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Development of an SSVEP Brain Computer Interface Robust to Data Nonstationarity

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Introduction: This paper seeks to demonstrate methods to design SSVEP Brain Computer Interfaces (BCI) that are robust to nonstationarities in EEG data. EEG signals are generated by nonstationary random processes for multiple reasons including but not limited to outside noise and user fatigue. Traditional data collection using stationary distribution assumptions needs to be done frequently to compensate. However, a high volume of data is needed to ensure classification accuracy, and these goals often conflict when factors such as user fatigue introduce nonstationarity to the data distributions. One solution to this problem is to intelligently incorporate incrementally available data alongside past data to adjust for changes in the EEG's statistical information. In this paper, the use of the Learn++.NSE [1] algorithm is proposed as the foundation of a BCI system that is robust to nonstationarities in EEG data.

Material, Methods and Results: Single channel EEG data (OZ on the international 10-20 system) was collected from ten end users who completed a binary communication task using checkerboards flickering at six and twenty Hz (University of Pittsburgh IRB No. PRO15060140). The data was filtered using a 2-45 Hz FIR bandpass filter. Four dimensional feature vectors were constructed by measuring the power spectral density at the first two stimuli frequency harmonics for each checkerboard, and four usage sessions occurred to generate one hundred feature vectors each. The features were chosen due to the fact SSVEP stimuli frequency harmonics are often present in the power spectral density estimation. The first through third sessions were separated by at least three days while the third and fourth sessions happened consecutively. Several classification schemes were selected to test performance with incrementally available data. Among these were an ensemble learning algorithm where LDA was the base learner, an LDA classifier that adds new data with no consideration between previous and incoming data, and an LDA classifier considering only the most recent data. The Learn++.NSE algorithm was chosen for the ensemble due to its ability to incorporate new incremental data from possibly nonstationary sources.

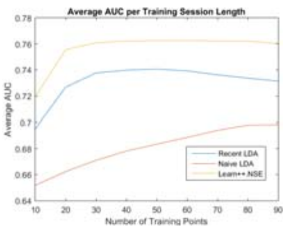

Figure 1- Comparison of the methods' AUC as a function of available training data. Results were averaged over ten participants.

The first two hundred vectors were defined as a base training set and were made available to all classifiers besides the recent LDA classifier. The one hundred vectors from the third session were divided into increments of ten. The last hundred vectors from the fourth session were used for testing. Each classifier was tested using each combination of $k = 1\text{-}9$ increments in addition to the base set as training data. The area under the curve (AUC) of the receiver operating characteristic curve was calculated on the test data set and averaged to obtain a performance estimate for the amount of data.

Discussion: Figure 1 shows the AUC as a function of data availability averaged over ten participants. In general the Learn++.NSE algorithm exhibited faster learning capability over the naïve LDA classifier. The figure demonstrates this capability as the accuracy increase per calibration segment was higher in the Learn++.NSE case compared to the naïve LDA classifier. The Learn++.NSE ensemble also had a positive AUC offset over the recent LDA classifier. These results indicate that the Learn++.NSE algorithm may offer responsiveness to nonstationarity while being able to utilize a previous knowledge base.

Significance: The findings from this offline study outline the foundation from which a robust BCI can be built. Learn++.NSE's ability to form classifier weights based on nonstationarity information contained in each member classifier results in the system's capability to respond to those nonstationarities. As Figure 1 shows, the AUC based on past and incoming information increases more quickly than blind consideration of all data received. Training data from past sessions also immediately increases performance over using only the most recent data. These combined results indicate that less calibration is needed to achieve a given performance level using Learn++.NSE over static classifiers. Assuming a nonstationarity due to user fatigue is induced at a fixed time, the system can be operated longer before that time is reached due to the lower calibration requirements. Lastly, the work shown here will also form the basis of an online learner that utilizes fuzzy labels to adjust to changes in EEG data.

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References
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