Detecting P300 ERPs with Convolutional Networks

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Introduction: It is well known that there is considerable variability in P300 Event-Related Potential (ERP) detection accuracy across individuals and even day-to-day for one individual. The location in time and the shape of the P300 can even vary from trial to trial. Convolutional Neural Networks (CNNs) have been shown to learn small patches of pixel intensities that occur at varying locations in order to identify objects in images. Similarly, CNNs can learn small sequences of EEG that occur at varying times to support the detection of P300s [1]. Here we present initial results of CNN classification of EEG recorded during brief visual presentations of single letters as the subject is counting the occurrences of target letters in order to elicit P300s. The CNN is found to perform better than linear discriminant analysis and fully-connected neural networks.

Material, Methods and Results: EEG data were collected at 1024Hz using the Biosemi ActiveTwo system. Sixteen participants volunteered including nine participants with no impairments in a laboratory environment and seven participants with severe motor impairments in the participants' homes. A total of 120 target trials and 360 non-target trials were collected from each participant. Eight channels were selected and the EEG signals were preprocessed using a linked-earlobe reference and a zero-phase bandpass filter from 0.5-20Hz followed by downsampling to 64Hz. Classifier hyper-parameters were tuned using 10 repetitions of 80% random subsampling validation over the first 2/3 of the data while the final 1/3 was reserved for testing generalization performance. Three classification methods were compared: 1) Regularized Linear Discriminant Analysis (LDA). 2) A Neural Network (NN) with 30 hidden units and softmax visible layer. 3) A CNN with two convolutional layers each consisting of 10 hidden units with a width of 10 along the time axis and 2:1 decimation. The convolutional layers are followed by a fully connected layer with 10 hidden units and a softmax readout layer. The NN and CNN were regularized using early stopping. The test single-trial balanced classification accuracy (balanced accuracy = average of target percent correct and non-target percent correct) averaged across all participants was 71.52% for LDA, 71.77% for NN and 75.22% for CNN.
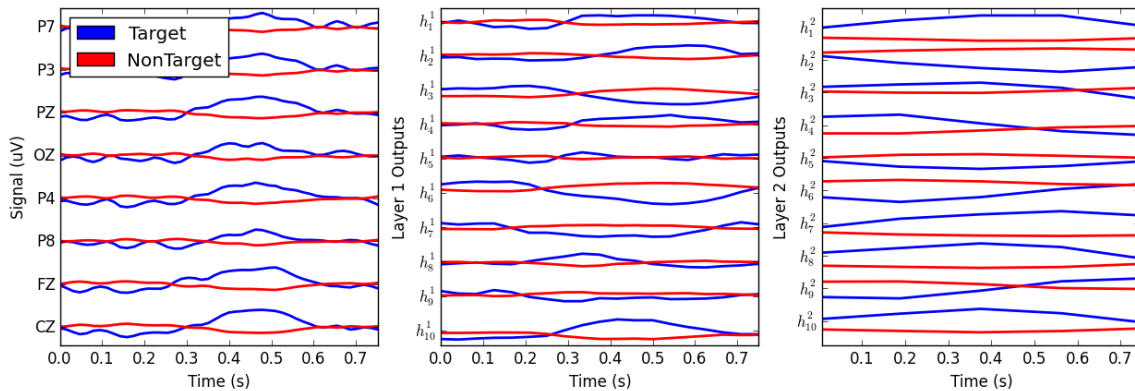
Figure 1. Left) The mean target vs non-target signal values for each channel. *Center)* The mean response for each hidden unit in the first convolutional layer. *Right)* The mean response for each hidden unit in the second convolutional layer.

Discussion: Fig. 1 shows the mean target and non-target signals and the mean response of each hidden unit in each convolutional layer for a single participant. In the first layer, it appears that each hidden unit isolates various components of the ERP, highlighting some early and mid-course components. As the signal progresses to the second layer, considerable separation is seen between target and non-target, especially near the center of the segments where the P300 waveform is typically observed.

Significance: Initial results suggest that CNNs perform slightly better than standard approaches. More sophisticated regularization methods, such as L2 or L1-norm penalties or dropout, as well as further exploration of network architecture may lead to additional performance improvements.

References
[1] Cecotti, H.; Graser, A., Convolutional Neural Networks for P300 Detection with Application to Brain-Computer Interfaces, in *Pattern Analysis and Machine Intelligence, IEEE Transactions on* , 33(2): 433-445, March 2011.