Transfer Learning for Online Error Detection in P300 Speller

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I. Introduction

In brain-computer interface (BCI) system, online error detection and correction of misinterpreted commands may improve the bit transfer rate of the system and increase users' satisfaction. Two major challenges in developing the system are: (1) the search of salient features for error detection from EEG signals and (2) variability of EEG across subjects in terms of baseline activity, brain folding, and electrode location.

This study explores the usage of various features, including error potentials (ErrP), common spatial patterns (CSP), and wavelet decompositions. To mitigate the problem of increasing feature dimensions, we use various sparse learning techniques. Transfer learning and classification techniques are applied in order to improve the performance of error detection in the P300 speller BCI.

II. EEG processing and analysis

The data we use for BCI speller error correction is provided through Kaggle as part of the IEEE Neural Engineering Conference (NER) 2015 BCI challenge and was originally collected by Perrin et al. (2012) [1]. In this P300 BCI speller experiment, 26 subjects participated in 5 sessions, each with 60-100 trials [1]. EEG recordings used 56 channels in the classical 10-20 set-up as well as 2 channels for EOG.

To preprocess the EEG data, we first bandpass filter from 1Hz to 40Hz before applying Artifact Subspace Reconstruction, an algorithm available in EEGLAB [2] for removing artifacts such as electrode shifting or jaw muscle clenching. We then downsampled the data to 80Hz. Finally, we epoched the data from 200 msec before to 600 msec after each feedback event so as to remove the baseline from each epoch using the time points before the feedback.

The tools we have used for feature extraction (in addition to the original time series data) are wavelet decompositions, common spatial patterns, and dictionary learning with sparse coding. Wavelets allow us to look at processes that may reside within a certain frequency band, as we suspect of the ErrP. Common spatial patterns provide an effective way to incorporate all the channels into a smaller number of features with higher discriminative power. These techniques are in no way mutually exclusive and can be applied in a cascaded fashion to provide new feature sets to try.

Our first choice of classifier to be used as a baseline is a support vector machine (SVM) on a conglomerate of all trials from all subjects. To deal with the large feature set we have created, we have made use of sparse learning techniques; in particular we have explored sparse logistic regression (SLR).

III. Preliminary results

At this time, there are no worthy results to report. We have results at a level of 0.5 area under curve (AUC) and 75% accuracy which is roughly the same as always saying the P300 speller is correct. That being said, we have not yet been able to implement all of the ideas we have explained above. We plan on using SVM and SLR to train an ensemble classifier where each classifier is trained on a unique subject, as well as one that will operate on all subjects and one for subjects that performed well with the P300 speller and one for the subjects that performed poorly with the same speller. These all feed into a top level classifier in an attempt to increase the transfer learning capability by making explicit the possible variations among subjects.

References

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