

Design and Development of a Haptic BCI

Karthikeyan Ganesan*, Karthiga Mahalingam, Melody Moore Jackson

*GT Brain Lab, 85, 5th St NW Atlanta, GA 30308. Email : karthikeyan@gatech.edu

Introduction: Brain Computer Interfaces (BCIs) traditionally deploy visual or auditory stimuli to elicit brain signals. However, these stimuli are not very useful in situations where the visual or auditory senses are involved in other decision making processes. In this paper, we explore the use of vibrotactile stimuli on the fingers as a viable replacement. Using a five-level Wavelet Packet feature extraction on the obtained EEG signals, along with a kernel Support Vector Machine (SVM) algorithm, we were able to achieve 83% classification accuracy for binary user choices. This new BCI paradigm shows potential for use in situations where visual and auditory stimuli are not feasible.

Materials, Methods, Results: The designed hardware consists of two Linear Resonant Actuator (LRA) motors which vibrate at two different frequencies, which are 5Hz apart (eg. 15 & 20Hz). The frequency of vibration is controlled by interfacing the motors to a Teensy 3.1 microcontroller. Real-time EEG signals are obtained at 250Hz through the OpenBCI acquisition system. The vibrating motors are placed on the fingertips to elicit steady state somatosensory evoked potentials (SSSEP). The 10-20 electrode placement system is used to collect EEG signals from F3,Fz,F4,C3,Cz,C4,P3,Pz, and P4 scalp locations. The obtained signals are bandpass filtered between 0.1Hz and 60Hz along with notch filtering at 50Hz. Further, the multi-channel signals are denoised with the multi-scale principal component analysis (MPCA) algorithm and decomposed with five-level Wavelet Packet decomposition [1]. Lower and higher order statistical features are obtained from each band of the decomposition. These features are then used in a downstream classifier for identifying user preferences. Higher order statistical (HOS) features along with a SVM classifier (Gaussian Kernel) are found to classify user choices with a classification accuracy of 83%. Figure 1 compares the performance of four classifiers on both lower order statistical (LOS) and higher order statistical (HOS) features.

Discussion: Results indicate that a combination of HOS features and a kernelized SVM algorithm act as an effective classification pipeline. Superior performance of HOS features indicate that the features are heavily-tailed Gaussian distributions. The kernel SVM algorithm is seen to perform better than other classifiers that model data to be a Gaussian distribution. This implies that features of one class are heavy left-tailed, whereas the corresponding features of the other class are heavy right-tailed.

Significance: This paper introduces a new type of haptic BCI and an associated algorithm that could be used where traditional stimuli cannot be used to fully capture user attention. The algorithm surpasses the current classification rate for a haptic BCI by 13% [2]. However, the lengthy pipeline of MPCA denoising, wavelet packet decomposition and kernelized SVM classification make it computationally less efficient and not viable for real-time usage. The efficiency of this algorithm can be improved by determining the optimal number of decomposition levels and exact sub-band that contains the most discriminating information, consequently reducing feature extraction time and execution time. Upon incorporating these improvements, the existing algorithm can be used in real-time haptic BCI systems.

Acknowledgements: The authors would like to thank the GT Brain Lab for providing the logistics and the National Science Foundation for funding this work (NSF Grant #1718705).

References:

- [1] Kevric J, Subasi A. Comparison of signal decomposition methods in classification of EEG signals for motor-imagery BCI system. *Biomedical Signal Processing and Control*. 2017 Jan 1;31:398-406.
- [2] Rutkowski TM, Mori H, Matsumoto Y, Cai Z, Chang M, Nishikawa N, Makino S, Mori K. Haptic BCI paradigm based on somatosensory evoked potential. *arXiv preprint arXiv:1207.5720*. 2012 Jul 24.

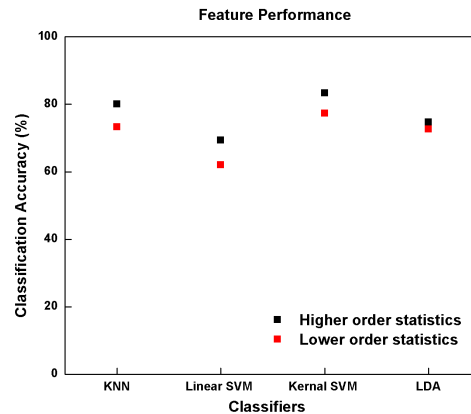


Figure 1: Performance plot of Lower and Higher Order Statistics