

Emotion Imagery BCI

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Introduction: A non-negligible portion of subjects has been shown to be unable to learn how to control a motor imagery (MI) based brain-computer interface (BCI), within a limited duration of training. There is a need for alternative imagery strategies for such users. In this study, imagery of self-induced emotion states were explored as an alternative to MI, using a standard motor imagery BCI paradigm and setup. Electroencephalogram (EEG) correlates of self-induced emotions have been previously used to recognize emotions, as in [1], and here, we hypothesize that emotion imagery (EI) can be used to modulate brain activity and used as a BCI control strategy. Preliminary results comparing the performance of three subjects ($N=3$, age range = 27-35) performing MI and EI are presented.

Material and Methods: EEG was sampled at 125 Hz from 16 channels across the cortex using the g®.Nautilus setup. Each subject underwent training with no feedback and feedback in a single session for both EI and MI in a typical MI timing paradigm, and feedback was provided using a game in which the character moved along the horizontal axis to complete the game challenge. One training run and one feedback run were performed for each imagery. In EI runs, participants recalled a real or imagined fictitious happy event and sad event for each class (left or right cue). For MI runs, participants were instructed to imagine left or right hand movement. Each run had 60 trials, 30 for each class.

After the first run of both EI and MI, leave-one-out cross validation (LOOCV) was conducted with a multistage signal processing framework which includes neural-time-series-prediction-preprocessing (NTSPP), spectral filtering (SF) in subject specific frequency bands and common spatial patterns (CSP) [2]. Features were extracted as log-variance of preprocessed EEG signals within a 2 second sliding window [3]. A linear discriminant analysis (LDA) classifier was then trained and applied in the feedback run.

Results: Offline LOOCV classifications accuracies (CA) for each run along with online single-trial CA results for run 2 and sample results from event-related (de)synchronization (ERD/S) analysis are reported (Table and Figure 1). The differences between EI and MI are not statistically significant ($p>0.05$) although the EI training results appear higher for all subjects. ERD/S analysis showed EI tasks separability in the temporal and frontal channels; visual separability happens after the cue (3 s). Most of the ERD or ERS appeared in the occipital and parietal electrodes; this can be seen on some of the topographic maps for subject 3 shown in Figure 1.

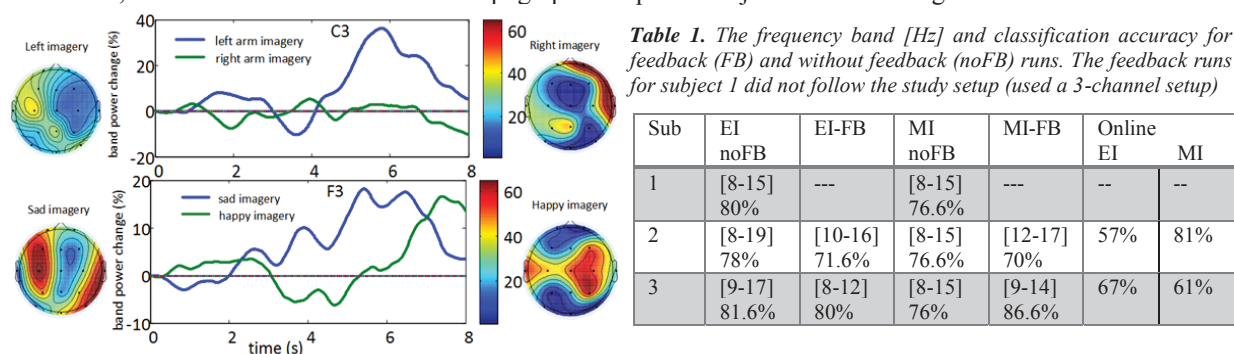


Figure 1. Band power change (%) respective to the baseline in feedback MI and EI runs for subject 3 in the bands [9-14] and [8-12] Hz is shown for two channels (C3 for MI and F3 for EI). Activity in other channels can be seen in the shown topographic maps for [4-6] s interval.

Discussion: These preliminary results show that EI can be used in the same way as MI; Wilcoxon signed rank tests showed no significant difference in MI and EI. However, more analysis needs to be carried out with a larger sample of participants and multiple training sessions. The subject “2” is an experienced/expert MI participant and performed well in online CA of MI but had poor performance in EI. Subject “3” on the other hand, the online EI performance is slightly higher than MI.

Significance: The results show for the first time that emotional imagery may be used as a replacement to motor imagery. Further validation is required to determine if emotion imagery could be used by BCI users who do not perform well with motor imagery.

References

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