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Improving Motor Imagery BCI with User Response to Feedback

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Introduction: It is well understood that feedback affects subject performance in motor imagery (MI) BCI [1]. However, there is still little evidence about how the response to feedback changes the MI signal, and whether the feedback signal can be used to classify MI more accurately. In this work, we show that feedback response and MI signals are both carried in similar frequency bands and investigate ways to improve MI classification.

Methods: EEG data were collected from 7 subjects asked to control a cursor with right and left hand motor imagery who were shown sham cursor movement as visual feedback. The cursor moved every 600 ms based on a pre-determined movement pattern *unrelated* to subject performance. The sham feedback (of which the subjects were unaware) is critical to examine the role of visual feedback on user's MI. Since the sham feedback is independent of the MI, any relationship between the MI signal and the visual feedback is due to a causal effect of the user's response to visual feedback on the read MI. A total of 6 spatial filters (3 per class) were chosen through common spatial patterns (CSP) [2] and the log power of the filtered signals were classified with linear discriminant analysis (LDA) trained with 10-fold cross-validation.

Results, and Discussion: Figure (1) shows classification results and standard error of classification rate for four of our subjects (including 3 of our best) the cyan line shows the significantly above chance level ($p = 0.05$) based on the number of trials [3] and the green line indicates 0.5 level. RvL indicates classifying between right versus left MI. GvB indicates classifier performance for a classifier trained to distinguish whether the last cursor movement was in the desired (Good) or non-desired (Bad) direction. Notice that GvB classification was successful in similar frequency bands as RvL classification [4] meaning that the information about whether the subject "liked" the movement or not may be confounded with the computer's read out MI signal. We hypothesize that a state-of-the art CSP feature extraction and LDA classification - i.e., solid black line on figure (1) - is in fact affected by feedback and there is potential to improve the standard procedure. We applied logistic regression to the output of GvB and RvL classifiers where we trained two distinct classifiers for when the cursor moves to the left or to the right; that is, to directly take into account the observed cursor movement. Results are shown with magenta line on figure (1). The combined classifier is able to improve the RvL in the frequency bands that GvB classifier is above chance level (~~ for p<0.1, * for p<0.05 and ** for p<0.01). Subjects received no training with real feedback (only the unrelated sham feedback), which may explain the overall low accuracies.

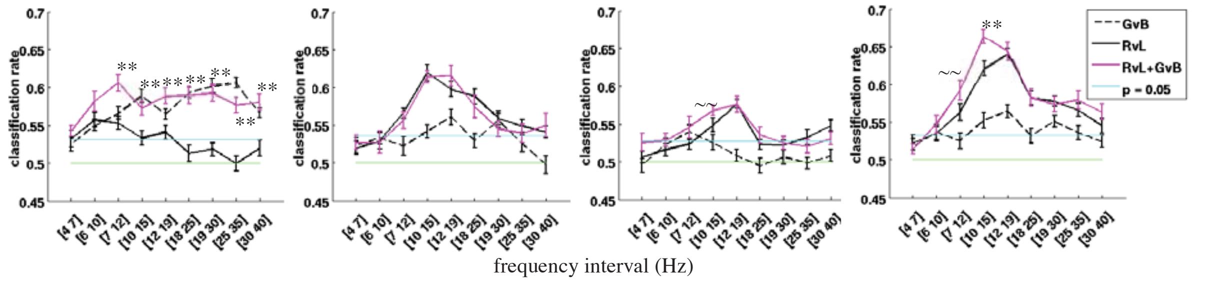

Figure 1. *Figures show correct classification rate versus frequency band for four subjects. Note that the RvL and GvB classifiers have above chance performance in similar frequency bands.*

Significance: The work shows that feedback response and MI signals are present in the same frequency bands that are used for MI classification. We proposed to apply logistic regression to combine RvL and GvB classifiers as a potential way to alleviate the effect of visual feedback. As GvB classification is more robust to non-stationary distributions [5], future work will investigate more sophisticated methods for combining these signals (Supported by NSF grants IIS 1219200, SMA 1041755, IIS 1528214).

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