchronization and desynchronization: basic principles," *Clinical neurophysiology*, vol. 110, no. 11, pp. 1842-1857, 1999.

8-C. S. Herrmann, "Human EEG responses to 1–100 Hz flicker: resonance phenomena in visual cortex and their potential correlation to cognitive phenomena," Experimental brain research, vol. 137, no. 3-4, pp. 346-353, 2001.

9-Wang, Yijun, Ruiping Wang, Xiaorong Gao, Bo Hong, and Shangkai Gao, "A practical VEP-based brain-computer interface," *IEEE Transactions on neural systems and rehabilitation engineering*, vol. 14, no. 2, pp. 234-240, 2006.

10-Müller-Putz, Gernot R., Reinhold Scherer, Christian Brauneis, and Gert Pfurtscheller., "Steady-state visual evoked potential (SSVEP)-based communication: impact of harmonic frequency components," *Journal of neural engineering*, vol. 2, no. 4, p. 123, 2005.

11-H. Cecotti, "A self-paced and calibration-less SSVEP-based brain–computer interface speller," *EEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 18, no. 2, pp. 127-133, 2010.

12-Waytowich, Nicholas, Vernon J. Lawhern, Javier O. Garcia, Jennifer Cummings, Josef Faller, Paul Sajda, and Jean M. Vettel, "Compact convolutional neural networks for classification of asynchronous steady-state visual evoked potentials," *Journal of neural engineering*, vol. 15, no. 6, p. 066031, 2018.

13-Nakanishi, Masaki, Yijun Wang, Yu-Te Wang, and Tzyy-Ping Jung, "A comparison study of canonical correlation analysis based methods for detecting steady-state visual evoked potentials," *PloS one*, vol. 10, no. 10, 2015.

14-Wang, Yijun, Ruiping Wang, Xiaorong Gao, Bo Hong, and Shangkai Gao, "A practical VEP-based brain-computer interface," *IEEE Transactions on neural systems and rehabilitation engineering*, vol. 14, no. 2, pp. 234-240, 2006.

15-Cheng, Ming, Xiaorong Gao, Shangkai Gao, and Dingfeng Xu, "Design and implementation of a brain-computer interface with high transfer rates," *IEEE transactions on biomedical engineering*, vol. 49, no. 10, pp. 1181-1186, 2002.

16-Nakanishi, Masaki, Yijun Wang, Yu-Te Wang, and Tzyy-Ping Jung, "A comparison study of canonical correlation analysis based methods for detecting steady-state visual evoked potentials," *PloS one*, vol. 10, no. 10, 2015.

17-Lin, Zhonglin, Changshui Zhang, Wei Wu, and Xiaorong Gao, ""Frequency recognition based on canonical correlation analysis for SSVEP-based BCIs," *IEEE transactions on biomedical engineering*, vol. 53, no. 12, pp. 2610-2614, 2006.

18-Nguyen, Trung-Hau; Wan-Young Chung, "A single-channel SSVEP-based BCI speller using deep learning," *IEEE Access*, vol. 7, pp. 1752-1763, 2018.

19-Lotte, Fabien, Marco Congedo, Anatole Lécuyer, Fabrice Lamarche, and Bruno Arnaldi, , "A review of classification algorithms for EEG-based brain–computer interfaces," *Journal of neural engineering*, vol. 4, no. 2, p. p. R1, 2007.

20-Faust, Oliver, Yuki Hagiwara, Tan Jen Hong, Oh Shu Lih, and U. Rajendra Acharya, ""Deep learning for healthcare applications based on physiological signals: A review," *Computer methods and programs in biomedicine*, vol. 161, pp. 1-13, 2018.

21-Jamison, Keith W., Abhrajeet V. Roy, Sheng He, Stephen A. Engel, and Bin He,, "SSVEP signatures of binocular rivalry during simultaneous EEG and fMRI," *Journal of neuroscience methods*, vol. 243, pp. 53-63, 2015.

22-Wolpaw, Jonathan R., Niels Birbaumer, Dennis J. McFarland, Gert Pfurtscheller, and Theresa M. Vaughan, "Brain–computer interfaces for communication and control," *Clinical neurophysiology*, vol. 113, no. 6, pp. 767-791, 2002.

23-A. T. SÖZER, "Enhanced Single Channel SSVEP Detection Method on Benchmark Dataset.," in In 2018 15th International Conference on Electrical Engineering, *Computing Science and Automatic Control (CCE), IEEE*, 2018.

24-Chen, Xiaogang, Yijun Wang, Masaki Nakanishi, Xiaorong Gao, Tzyy-Ping Jung, and Shangkai Gao, "High-speed spelling with a noninvasive brain–computer interface," *Proceedings of the national academy of sciences*, vol. 112, no. 44, 2015.

25-Aznan, Nik Khadijah Nik, Stephen Bonner, Jason Connolly, Noura Al Moubayed, and Toby Breckon, "On the classification of SSVEP-based dry-EEG signals via convolutional neural networks," *in In 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC), IEEE*, 2018.

26-Podmore, Joshua J., Toby P. Breckon, Nik KN Aznan, and Jason D. Connolly, "On the relative contribution of deep convolutional neural networks for SSVEP-based bio-signal decoding in BCI speller applications," *EEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 4, pp. 611-618, 2019.

27-C. S. Herrmann, "Human EEG responses to 1–100 Hz flicker: resonance phenomena in visual cortex and their potential correlation to cognitive phenomena," *Experimental brain research*, vol. 137, no. 3-4, pp. 346-353, 2001.

28-Jamison, Keith W., Abhrajeet V. Roy, Sheng He, Stephen A. Engel, and Bin He, "SSVEP signatures of binocular rivalry during simultaneous EEG and fMRI," *Journal of neuroscience methods*, vol. 243, pp. 53-63, 2015.

29-Diez, Pablo F., Vicente Mut, Eric Laciar, and Enrique Avila, "A comparison of monopolar and bipolar EEG recordings for SSVEP detection," *in In 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology, IEEE*, 2010.