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# Feature selection algorithms to optimize corticomuscular coherence-based BCI for hand motor rehabilitation

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*Introduction:* Recently we explored CorticoMuscular coherence (CMC) as control feature for a hybrid Brain-Computer Interface (BCI) for post-stroke rehabilitation. Results highlighted how the CMC was effective in (i) detecting movement attempts with high classification speed and accuracy [1][2] and (ii) capturing motor abnormalities in stroke patients [3]. Identifying the optimal CMC control features, i.e. couples of electroencephalographic (EEG) and electromyographic (EMG) channels, is mandatory for rehabilitation protocols supported by a hybrid BCI. Here we explored the CMC feature selection process in a sample of healthy participants performing right hand finger extension, comparing two feature selection algorithms: the stepwise regression (SW), already validated in [4] as effective approach in selecting features for a sensorimotor-rhythms based BCI supported motor imagery training, and the decision tree (DT) because of its ease of interpretation.

*Material, Methods and Results:* EEG (61 channels, 1000Hz) and EMG (8 channels per side, 2000Hz) data were collected from 16 healthy participants while performing 20 trials of right hand movement and 20 trials of rest. EEG and EMG data were pre-processed and CMC was evaluated for each pair and frequency band ($\alpha$ 8-12 Hz, $\beta$ 13-30 Hz, $\gamma$ 31-60 Hz) as in [2]. The original feature space for each participant was composed by CMC values extracted for each EEG-EMG couple, trial and band. According to neurophysiological and rehabilitative principles, we reduced such space to the CMC couples considering only the EEG channels over the sensorimotor strip (FC, C, CP, and P electrodes) and EMG from target muscle. The SW and DT algorithms were optimized in their setting parameters and tested in the framework of a 10-iterations cross-validation on the reduced feature space. For each iteration, we shuffled the trials and used 80% of the trials as training set and the remaining 20% as testing set. A linear kernel support vector machine and a decision tree classifier were used as classification models for the SW and DT, respectively. Classification accuracy, sensitivity and specificity were computed for each algorithm and band and statistically compared via 2-way repeated measure ANOVA (within main factors: ALGORITHM - 2 levels and FREQUENCY BAND - 3 levels). Both algorithms returned classification accuracy higher than 90% with no significant differences ($F(1,15)= 0.241$, $p>0.05$). Conversely, statistical differences were found in terms of sensitivity where DT outperformed SW ($F(1,15)=10.8$, $p<0.01$) and specificity where SW outperformed DT ($F(1,15)=13.7$, $p<0.01$). No differences were observed for the FREQUENCY BAND factor. As for the selected features, we computed for each algorithm and frequency band how many times each CMC feature was selected across participants and iterations. Figure 1 shows a spread-out scalp distribution of the features selected by DT. Conversely, the CMC features selected by SW (Fig.1) resulted more consistent across participants and prevalent on the hemi scalp contralateral to the moved hand.

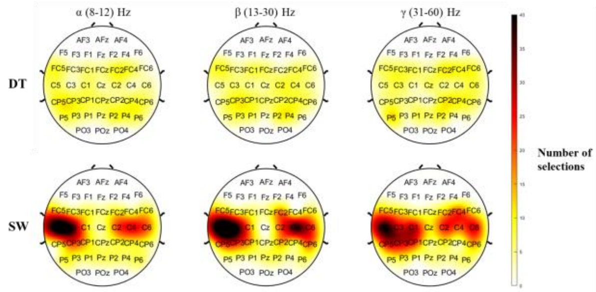


***Figure 1**. Scalp distribution (n=16 healthy participants performing the finger extension of the right hand) of the CMC features selected (EMG counterpart on the target muscle) by means of the Stepwise Regression (SW) and Decision Tree (DT) algorithms for each frequency band ($\alpha$, $\beta$ and $\gamma$, column). The colour codes for the times each feature was selected across participants and cross-validation iterations*

*Discussion:* Stepwise regression algorithm returned high (90%) classification accuracy, selecting features consistently across healthy participants. The scalp distribution of the most selected features reflected the neurophysiologic assumption of contralateral sensorimotor cortical involvement during hand motor tasks. Future studies will evaluate the algorithms behaviour with patients' data, to best fulfil neurorehabilitative requirements.

*Significance:* This work provides hints to optimize the CMC-based BCIs feature selection for post-stroke rehabilitation.

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