FACULTY OF APPLIED SCIENCES
UNIVERSITY
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STUDENT
SCIENTIFIC CONFERENCE 2023

Classification of Event-Related Potential Signals with a Variant of UNet Algorithm Using a Large P300 Dataset

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1 Introduction

An EEG-based event-related potential (ERP) is a signal that can detect high-level cognitive activity in the brain stimulated by specific events, which has various applications, such as object detection and medical diagnosis. In this study, we concentrated on the visual P300 ERP, which is simple to set up and widely used in developing BCIs compared to other BCI paradigms. P300 refers to a spike in activity that occurs 300 ms after the target stimulus is presented. There is a challenge in classifying the P300 events with sufficient accuracy to facilitate effective communication. Classifiers are designed to distinguish between two types of brain responses: those triggered by the stimuli a user is focused on (target) and those caused by two other stimuli the user is attempting to ignore (non-target). Preprocessing, feature extraction, and classification are typical processing steps for P300 component detection. Early researchers usually used traditional machine learning algorithms as classifiers to distinguish P300 signals; Using such approaches entails intense preprocessing, leading to poor performance due to their limited representation. Recently, deep neural networks have been extensively used by scholars to extract features automatically. This paper's primary contribution is evaluating a variant of the UNet algorithm for classifying P300 BCI data. The UNet architecture consists of an encoder-decoder structure, which results in a U-shape. This network includes down-sampling, up-sampling, and skip connection segments. Features are passed from the encoder path to the decoder path using skip connections to recover the spatial information lost during down-sampling. Although this network structure was designed for 2D image segmentation tasks, it would be an effective tool for signal classification since its excellent adaption to 1D time-series data has been demonstrated.

2 Methodology

The following steps of data preprocessing were applied to the dataset: **1.** ERP trials were extracted from each participant of the experiments. These epochs, which are available in (Mouček et al., 2017), are connected with two stimuli, one of them was the number that the person was focusing on (the target), and the other one was randomly chosen from the other numbers that ranged from 1 to 9 (the non-target). A time window of 1200 milliseconds was used, starting 200 ms before the stimulus and ending 1000 ms after it. The prestimulus interval of -200 to 0 ms was considered for baseline correction. This resulted in an 11 532 × 3 × 1200 (number of epochs × number of EEG channels x number of samples) data matrix. **2.** The amplitude threshold was set to 100 µV to avoid epochs that have been significantly affected, usually by eye blinks. Therefore, approximately one-third of epochs were removed. The feature extraction method was based on averaging time intervals of interest, and the averages across all EEG channels were combined (windowed means feature extraction, WM). The time window for P300 BCIs is typically between 300 ms and 500 ms after the stimulus, which was split into

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20 equal segments. The mean and variance were adjusted to zero for these feature vectors as a final step. Before classification, 25% of the samples were separated for testing purposes, and the remaining 75% was utilized for training. Five hundred iterations of Monte Carlo cross-validation (CV) were performed to optimize parameters. After each cross-validation, the outcomes of the holdout testing set were determined, and the mean of the results was taken at the end of the processing. The 1D-UNet model (a kind of Convolutional Neural Network (CNN)) used in this paper was implemented in Keras. The network has a U-shaped architecture because it has both contracting and expansive paths. The path that contracts is a typical convolutional network consisting of repeated convolutions, rectified linear units (ReLU), and max-pooling operations. The spatial information is decreased while feature information is increased during the contraction. Using a series of up-convolution and concatenation, the expansive pathway integrates high-resolution characteristics from the contracting path with feature and spatial information. Our proposed UNet has 56 layers. The encoder includes conv1d, batch normalization, leaky relu, and max pooling layers. The decoder consists of upsampling, concatenate, conv1dtranspose, batch normalization, and leaky relu layers. We use flatten, dropout, and dense layers for the final layers. For the first four dense layers, the Relu function is employed, and for the final dense layer, the softmax function is used. The following hyperparameters are used: Adam optimizer, Binary cross entropy loss function, learning rate value was 0.001, the number of epochs was 500, and batch size was 1200.

3 Results

The primary objective of the current research was to apply a type of 1D-UNet for the classification of P300 BCI data. Raw ERP epochs were used for this model (with the dimensionality of 3×1200) from three EEG channels (Fz, Cz, Pz). The accuracy and precision of this model were 64.5% in the single trial, which was the best result after modifying the hyperparameters. The comparison of our proposed method with previous methods is shown in Tab. 1, which contains the accuracy and precision of each model applied to this dataset. The result we achieved is comparable with state-of-the-art.

Method	Accuracy	Precision
My proposed method (UNet)	**64.5%**	**64.5%**
CNN (Vařeka L (2020))	62.18%	62.76%
RNN (Vařeka L (2020))	56.92%	57.61%
SNN (Honzík V, Mouček R (2021))	63.43%	64.47%

Table 1: Table sample

References

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