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Classification of motor imagery with distractions

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Introduction: In order to be operative in everyday life situations, BCI research needs to leave the very controlled lab environment and be adapted to real world scenarios. Therefore, we recently conducted a systematic motor imagery-based BCI study where participants not only had to imagine left and right hand movements but also had to deal with five different distraction tasks, simulating a pseudo-realistic environment. Since standard CSP analysis led only to poor performance rates, we now propose a 2-step approach where we want to find out first which distraction task was applied in a particular trial and then apply a classifier trained on the respective distraction task to determine whether a left or right hand motor imagination was conducted.

Material, Methods and Results: We recorded 16 healthy participants and used the best 8, who reached performance above chance level, for further analysis. The volunteers performed left and right hand motor imagery (MI) tasks while also watching a flickering video, searching the room for a particular number, handling vibro-tactile stimulation, listening to news or closing their eyes. Detailed description of the study can be found in [1]. The experiment was divided into 7 runs, the first containing pure MI tasks without any distractions which we used for calibration. After basic preprocessing, we used Common Spatial Patterns (CSP) [2,3] for feature extraction (3 per class) and used the first run to train an LDA-based classifier [4]. Testing on the remaining 6 runs (containing MI+distraction) only led to low performance results. One reason for that might be the major feature shifts between training and testing due to the different distraction tasks [1]. Performance rates already increased when we computed one classifier for each distraction such that training and testing data contained the same tasks. After further analysis, we discovered that one can easily separate the tasks where participants were searching the room (numbers) from the remaining tasks (1 CSP filter per class). Muscle artifacts resulting from turning the head are one of the main reasons for that. Therefore we used a 2-step approach where we first tried to determine in which of both groups the trial was conducted and then used one of two classifiers, trained on the respective group, to decide whether a left or right hand MI had been carried out. Classification rates for this 2-step approach can be found in Table 1. Comparing those results to our original approach, the overall classification rates increased by around 9%. In Figure 1 we plotted performance rates in both groups for our original approach against the ones for the 2-step approach. Except for smaller deviations the 2-step approach clearly outperforms standard CSP analysis. Alternative grouping scenarios led to lower performance rates.

	csp	od	njy	njz	nkm	nko	nkq	nkt	obx	overall
	overall	94.91	70.60	77.08	69.68	83.53	71.40	77.55	87.50	79.03
1st step	**cond**	99.31	94.68	96.06	79.40	94.87	98.59	97.69	99.07	94.96
2nd step	**numbers**	83.56	45.33	66.67	59.70	75.64	47.83	70.31	75.00	65.51
	not numbers	97.21	75.91	79.06	71.51	85.27	75.90	78.80	90.00	81.71

Table 1. *Classification rates for all 8 participants: 'overall' contains weighted average classification rates of the 2nd step, 'cond' marks the 1st step to separate the data into numbers and not numbers tasks. Results for the 2nd step are represented in the last two rows.*

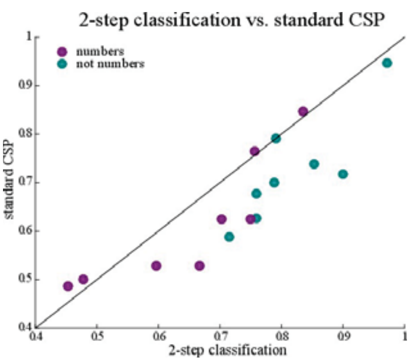

Figure 1. *CSP vs. 2-step approach*

Discussion: Bringing BCIs out of the controlled lab environment and into the real world presents one of the main challenges in BCI research. The study itself already revealed interesting and important findings. Boosting the classification results to a level where we can assume actual BCI control by adding more information to the classification process should encourage the BCI community to continue its path on building reliable BCI systems.

Significance: This new approach marks an important step towards using BCIs in real-world environments. It shows that it is possible to expose a participant to different distortion scenarios within one experiment and still classifiy the data succesfully.

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