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Comparative covariance example selection: a weak labelling approach to MI BCI classification

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Introduction: Motor Imagery (MI) Brain computer interfaces (BCI) require a significant training period to train the user and the BCI system. The effectiveness of this training can be increased by providing feedback to the user [1], however if the feedback is incorrect, it can cause the user to perform "incorrect mental tasks". Labeling these examples as correct examples will negatively affect system performance and not knowing where after the cue these poor examples are creates a weak-labeling multi-instance learning problem [2]. In this paper we propose a method to select correct examples to train MI systems.

Material, Methods and Results: We opted to use a filter matching approach to select what we believe to be correct examples. After applying a 4-40Hz 4th order butterworth filter, each participant's cross-sessional left- and right-hand mental tasks were segmented into 1 second epochs. A "perfect" example of mu rhythm event related de-synchronization with the same epoch length is then generated by creating a sinusoid for each channel at 10Hz to mimic alpha activity using the equation $x_n = \sin((2\pi n f)/fs)$ where f is the desired frequency and fs is the sampling frequency of our signal. Using the same equation the channels C2 & C4 for left examples and C1 & C3 for right examples are set to a sinusoid at 20 Hz, mimicking the beta activation seen in motor imagery. We can then score the similarity between the cross channel covariance matrix of each example and the "perfect" example covariance matrix using the forbinius inner product ($score \subseteq \mathbb{R} = tr(\bar{A}^T B)$).
After normalizing each participants instruction scores we then select all examples with a score above a threshold. Applying this method to the Physionet BCI2000 motor imagery dataset [3] and selecting 15 electrodes over the motor cortex with a score threshold > 0.5, we achieved a statistically significant increase in a 5 fold classification accuracy compared to not selecting examples ($p < 0.05$, wilcoxon signed rank test) for each participant using a simple 4 component common spatial pattern (CSP) transformation followed by a linear class balanced SMV (Figure 2). A simple CSP classifier was chosen to assess the effectiveness of the proposed method and provide spatial information on the selected examples (Figure 1).

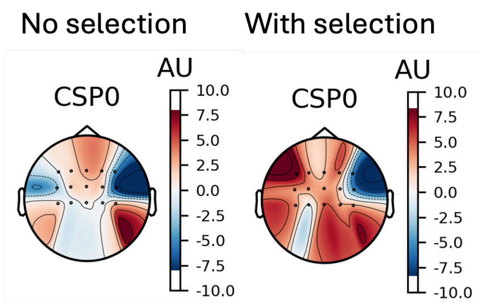

Figure 1: *CSP pattern plots of left and right hand motor imagery sets. Left is all examples while right is with example selection*

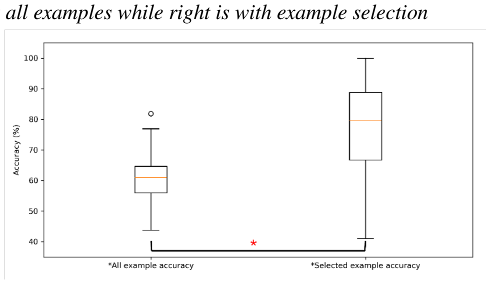

Figure 2: *Boxplot of classification accuracies per participant with and without example selection. * indicates a significant difference*

Conclusion: The findings of this study suggest that example selection methods can improve classifier accuracy and may provide more accurate feedback to the user during human in the loop MI BCI training. Further testing is required to assess the effectiveness during training and how it effects the accuracy of more complex classifiers.

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