MACHINE-LEARNING FOR EXTRACTING NEURONAL SIGNATURES OF NATURAL MOTOR COMMANDS FROM SINGLE-TRIAL MULTI-CHANNEL EEG DATA IN UNTRAINED SUBJECTS

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The Leitmotiv of our BCI approach is 'let the machines learn', i.e., we aim to minimize the need for subject training while the major learning load imposed on two coupled adapting systems (human subject and computer) is to be accomplished by the machine. Key ingredients in our approach are (1) a behavioral context in which the subject can use well-established motor competences overlearned in daily life, which (2) are embedded in a 'naturalistic' BCI design, while (3) in the background the algorithmic flow is controlled by state-of-the-art machine learning (ML) techniques that extract relevant information from high-dimensional noisy EEG data. Concerning the selection of brain signals, we presently investigate event-related potentials (ERPs), with a focus on non-oscillatory lateralized pre-movement potentials. Our analyses suggest that here the classification problem of discriminating ERPs characteristic for different intended motor outputs is linear: the use of linear models results in better classification generalization as compared to more complex non-linear models if the number of training samples is limited as it is typically the case in BCI paradigms. Ongoing studies analyse two different ERP types: 1) We predict the laterality of imminent left vs. right hand finger movements in a natural keyboard typing condition: when classification is based on the lateralized Bereitschaftspotenzial, 5 of 10 subjects, who all were untrained for BCI, achieved a theoretical information transfer rate of greater than 15 bits per minute (bpm), and further 4 subjects reached 6-10 bpm. 2) We detect cerebral error potentials from single false-response trials in a forced-choice task (d2-test), reflecting the subject's recognition of an erroneous motor response: based on a tailor-made classification procedure that allows to bound the rate of false positives at 2%, the algorithm manages to detect 85% of error trials in 7/8 subjects. The design here is to concatenate such error detector to the output of a BCI-classification of intended motor actions: the latter, as a 'first-pass' classification, is fed back instantaneously so that the subject's brain can detect eventually erroneous classifications, 'label' them by emitting an error potential and thereby initiate an on-line 'second-pass' BCI-reclassification to raise the BCI bit rate.

These results of our ERP-ML approach constitute an interesting BCI benchmark adding to established techniques working with feedback of slow cortical potentials or brain oscillations.