Enhancing Error Related Potentials Classification Using Data Augmentation

The seminar will be given in Hebrew

Brain computer interfaces (BCIs) are systems which allow their users to control a variety of electronic devices directly from brain activity. One way to measure brain activity is by placing non-invasive electrodes on the scalp, a method known as Electroencephalography (EEG). EEG can be used to detect Event related potentials (ERPs) which are responses to specific events. Previous EEG researches revealed ERP evoked in response to errors during continuous reaching movements, known as Error-related potentials (ErrPs). ErrPs can be integrated with conventional BCIs to form a hybrid-BCI system that can take corrective actions on the detection of ErrPs to prevent the erroneous action from being executed, ultimately improving the efficiency of the BCI. ErrPs classification is challenging due to the low signal to noise ratio, and, since BCI experiments vary across different trials, sessions, and subjects. In addition, the lack of sufficient number of observations limits the ability to train classifiers with a good generalization. This research focuses on the enhancement of ErrP classifiers using data augmentation. Statistical models of available experiments, with limited number of erroneous trials, were used to create generative models that can mimic the statistical behavior of these trials. The first model considers the ErrP signal as the synchronized average of the available trials since the on-going EEG signal is not synchronized to the erroneous event and thus, can be treated as an uncorrelated noise. The second model also acknowledges the possibility of trial-to-trial variations of ErrP latency. The generative models were tested under synchronous and asynchronous ErrP classification using popular classification algorithms in ERP studies including Bayesian discriminant analysis. The Conclusion is that the integration of these models can enhance the asynchronous classification score of ErrPs by balancing the bias and variance errors of the classification models.