Low frequency EEG-based movement decoding for the continuous online control of a robotic arm

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Introduction: Continuous decoding of voluntary movement would be desirable for closed-loop and natural control of neuroprostheses. Recent studies have shown the possibility to infer hand positions and velocities from the low-frequency (LF) electroencephalographic (EEG) activity [1], [2]. So far, this has only been performed offline. Here, we present for the first time two studies showing online control of a robotic arm by means of continuously decoded movements from LF-EEG.

Material, Methods and Results: Fifteen healthy participants took part in the two studies. The paradigm implemented a pursuit tracking task, where participants had to track a moving target on a screen with a robotic arm. The participants' two-dimensional right-hand movement, EEG, and electrooculographic signals were simultaneously recorded. In the first part of each experiment, participants performed some calibration runs with the robot fully controlled by their right-hand/arm movement. After the EEG decoding model was fitted to predict the right-hand movements, the robotic arm control was gradually switched from real to EEG-based decoded movements, first with 33%, then 66%, up to the final condition of 100% EEG control.

The EEG processing pipeline included filtering (0.18-1.5Hz), eye artefact [3] and pops/drifts [4] attenuation, partial least squares (PLS) regression, and Kalman filtering. In the first study (10 participants), a linear Kalman filter estimated positions, velocities and accelerations. Grand average correlations between real and decoded trajectories were r_{kal}=[0.30, 0.32, 0.29, 0.26] (for 0, 33, 66 and 100% EEG control). Correlations with only PLS were also computed. Although all correlations were significantly (α=.05) higher than both chance (r_{chance}=[0.13, 0.12, 0.11, 0.11]) and PLS (r_{PLS}=[0.25, 0.26, 0.22, 0.20]), we found an amplitude mismatch between real and decoded trajectories (amplitude ratio 0.4). In a second study (5 participants), we used a nonlinear square-root unscented Kalman filter to integrate positions, velocities, and speed. Grand average correlations were r_{kal}=[0.43, 0.34, 0.27, 0.23] and r_{PLS}=[0.35, 0.26, 0.22, 0.16]. The amplitude ratio between real and decoded movements was 1.07. Source projection of the decoder patterns highlighted parieto-occipital activation for the velocities (both studies), primary motor cortex for the speed (study 2).

Discussion: Both Kalman approaches permitted to successfully integrate the information in the decoding models, as documented by the significant increase between r_{PLS} and r_{kal}. The integration of speed in study 2 additionally adjusted the amplitude of decoded trajectories, suggesting an informative role. Parieto-occipital and motor cortex activations are in line with the task type (visuomotor) and offline studies [2].

Significance: Continuous low frequency EEG-based movement decoding for the online control of a robotic arm was achieved. Two (linear and nonlinear) Kalman approaches to integrate decoding information were introduced. The role of speed for trajectory decoding was further elucidated.

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