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Effective SSVEP Frequency Pair Selection over the GoogLeNet Deep Convolutional Neural Network

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***Abstract*—The acquired Electroencephalography (EEG) signal while applying a blinking image on a screen is called steady-state visually-evoked potential (SSVEP). SSVEP is a popular control signal of the EEG in real-life applications because of the advantages such as; higher information transfer rate, simplicity in structure, and short training time. Most of the studies related to the SSVEP tried to discriminate which image (frequency) is gazed at while recording and turn this frequency into control commands. In this study, we focused on the selection of the stimulating frequency pair, which has the best accuracy rate, to investigate whether there is a correlation between stimulation frequencies. To achieve this goal, first of all, recorded SSVEP signals, which include seven different frequencies (6 - 6.5 - 7 - 7.5 - 8.2 - 9.3 - 10 Hz) were converted into spectrogram images. After dividing the spectrogram images into folders with respect to the frequencies, they were routed to GoogLeNet deep learning algorithm for binary classification. Consequently, we obtained the best performance in 8.2 & 10 Hz frequency pairs with 91.28% accuracy.**

***Keywords*—brain–computer interface; steady-state visual evoked potential; convolutional neural networks; deep learning; classification**

I. Introduction

A steady-state visual evoked potential (SSVEP) based brain-computer interface (BCI) is a EEG signal based computer system that records, analyzes, and converts brain signals into commands. These commands are sent to an output device for controlling [1]. SSVEP-based BCI's major aim is to help people with neuromuscular disorders such as; amyotrophic lateral sclerosis (ALS), cerebral palsy, stroke, or spinal cord hurt etc. replace or recover function(s). With the development of technology, they might improve in the future [2].

SSVEP-based BCI systems proved a robust performance using various methods from different laboratories in different countries [3]–[6]. They have attracted many researchers due to its high information transfer rate (ITR), high signal-to-noise ratio (SNR), simplicity in configuration, and users' shorter training time [7]. At the same time, many signal processing algorithms were used to contribute to these characteristics of the signal. Different preprocessing methods (filtering, windowing, dimensionality reduction etc.), feature extraction methods (Wavelet Transform, Wigner-Ville Distribution, Time-Frequency Distributions, Hilbert Huang Transform, etc.) and classification methods like machine learning (Support Vector Machines, Naive Bayes, Ensemble Learning, etc.) and deep learning (Convolutional Neural Networks, Long Short Term Memory Networks, Recurrent Neural Networks, Radial Basis Function Networks, Multilayer Perceptrons etc.) were tried to improve the signal processing steps [3]–[10].

In this study, we compared the classifier performances of binary combinations commands of flickering frequencies (6 - 6.5 - 7 - 7.5 - 8.2 - 9.3 - 10 Hz) to determine which frequency pair has the highest performance using deep learning method. For this purpose, firstly SSVEP signals recorded from four different subjects in 15360x21 data size. Then, a total of 2016 spectrogram images were obtained, 288 for each frequency. These images were used for classification using the Convolutional Neural Network (CNN) type deep learning algorithm (GoogLeNet Deep Learning Algorithm). In conclusion, we achieved 91.28% accuracy in 8.2&10 Hz frequency pairs. The combination of these methods leads to an appropriate detailed and comparative analysis that represents the robustness and effectiveness of modern approaches.

The rest of this paper is organized as follows: SSVEP Database, the system and implementation details used in this study are presented in Section 2. Results are explained in Section 3. Finally, Section 4 concludes this study.

II. Materials and Methods

A. SSVEP Database Description

In this study, the dataset (AVI SSVEP Dataset) include of SSVEP signals recorded by Adnan Vilic was used [11]. The AVI SSVEP Dataset is public and accessible online. The data set consists of SSVEP signals, which is the control signal of the EEG, measurements of the triggered responses of SSVEP signals from four healthy individuals. In this experiment, individuals have seated 60 cm away from a monitor staring at a single flickering target whose color changed rapidly from black to white. The test stimulus is a flashing box at 7 different frequencies (6 - 6.5 - 7 - 7.5 - 8.2 - 9.3 - 10 Hz) presented on the monitor. All EEG data were recorded using three electrodes (Oz, Fpz, and Fz) from the standard international 10-20 system for electrode placement. The sampling frequency of the EEG signal is 512 Hz. The reference electrode was positioned in Fz with the signal electrode in Oz and Fpz in

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the ground electrode. The dataset was acquired through four sessions, i.e. one session for each participant. Each session was conducted with three identical experiments. Each experiment yielded EEG data for seven frequencies with short breaks among them and took 30 seconds. In addition, an analog notch filter was applied to the data obtained at interference frequency (50 Hz) [11].

B. Convolutional Neural Network Architecture

Convolutional Neural Network (CNN) is a kind of deep learning algorithm based on artificial neural network (ANN) architecture which is inspired by the brain working system that includes many hidden layers [12]. Conventional neural network technique basically includes three layers: input layer, hidden layer, and the output layer. An ANN includes more than three layers that have several hidden layers in its structure. In the hidden layer which includes many neurons, the input is transformed into something that the output layer.

Many algorithms related to ANNs have been developed and used in many research areas. On the contrary a conventional ANN, CNN is an extremely deep ANN in which layers have neurons arranged in three dimensions (width, height, depth) [13]. CNN are designed to recognize and discriminate visual patterns directly from pixel images with minimal signal processing.

Currently, various CNN algorithms are available such as AlexNet, GoogLeNet, SqueezeNet, and ResNet. Among them, one of them is so popular nowadays: GoogLeNet architecture beacuse of the first CNN architectures to recede from stacking the convolution and pooling layers in a consecutive structure. It consist 22 layers with specific functions. Besides, GoogLeNet CNN model has an advantage with respect to memory and power usage [14]. For this reason, in this study we used GoogLeNet Deep CNN model for effective signal processing. Scope of this study, we set a CNN model which is shown in Fig.1.

C. Implementation Details

In the data used in this study, there are a total of 15360 samples (512 Hz) in a 30-second recording for each session. We extracted the spectrograms of the SSVEP data as 1 spectrogram photograph in 160 samples. The total number of spectrogram photographs for 7 frequencies is 2016. Then, the GoogLeNet model was created using the Matlab Toolbox named Deep Learning Toolbox. The dataset was divided into 70% training dataset and 30% validation dataset. Validation of the model was performed by randomly giving validation datasets during training. The signal processing flowchart performed in this study is shown in Fig.2.

III. Results and Discussion

We tested our GoogLeNet Deep CNN model on publicly available AVI SSVEP Dataset [11]. The proposed GoogLeNet Deep CNN model was divided into two modes which are training mode and validation mode. The GoogLeNet model is trained during training mode before it can be employed to

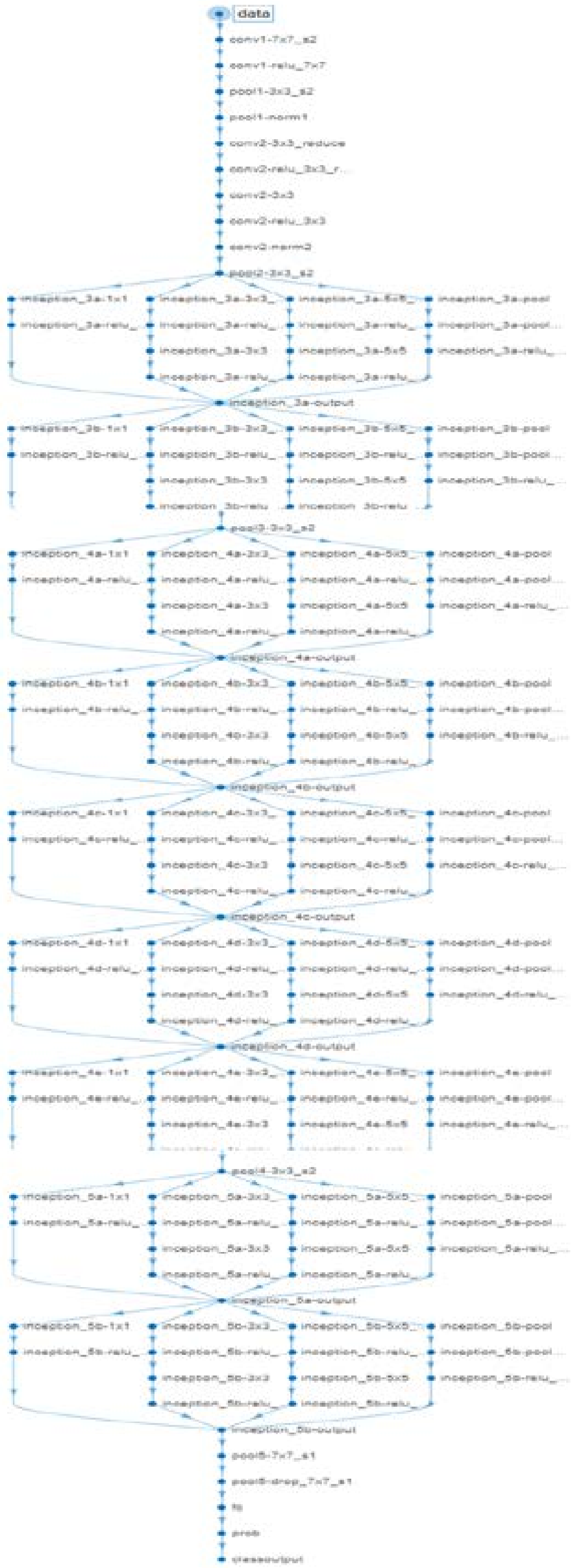

Fig. 1. GoogLeNet Deep CNN Model

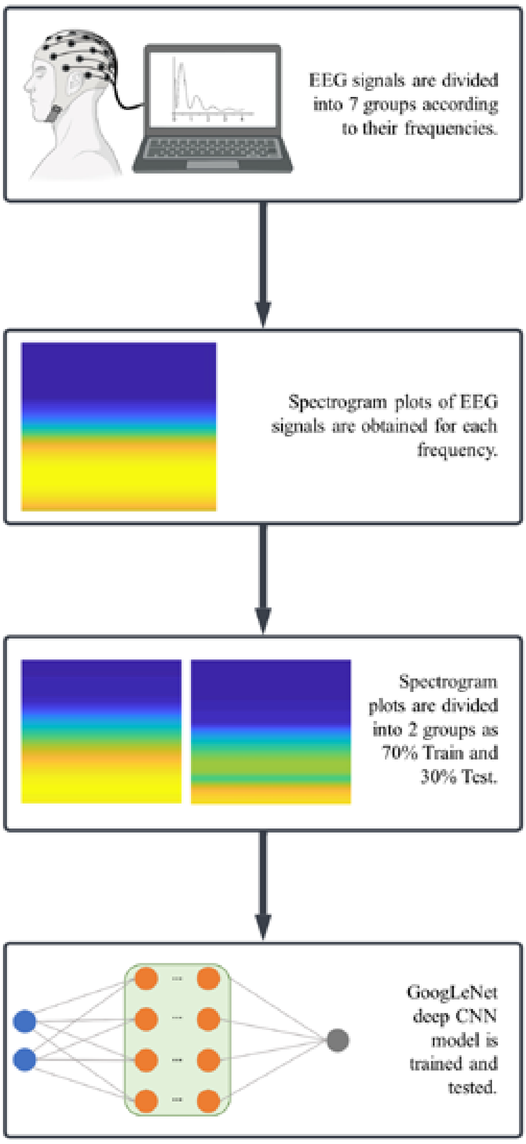

Fig. 2. Process of the training CNN model.

predict the SSVEP frequencies in the operation mode. A lot of testing experiments were conducted to find out the optimal setting parameters of the model which can be applied in the real-time operation mode. From the analysis, considering the reliability of the system, the proposed GoogLeNet Deep CNN model is observed to achieve best performance of 91.28% accuracy in 8.2&10 Hz frequency pair in Subject 3's data which is presented in Table I. In addition, the state-of the-art methods have been previously tested on this dataset [4], [6], [9], [10], [15], and in our evaluations, we compare against specifically those that have been reported to perform well.

Experimental results showed that, considering the four participants, the accuracy values varied between 44.19% and 91.28%. In addition, high accuracy values were obtained in

TABLE I
CLASSIFICATION PERFORMANCE OF GOOGLENET ARCHITECTURE

Frequency Pairs (Hz)	Subjects' Accuracy Values (%)			
	S1	*S2*	*S3*	*S4*
6 & 6.5	61.63	61.05	58.72	64.53
6 & 7	83.14	53.49	60.47	53.49
6 & 7.5	73.84	59.30	80.81	56.40
6 & 8.2	86.05	80.81	52.33	54.07
6 & 9.3	75.00	53.49	53.49	73.84
6 & 10	86.63	58.72	83.14	60.47
6.5 & 7	57.44	58.14	52.91	44.19
6.5 & 7.5	59.49	70.35	72.67	66.28
6.5 & 8.2	56.92	**85.47**	63.95	50.00
6.5 & 9.3	56.41	54.07	53.49	50.58
6.5 & 10	65.13	70.93	77.91	49.42
7 & 7.5	55.23	52.33	70.93	59.88
7 & 8.2	51.15	55.23	65.12	52.91
7 & 9.3	50.58	62.21	53.49	59.88
7 & 10	76.16	55.81	68.60	58.14
7.5 & 8.2	51.16	58.72	87.79	70.93
7.5 & 9.3	55.81	54.65	79.65	**79.65**
7.5 & 10	62.79	51.74	54.07	72.09
8.2 & 9.3	52.91	72.67	59.30	54.65
8.2 & 10	**87.18**	62.21	**91.28**	53.49
9.3 & 10	76.16	57.56	81.98	50.00

different frequency pairs. So the results generally differed from person to person. The performances of the participants were obtained as a result of the analysis as follows: the proposed method achieved the highest accuracy of 87.18% in 8.2&10 Hz frequency pair in Subject 1, 85.47% in 6.5&8.2 Hz in Subject 2, 91.28% in 8.2&10 Hz frequency pair in subject 3, and 79.65% in 7.5&9.3 Hz in Subject 4 respectively. As shown in Figure 3, the proposed GoogLeNet-Deep CNN based classifier obtained highest accuracy performance of 91.28% in 8.2&10 Hz frequency pair.

In addition, the subjects were compared among themselves, the best results was obtained in Subject 3, Subject 1, Subject 2, Subject 4, respectively. It is an indicator of whether people can focus on the image at the frequency shown during the experiments, which is effective in their individual performance.

On the other hand, the results were evaluated in terms of frequency pairs which include a total of 21 combinations of them. We obtained that the 8.2 & 10 Hz frequency pair gave valuable results that can be used in real-life applications as a command in both subjects 1 & 3. And also the accuracy values of all subjects were compared, it was analyzed that frequency pairs with a frequency difference of $\sim$ 2 Hz like 8.2&10 Hz, 7.5&9.3 Hz, 6.5&8.2 Hz were more successful. These results demonstrate that GoogLeNet Deep CNN model

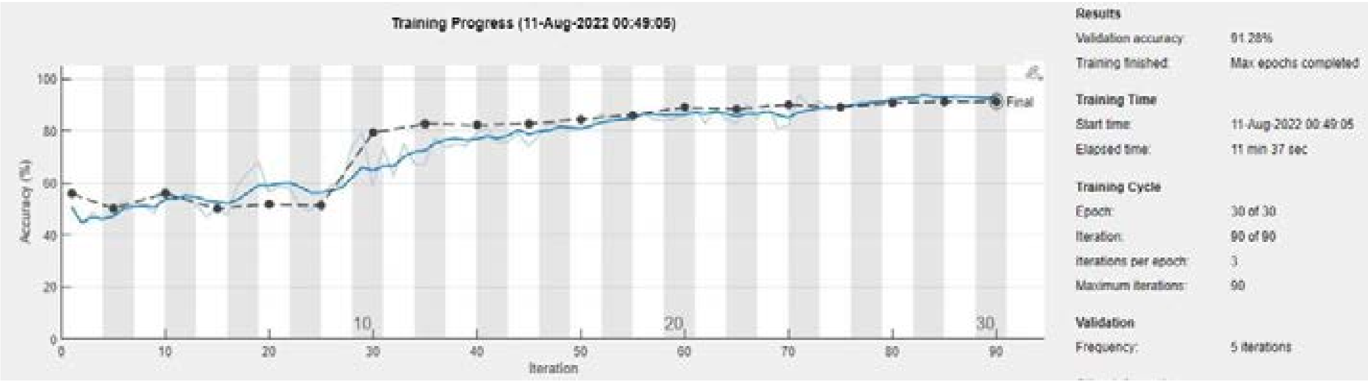

Fig. 3. Training Result.

based approaches could use the new benchmark technique for SSVEP classification.

IV. Conclusion

SSVEP based BCI systems could provide high accuracy, but requires a complicated set-up and long-continued signal processing phase prior to use, which could be a challenge in real-world applications. The recent study aimed to develop a practicable and simple BCI system considering real-life feasibility based on the SSVEP signals. For this reason, tending to simplify the system, we used only one signal channel (Oz) dataset and a simple SSVEP frequency detection approach based on GoogLeNet Deep CNN model was introduced.

In this paper, as mentioned earlier, we introduced a deep convolutional neural network architecture, which called GoogLeNet Deep Learning model, constructed around a common computational building block, for the classification of SSVEP data. Then we evaluated the performance of our model on SSVEP data recorded from four subjects. As compared with current state-of-the-art methods like machine learning algorithms, our approach requires no preprocessing stage, no feature extraction stage and also it demonstrates high overall classification accuracy across subjects.

Finally, the experimental results show that the proposed method can be used as an accurate and robust system in real-time BCI applications. Besides, further studies will be performed to investigate the SSVEP frequencies that the proposed BCI can detect with a relative high performance to extend its feasible application and also would involve larger datasets the classification and generalisation performance. Last but not least, the combination of the GoogLeNet Deep CNN and some other models may also suggest a way to boost overall performance.

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