Novel single trial movement classification based on temporal dynamics of EEG

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Abstract

Various complex oscillatory processes are involved in the generation of the motor command. The temporal dynamics of these processes were studied for movement detection from single trial electroencephalogram (EEG). Autocorrelation analysis was performed on the EEG signals to find robust markers of movement detection. The evolution of the autocorrelation function was characterised via the relaxation time of the autocorrelation by exponential curve fitting. It was observed that the decay constant of the exponential curve increased during movement, indicating that the autocorrelation function decays slowly during motor execution. Significant differences were observed between movement and no moment tasks. Additionally, a linear discriminant analysis (LDA) classifier was used to identify movement trials with a peak accuracy of 74%.

1 Introduction

Neural correlates of movement have been increasingly explored for applications in brain-computer interfacing (BCI) as they enable very intuitive control [1]. Previous studies have suggested the possibility of the involvement of various complex oscillatory processes in motor command generation [2]. Most research focuses on the spectral domain of the EEG for detecting movement [1]. This project takes a different approach on understanding the motor commands by studying the temporal dynamics of the EEG using novel features.

The principle of Event Related (De)synchronization (ERD/S) corresponding to attenuation and increase predominantly in mu power and beta power [3] respectively is widely used for detecting movements. Single trial analysis is important for online BCI implementation. Although theses spectral features are able to reliably detect the motor command, they may not completely describe all aspects of motor command generation available in the EEG and do not indicate how one part of the EEG depends on another. Moreover, it is challenging to compute accurate instantaneous frequency distributions without compromising the temporal resolution and inducing delays in the motor command detection. Utilizing EEG signals' high temporal resolution, we have developed a novel method of detecting motor commands on a single trial basis by performing time domain analysis. Continuous autocorrelation analysis has been used for extracting temporal features from EEG.

In this study, different correlation based time domain analysis methods were explored for understanding the neural basis of motor command generation. Previous studies report that the first zero-crossing time, the time at which the autocorrelation function crosses 0, increases before and during voluntary movement [2]. Autocorrelation analysis was motivated by looking at temporal dependencies in the EEG This approach was expanded by considering the evolution of the autocorrelation function over time and studying changes in relaxation time of the decay of the autocorrelation.

2 Methods

2.1 Experimental Paradigm

EEG was recorded from three participants. All the participants were males (2 right handed and 1 left handed) with ages 25, 23 and 29 years. An experimental paradigm was developed for recording self-paced index finger tapping of the right and left hand using tools from the BioSig toolbox [4]. A fixation cross was displayed on the screen placed at eye level for 2 sec at the beginning of each trial and followed by a textual cue for right or left hand finger tapping or resting. Participants were asked to perform a self-paced single finger tap at a random time of their choice within the 10 sec window following the cue. Each trial was followed by a random break of 1 to 1.5 sec. The experiment was broken down into separate runs of 12 trials with 4 cues per class displayed in random order to avoid pattern learning by the participants. The experimental setup is illustrated in Figure 1.

A special tapping device was developed using a programmable microcontroller to record the tapping signals from both each finger. In order to mark the exact onset of the movement in EEG, both EEG and finger tapping signals were recorded simultaneously and co-registered using tools developed as part of the TOBI framework [5]. EEG from 19 electrodes (impedances kept below 8kΩ) was recorded using a Deymed TruScan amplifier with a sampling frequency of 1024 Hz. Forty trials for each of the three conditions were recorded for each participant.

2.2 EEG pre-processing and Artifacts removal

Signal pre-processing was done using a fourth-order Butterworth filter. DC offset in the signal was removed using a high-pass filter with a cut-off frequency of 0.5Hz. Power line noise was filtered using a notch filter at 50Hz. Finally, high frequency noise was eliminated using a low-pass filter with a cut-off frequency of 60Hz.

Independent Component Analysis [6] was used to remove artefacts from the recorded signals. Independent components (ICs) with artefacts were identified manually. Artefact-free EEG was reconstructed by eliminating these ICs. EEG was then segmented into individual trials. Trials of length 6 sec were obtained by extracting 3 sec before and 3 sec after the onset of movement.

2.3 Autocorrelation analysis based on exponential decay

In order to examine the time development of the relaxation time of brain activity before, during, and after the movement, the autocorrelation function was calculated to extract the relaxation. The autocorrelation function shows the degrees of un-correlation as a function of time from initial state.

For a given signal $A(t)$, the auto-correlation is defined by $C(\Delta t) = \langle A(t)A(t-\Delta t)\rangle$, where $\langle\ldots\rangle$ represents the average over time. At the initial time, $C(0) = \langle A^2\rangle$, and after infinite time, the signal is completely uncorrelated, giving $C(inf) = \langle A\rangle^2$. How the signal becomes uncorrelated as a function of time may be described by $C(t) = \langle A^2\rangle e^{(-t/\tau)}$ to describe the general trend of the relaxation process when the average of the signal $\langle A\rangle = 0$. If the auto-correlation is normalized, $C(t) = e^{(-t/\tau)}$ where τ represents the relaxation time of the signal and is an indicator of the relaxation process.

Autocorrelation functions were derived for the 30Hz low-pass filtered EEG. A windowing approach was used for determining instantaneous autocorrelation. Windows of length 1s and shifted by 100ms were extracted. Normalised continuous autocorrelation was performed on each window at all lags with non-zero values.

The exponential curve $y=K.e^{(-t/\tau)}$ was fitted to the local maxima of the positive lags of the autocorrelation function obtained from each window of the trial and the decay constant τ of the fitted curve was extracted as a feature (see Figure 2).The constant K was set to 1. The τ values for all the windows for each trial were plotted (see Figure 3).

Figure 1: Experimental Setup

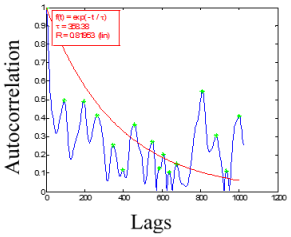

Figure 2: Curve Fitting

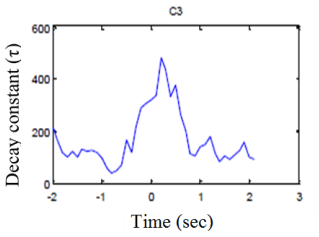

Figure 3: Plot of changes in τ. Time is reported relative to movement onset.

2.4 EEG analysis and classification

The 9 EEG channels around the motor cortex (F3, Fz, F4, C3, Cz, C4, P3, Pz, and P4) were analysed. Before beginning further analysis and classification with the novel time domain method, to assess the quality of data, EEG was validated for the presence of ERD using event-related spectral perturbation. To observe ERD, average spectrograms of resting state trials were subtracted from average spectrograms of movement trials. Figure 4 shows the decrease in mu power around movement onset.

To analyse the results obtained by plotting τ for single trials, element-wise 2 sample *t*-test were performed to identify statistically significant differences between right hand tapping vs. rest and left hand tapping vs. rest. A Linear discriminant analysis (LDA) classifier was used to classify the trials. LDA was applied in a sliding window (length 1s, step size 0.1s). A 10x10 cross-fold validation scheme was used with binary classification of left tap vs. no tap and right tap vs. no tap.

3 Results

Increases in the value of τ around the onset of movement were clearly observed in most trials. The τ values of the resting state trials appeared stable throughout the trial (see Figure 3). Features around the onset of the movement showed statistically significant differences between tap vs. rest conditions (see Figure 5). The most responsive channels for right and left hand tap differed between participants. Using the autocorrelation function decay constant movement could be detected from single trials.

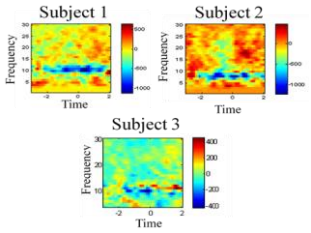

Figure 4: ERD on channel C3 for each participant

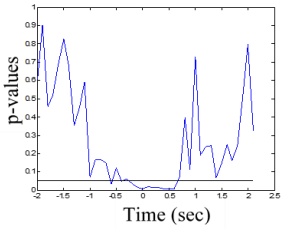

Figure 5: T-Test for left hand trials, participant 3. The horizontal line indicates statistical significance ($p<0.05$).

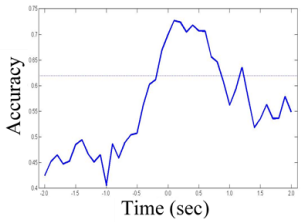

Figure 6: Classification accuracy for left hand, subject 3. The horizontal line indicates statistical significance ($p<0.05$).

LDA classification accuracies for all the participants were plotted for the classification of movement of right vs. rest and left vs. rest. The accuracy obtained was considered statistically significant at $p<0.05$. A peak accuracy of 74% was achieved for participant 3 (shown in Figure 6). Table

1 shows classification accuracies for all the participants. Significant accuracies were obtained for all the participants, except for participant 1 right hand tapping condition. It's interesting to note that participant 3, who exhibited the smallest ERD response, gave the best results using this temporal method.

Participant	Right hand tapping classification accuracy (%)	Left hand tapping classification accuracy (%)
1	58.0	**68.4**
2	**66.0**	**69.0**
3	**68.0**	**74.0**

Table 1: Movement classification accuracies. Statistical significance ($p<0.05$) is indicated in bold.

4 Conclusions and future work

A novel approach to extract features from the temporal dynamics of brain oscillations on a single trial basis was used to study the neural mechanisms of movement. This time domain single trial analysis has great potential for online BCI. Oscillations of a wide frequency range were taken into account without limiting the feature search into pre-determined frequency bands. This has led to the novel discovery of the behaviour of the autocorrelation function during voluntary movement. The autocorrelation function decays slower during movement as compared to rest. When there is no movement, decreases in the autocorrelation function are sharp. This suggests that during rest, the oscillatory processes and relaxation process of the autocorrelation function are distinct. However, during movement, coupling occurs between relaxation and oscillatory processes. Thus, the relaxation time of autocorrelation is a measure of temporal dependency in EEG.

Since the study performed was very novel, initial analysis was done on only three participants to validate the proposed hypothesis. There is large scope for further work. To validate and confirm the robustness of this method, EEG analysis will be done on more participants and a comparison will be made to ERD based classification of movement. The system will be then adapted for use in online BCI.

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