Time varying EEG Bandpower Estimation Improves 3D Hand Motion Trajectory Prediction Accuracy

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Introduction: Motion trajectory prediction (MTP) employs a time-series of band-pass filtered EEG potentials for reconstructing the three dimensional (3D) trajectory of limb movements with a multiple linear regression (mLR) block. While traditional multiclass classification methods use power values of mu (8-12Hz) and beta (12-30Hz) bands for limb movement based classification, recent MTP brain-computer interface (BCI) studies report the best accuracy using a 0.5-2Hz band-pass filter [1]. We recently [2] introduced a novel approach for MTP BCIs where the time-series of band-pass filtered EEG potentials were replaced with the time-series of power values of subject specific frequency band(s) prior to the application of mLR. Here we present an analysis of three subjects performing 3D arm movements and comparing the accuracy rates of the standard EEG potential model and the proposed spectrum power based approach.

Material, Methods and Results: The experiment involved two runs with six blocks/run and 15 movements/block (i.e., trials/block), between the home position and one of six target positions (Fig. 1A). Movements were synchronized with an auditory cue. Sixty-one EEG channels and kinematic data (x, y, and z hand position coordinates) were recorded simultaneously with a gHIamp80 (g.tec, Austria) and Kinect camera, respectively.



Figure 1A. Experimental setup. Home (H) and the six target positions (1-6).

Figure 1B. Illustration of the thirty-one Laplace filtered EEG channels from which ten channels (see labels) were selected for kinematic data estimation. **Figure 2.** Comparison of achieved accuracy (i.e. R: correlation of registered and calculated test velocity trajectory components) for potential and spectrum power models in x, y, and z directions.

Thirty-one EEG channels were re-referenced with a Laplace filter (Fig. 1B). Data intervals with high level transient noise (> $|\pm 300\mu$ V|) were removed along with their corresponding kinematic data. A 0.5-40Hz, 8th order Butterworth band-pass filter and independent component analysis (ICA) were applied for removing electrooculographic (EOG), electromyographic (EMG), and noise components. Ten ICA filtered EEG channels covering the sensorimotor cortex (Fig. 1B) were selected. For the potential model, channels were band-pass filtered in six specific bands (0.5-2Hz, 4-8Hz, 8-12Hz, 12-18Hz, 18-30Hz, and 30-40Hz). For the spectrum power model, signal bandpower was calculated in 500ms sliding window to replace the commonly used EEG potential time series. Parameter optimization is described in [2]. Correlation between registered and reconstructed velocity trajectories was assessed in an inner-outer (nested) cross-validation. The time lag, embedding dimension, frequency bands and EEG channels were optimized from the inner fold test correlations. The mean of the outer test fold correlations for the selected best architectures are reported for each subject and for each run (Fig. 2).

Discussion: Although the potential model provided best accuracy (R~0.2) in 0.5-2Hz (low delta) band, the spectrum power model yielded significantly higher accuracy (R~0.4) in the 4-8Hz (theta), 8-12Hz (mu), and 12-18Hz (low beta) bands. The current findings show parallelism with classical sensorimotor rhythm SMR-BCIs result that involve classification of different limbs e.g., left vs right hand movement, wherein the best accuracy is achieved using power values of mu (8-12Hz) and beta (16-28Hz) bands.

Significance: Significant improvements in the accuracy of 3D MTP can be achieved by replacing the time-series of delta band-pass filtered EEG potentials with the time-series of power values of the theta, mu, and beta bands. These bands, which are commonly used in classical SMR BCIs might encode movement trajectory relevant information, which is not accessible by the commonly used potential model [1] as a result of the approach used to time embed time series for the regression models. As the ultimate goal is to decode imagery of motion trajectory for movement-free control with a BCI, which is more challenging than decoding real movements, improvements in MTP approaches methods are necessary.

References

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