NAO race: exploring social context on motor imagery performance

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Introduction: Motor imagery (MI) has been suggested to facilitate motor recovery after stroke. Particularly promising seems the combination of MI and neurofeedback, albeit most feedback implementations are not necessarily supporting MI skill learning [1]. We compared the effect of single player versus multiplayer scenarios [2]. For feedback, foot motor imagery signals were used to control NAO walking distance. Using this feedback we ensured that the imagined action matched to the feedback signal provided, albeit in a discrete way.

Material and Methods: 25 individuals (mean age = 24.9; 14 females) participated in the experiment, comprising 4 experimental blocks (each 40 trials). In the first block, participants physically performed repeated foot movements while sitting. In the subsequent blocks, the same movement was performed mentally. In block two, no feedback was given (training), whereas in blocks three and four, a discrete EEG-based robotic feedback of four different length was provided. Feedback was based on the classification (LDA) output of the power in the 8 to 30 Hz frequency band. In one of these sessions (pseudorandomized across participants), the participant was by himself (solo), while in the other, a race against a confederate steering a second NAO robot was implemented (duet). Intensity and easiness of MI were assessed after each block by means of questionnaires. EEG data were recorded from 24 scalp sites (Easycap, Herrsching, Germany) using a wireless, mobile amplifier (mBrainTrain, Belgrade, Serbia). OpenViBE was used for data acquisition, stimulus presentation and NAO robot (Aldebaran, Paris, France) control [3]. For offline analysis, we followed a previously established procedure [4].

Results: Online accuracy was on average 61.2% (SD = 8.45%). Offline, for each individual, the channel with the strongest event-related desynchronization (ERD), across all MI blocks, was selected (Fig. 1). Significant differences between MI blocks were found in ERD ($F_{2,48} = 6.02$, p = .012, $\eta^2 = .20$), intensity ($F_{2,48} = 6.23$, p = .005, $\eta^2 = .21$) and easiness ($F_{2,48} = 6.3$, p = .005, $\eta^2 = .21$), by repeated measures ANOVA. Follow-up paired t-tests revealed stronger responses during solo (ERD: $t_{24} = -2.78$, p = .01; intensity: $t_{24} = 3.18$, p = .004; easiness: $t_{24} = 2.65$, p = .01) and duet (ERD: $t_{24} = -2.44$, p = .01; intensity: $t_{24} = 2.60$, p = .02; easiness: $t_{24} = 3.08$, p = .005) compared to training. No difference between solo and duet could be observed (ERD: $t_{24} = -.38$, p = .71; intensity: $t_{24} = -2.78$, p = .01; easiness: $t_{24} = -2.78$, p = .01; easiness: $t_{24} = -2.78$, p = .01; intensity: $t_{24} = -2.78$, p = .02; easiness: $t_{24} = -3.08$, p = .005) compared to training. No difference between solo and duet could be observed (ERD: $t_{24} = -.38$, p = .71; intensity: $t_{24} = -2.78$, p = .01; easiness: $t_{24} = 0.42$, p = .68).



Figure 1. Grand average of MI induced relative power at the selected channel (A) and the distribution of the selected channel (B).

Discussion and Conclusions: In line with previous findings, we showed that EEG-based robotic feedback is feasible, as it enhances task specific activity. Our results suggest that this also applies to multiplayer scenarios. However, in contrast to our prediction, MI induced ERD was not enhanced in the multiplayer compared scenario. The type of social context applied, and the discrete feedback signal implemented, may have contributed to this null finding. Further research, specifically with respect to different frequency bands and other EEG components, is necessary to identify potential benefits of social context on neurofeedback performance. *References:*

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