Change-point Analysis of Single-trial EEG of Auditory and Visual Oddball Tasks

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***Abstract*— the brain rhythms defined by specific frequency-bands of electroencephalography (EEG) signal are generally thought to represent diverse cognitive processes which wax and wane with sub-second resolutions at different parts of the cortex. Furthermore, single-trial analysis of EEG is believed to show more realistic pictures of ongoing and event-related activities of the brain with millisecond resolution. Here, we present a nonparametric multiple change-point detection and estimation method for analysis of single-trial EEG recorded during auditory and visual oddball tasks. In a simple attention task like oddball, the frontal cortex of the brain is responsible for distinguishing and responding appropriately to target and standard events. With sub-second resolution at the frontal cortex, we show that the α-band activity changes according to "inhibition timing" hypothesis and the β-band activity is in line with "maintaining the status quo" hypothesis.**

Keywords*— *electroencephalography; auditory/visual oddball task; single-trial analysis; change-point analysis; (α, β)-band powers; frontal cortex.

I. Introduction

On-going brain activity alternates in response to endogenous and exogenous events. Electroencephalography (EEG) is one of the foremost tools to explore non-invasively this activity in human brain. Most notably, it is suitable for measuring the activity over the superficial layer of the scalp - cerebral cortex - with millisecond resolution. The cerebral cortex plays a major role in all higher cognitive processes like attention, perception, decision-making, and planning. In a simple attention task like auditory/visual oddball, the most relevant part of the brain which distinguishes target events from standard ones and plans the desired action, is frontal cortex. While traditional event-related potential can capture the average brain activity reliably, single-trial analysis of EEG signal recently has gained interest due to its ability to measure realistically the endogenous wax and wane of brain activity inherent to each trial [1] [2].

Furthermore, it is believed that the frequency-band components of the EEG signal have important implications about different cognitive processes. EEG is normally divided to five frequency-bands: δ-band (0.5-4 Hz), θ-band (4-8 Hz) α-band (8-14 Hz), β-band (14-30 Hz), and γ-band (30-100 Hz). The amplitudes (powers) and phases of these frequency-band components carry information about cognitive processes in the brain. As an instance, the α-band power which is the most prominent EEG component particularly over the posterior part of the brain is generally thought to correlate with inhibiting and idling state of the cortex. Based on "inhibition timing" hypothesis, the α-band activity represents suppression and selection, two important aspects of attention [3]. On the other hand, based on a relatively recent hypothesis, the β-band activity whose magnitude is more prominent in sensorimotor cortex is believed to signal "maintaining the status quo" in different parts of the cortex [4].

In this study, we develop a nonparametric method for single-trial analysis of EEG in the general framework of change-point analysis [5] [6]. While change-point analysis is a well-established method in signal processing; it has rarely used for EEG single-trial analysis. Moreover, our method is best suited for multidimensional data with unknown number and location of change-points using minimum distribution assumptions. Change-point estimation is based on U-statistics and hierarchical clustering with bisection approach for its computational efficiency [6]. We use this method to divide the multidimensional EEG signal of the electrodes of frontal cortex to different temporal windows and then calculate the single-trial relative powers of α and β-band components. Our results provide support for α-band "inhibition timing" and β-band "maintaining the status quo" hypotheses.

II. Materials and Methods

The EEG data we use is a part of the simultaneous EEG-fMRI data collection described in [7]-[9] but we reproduce much of the relevant information here for ease of reading and refer the reader to those previous studies for further details. The EEG dataset (combined with BOLD fMRI data) is freely available via the OpenfMRI data repository (https://openfmri.org/dataset/ds000116).

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A. Auditory and Visual Oddball Paradigms

Seventeen subjects (six females; mean of 27.7 years; range of 20–40 years) participated in three runs of each of the auditory and visual oddball paradigms. The 375 (125 per run) total stimuli per task were presented for 200 ms each with a 2–3 s uniformly distributed variable inter-trial interval (ITI) and target probability of 0.2. For the visual task, the target was a large red circle (3.45° visual angle) and the standard was a small green circle (1.15° visual angle), both on iso-luminant gray backgrounds. For the auditory task, the standard stimulus was a 390 Hz pure tone and the target sound was broadband "laser gun". Because our study is about task-related cognitive states, subjects were asked to respond to the target stimuli, using a button press with the right index finger on a button response pad.

B. EEG Data Acquisition

The EEG was recorded using an EEG system with differential amplifier and bipolar EEG cap. The cap was composed of 36 Ag/AgCl electrodes including left and right mastoids, arranged as 43 bipolar pairs. This oversampling of the electrodes ensured that the data forms a complete set of electrodes even when there is a need to discard noisy channels. The original data is from a simultaneous EEG-fMRI experiment and thus, the EEG signal is contaminated with gradient and Ballistocardiogram (BCG) artifacts. To enable removal of the gradient artifacts in our offline preprocessing, the 1-kHz-sampled EEG signal was synchronized with the MR-scanner clock at the start of each of 170 functional image acquisitions.

C. EEG Data Preprocessing

We followed closely the standard offline preprocessing of EEG described in [2] [7]-[9] using MATLAB (MathWorks). First, we removed the gradient artifacts by subtracting the mean EEG signal across all functional volume acquisitions from the initial EEG signal. We then applied a 10 ms median filter to remove any residual spike artifacts [10]. Secondly, we used the following digital Butterworth filters in the form of a linear-phase finite impulse response (FIR) filters: a 1Hz high pass filter to remove direct current drift, 60 and 120 Hz notch filters to remove electrical line noise and its first harmonic, and a 100 Hz low pass filter to remove high-frequency artifacts not associated with neurophysiological processes. BCG artifacts share frequency content with EEG activity and existing BCG removal algorithms cause loss of signal power in the EEG. Therefore, we performed single-trial analysis based on the change-point analysis method on the event-related potential before BCG artifacts removal. However, to isolate the N100, P200, and P300 components (Fig. 1) and compute the scalp topographies, BCG artifacts were removed from the EEG data using a principal components analysis method [2] [11]. First, the data were low pass filtered at 4 Hz to extract the signal within the frequency range in which BCG artifacts are observed and then the first two principal components were calculated. The projection of channel weightings corresponding to those components subtracted out from the broadband data. These BCG-free data were then re-referenced from the 43 bipolar channels to the 34 electrodes space to isolate the N100, P200, and P300 components (Fig. 1). By visual inspection, trials containing motion or blink artifacts and also those with incorrect responses, were discarded from both auditory and visual datasets.

D. EEG Change-point Analysis

We defined the stimulus-locked -1000 ms to 1000 ms EEG epoch as a trial. We chose this interval because it ensures no overlap between adjacent trials due to ITI and also provides pre-stimulus potential for subsequent frequency-band analysis. We combined all target trials across three runs of each one of the auditory and visual tasks for each subject (at most 75 trials for each subject and task). We did the same for the standard trials (at most 300 trials for each subject and task).

We are interested in task-related EEG response which is the brain activity for distinguishing target from standard events and subsequent appropriate action. The EEG signal of the electrodes at the frontal cortex is believed to indicate this activity. As a result, we used the referencing matrix of each subject to transfer the EEG signal from the 43 bipolar channels to the 34 electrodes space and then chose 7 frontal cortex electrodes (Fp1, Fp2, AF3, AF4, F3, Fz, F4 in international 10-20 system) for change-point analysis.

We performed change-point analysis on average event-related potential obtained from 7 frontal cortex electrodes independently for each subject, task (auditory/visual), and trial type (target/standard). By doing this, we increased the signal-to-noise ratio of task-related EEG potential. However, our subsequent single-trial analysis based on frequency-band components was rested on individual trials. Also, to decrease the computational demand of our change-point analysis, we averaged the EEG signal over 10 ms sliding window, so instead of having EEG epochs with 2000-point length (1000 Hz), we had epochs with 200-point length (100 Hz) covering stimulus-locked -1000 ms to 1000 ms interval. We think this does not change the accuracy of our change-point analysis (particularly considering the low signal-to-noise ratio of the EEG datasets obtained in the MR environment), while it substantially increases the computational efficiency (Our change-point method runs at $O(kT^2)$; k is the number of the change-points and T is the sample-length of a signal).

Our change-point formulation has closely followed a recently developed nonparametric multiple change-point detection and estimation method which has just one assumption behind its applicability; the multidimensional signal must have μ-th absolute moment for some $\mu \in (0,2)$ [6]. By combining it with hierarchical estimation (bisection method) and significance testing (permutation), we efficiently and reliably isolated up to 10 change-points from our EEG epochs.

In the following formula, μ = 1 and T = 200 (the length of our EEG epoch) and Z_κ is a point in a 7-dimensional EEG epoch time-series, κ ϵ (1,200). In (1), we vary κ along an EEG epoch and then move τ along the resultant temporal window, τ ϵ (1,κ). As a result, we have two separate time-series with two probability distributions: F_x for X_τ and F_y for $Y_\tau(\kappa)$. Based on this definition, we calculate $\hat{E}$ from (2) and $\hat{Q}$ from (3). According to (4), if τ is a change-point, then F_x is not equal to F_y and $\hat{Q}$ must go to infinity. Using (5), by spanning an EEG epoch with κ and τ, we are able to find the maximum possible value for $\hat{Q}$ and the corresponding estimated change-point, τ. For more complete description, please refer to [6].

$$\begin{aligned} &1 \le \tau < \kappa \le T \\ &X_\tau = \{Z_1, Z_2, \ldots, Z_\tau\} \\ &Y_\tau(\kappa) = \{Z_{\tau+1}, Z_{\tau+2}, \ldots, Z_\kappa\} \end{aligned} \quad (1)$$

$$\hat{E}(X_\tau, Y_\tau(\kappa); \mu) = \frac{2}{\tau \times (\kappa - \tau)} \sum_{i=1}^{\tau} \sum_{j=\tau+1}^{\kappa} \left|X_i - Y_j\right|^\mu - \frac{2}{\tau \times (\tau - 1)} \sum_{1 \le i < k \le \tau} \left|X_i - X_k\right|^\mu - \frac{2}{(\kappa - \tau) \times (\kappa - \tau - 1)} \sum_{\tau+1 \le j < k \le \kappa} \left|Y_j - Y_k\right|^\mu \quad (2)$$

$$\hat{Q}(X_\tau, Y_\tau(\kappa); \mu) = \frac{\tau \times (\kappa - \tau)}{\kappa} \hat{E}(X_\tau, Y_\tau(\kappa); \mu) \quad (3)$$

$$\begin{aligned} &If\ X_\tau \sim F_x, Y_\tau(\kappa) \sim F_y \ \wedge\ \hat{Q}(X_\tau, Y_\tau(\kappa); \mu) \to \infty \ \Rightarrow\ H_A : F_x \neq F_y \\ &If\ X_\tau \sim F_x, Y_\tau(\kappa) \sim F_y \ \wedge\ \hat{Q}(X_\tau, Y_\tau(\kappa); \mu) \to 0 \ \Rightarrow\ H_0 : F_x = F_y \end{aligned} \quad (4)$$

$$\hat{\tau} = \arg\max_{(\tau, \kappa)} \hat{Q}(X_\tau, Y_\tau(\kappa); \mu) \quad (5)$$

$$\begin{aligned} &\hat{\tau}_0 = 0 < \hat{\tau}_1 < \hat{\tau}_2 < \ldots < \hat{\tau}_{k-1} < T = \hat{\tau}_k \\ &\hat{C}_i = \left\{ Z_{\hat{\tau}_{i-1}+1}, \ldots, Z_{\hat{\tau}_i} \right\} \\ &\hat{\tau}_k^* = \arg\max_{i \in (1, \ldots k)} \hat{Q}(X_{\hat{\tau}(i)}, Y_{\hat{\tau}(i)}(\hat{\kappa}(i)); \mu) \end{aligned} \quad (6)$$

We performed this estimation hierarchically to find the desired number of significant change-points in our EEG epochs based on (6) (see Figs. 2-3 for average results across subjects). Also, to test the significance of our change-point detection, we performed permutation test. We permuted the signal values on our EEG epoch time-series (length = 200 points) 100 times for each subject, task, and trial type separately. Then, we ran the same hierarchical change-point detection and estimation procedure by using (6) for each permutation run (see Fig. 4 for average results across subjects). Finally, we compared the distribution of $\hat{Q}_{\max}$ for permuted EEG epochs with the original EEG epochs to verify the significance of our detected change-points.

E. EEG (α, β)-band Single-trial Analysis

For single-trial analysis of EEG, we considered EEG α and β-band components due to their relevance to our simple paradigm and minimum contamination with BCG artifacts. After calculating the change-points of average event-related potential for each subject, task, and trial type separately; we returned to our target and standard single-trials and divided the stimulus-locked -1000 ms to1000 ms trial interval to distinct temporal windows each one of them starts at -1000 ms and ends at a change-point (CP). (We did this instead of considering the time-span between two consecutive change-points, because the change-points were close to each other and the time-gaps were not sufficient to let us reliably calculate the powers of α and β-band components.)

Afterward, we calculated average α and β-band powers for the temporal windows of each one of the trials, and the average broadband (BB) power (0-100 Hz) of the same trial. By dividing the α and β-band powers of all temporal windows of a trial to the broadband power of the same trial by using (7) and obtaining the relative powers of α and β-band components, we simultaneously achieved two objectives: 1) We normalized the α and β-band powers of the temporal windows of a trial on the same ground. 2) We removed any baseline effects of EEG signal so we were able to combine all the relative powers across all the trials for each subject, task, and trial type separately.

$$\begin{aligned} &1 \le i \le k \\ &P_{\alpha_{rel}}^{CP_i} = \frac{P_\alpha^{CP_i}}{P_{BB}^{trial}} \\ &P_{\beta_{rel}}^{CP_i} = \frac{P_\beta^{CP_i}}{P_{BB}^{trial}} \end{aligned} \quad (7)$$

Furthermore, to have a summary statistics of α and β-band relative powers across all temporal windows and subjects (but independently for each task and trial type), we divided the 2000-point length stimulus-locked EEG epoch to 20 equal bins each one has 100-point length. Then we placed the α and β-band relative powers of all subjects in one of those bins based on their temporal windows' positions. Afterward, for each bin, we calculated the mean and standard error of the mean separately for α and β-band relative powers. We presented these results in Figs. 5-8 independently for each task and trial type.

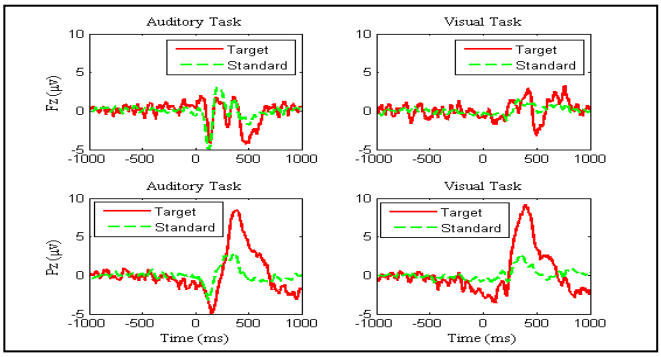

Fig. 1. Traditional average event-related potential of Pz and Fz electrodes.

III. Results and Disscusion

All subjects responded with high accuracy and speed. For the auditory task, 98.3 ± 2.0 % of targets was correctly detected with 404.1 ± 58.3 ms reaction time (RT) and for the visual task 98.4 ± 3.1 % of targets was correctly detected with 397.2 ± 38.9 ms RT.

A. Traditional Event-related Potential

The average (across subjects) event-related potential (ERP) which spans stimulus-locked -1000 ms to 1000 ms interval for Pz and Fz electrodes were displayed in Fig. 1 (independently for each task and trial type). P300 component which is an endogenous potential elicited in the process of attention, categorization, and decision-making is more prominent in the parietal sites between 300 ms to 500 ms. On the other hand, N100 and P200 are more prominent in the frontal sites. They are all visible for average ERP of auditory and visual target trials in Fig. 1.

B. EEG Change-point Analysis

The average locations (across subjects) of the first 10 change-points in -1000 ms to 1000 ms stimulus-locked interval is displayed in Fig. 2 (independently for each task and trial type). The first change-point of target trials for both tasks is approximately matched with the behavioral response (RT). In Fig. 3, the $\hat{Q}_{\max}$ values of the detected change-points were plotted. The plot has a plain trend starting from large values and decreasing gradually. Also, in Fig. 4, the $\hat{Q}_{\max}$ values of the change-points of permuted trials were plotted and, as expected, they have significantly lower $\hat{Q}_{\max}$ values compare to Fig. 3. The results clearly show that the detected change-points are significant for both tasks (auditory/visual) and both trial types (target/standard).

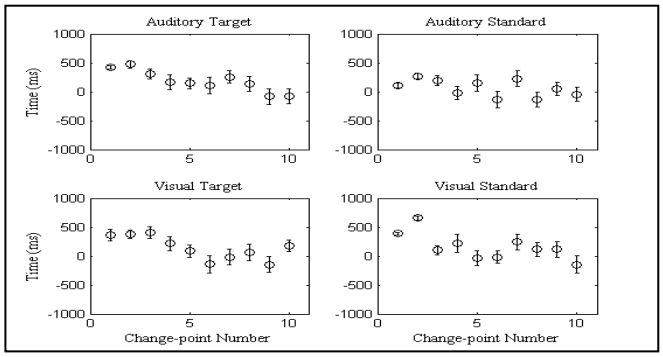

Fig. 2. The 10 more significant change-points and their standard errors.

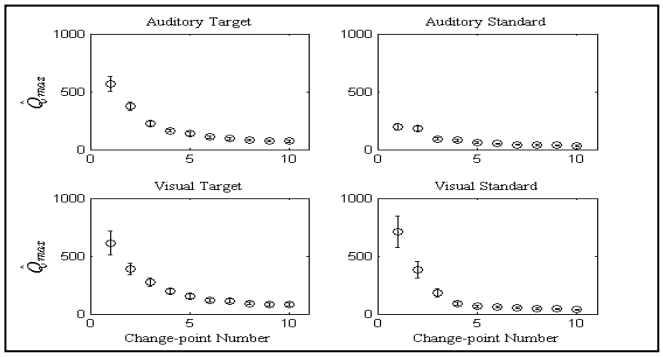

Fig. 3. The $\hat{Q}_{\max}$ values of the change-points and their standard errors.

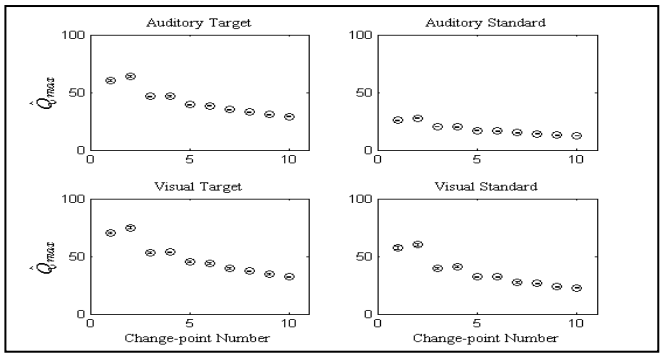

Fig. 4. The $\hat{Q}_{\max}$ values of permuted trials and their standard errors.

C. EEG (α, β)-band Single-trial Analysis

We summarized the average results across all temporal windows and subjects (but independently for each task, trial type, and frequency-band component) in Figs. 5-8.

In Figs. 5 and 7, for auditory and visual target trials respectively, the α-band activity is higher at the beginning and gradually decreases as the change-point moves to the right in the stimulus-locked EEG epoch. This is in accordance with the "inhibition timing" hypothesis [3] which states that the α-band power is negatively correlated with the brain activity; it is higher at the pre-stimulus interval but it decreases as the frontal cortex gets engaged with task-related decision-making regarding the response to the target trials.

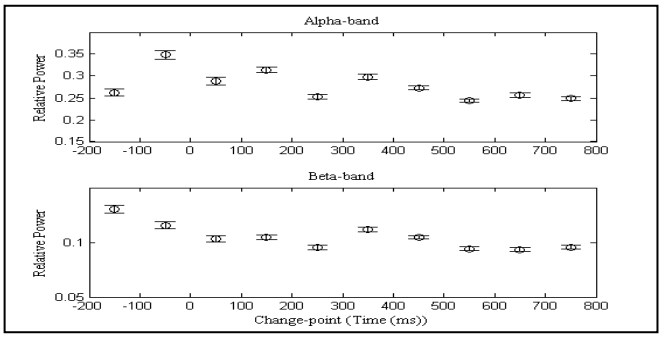

Fig. 5. α and β-band relative powers of auditory task target trials.

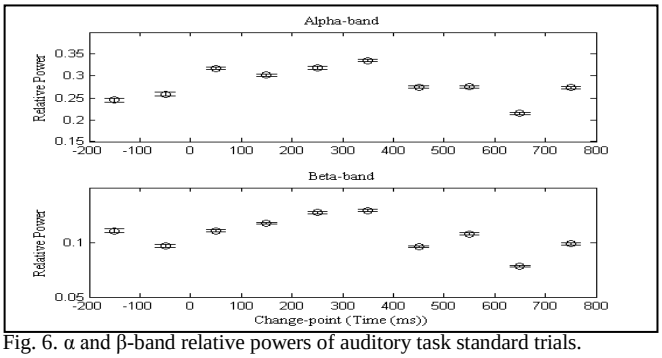

Fig. 6. α and β-band relative powers of auditory task standard trials.

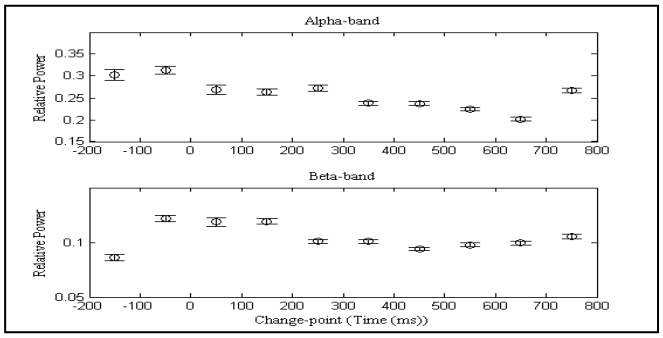

Fig. 7. α and β-band relative powers of visual task target trials.

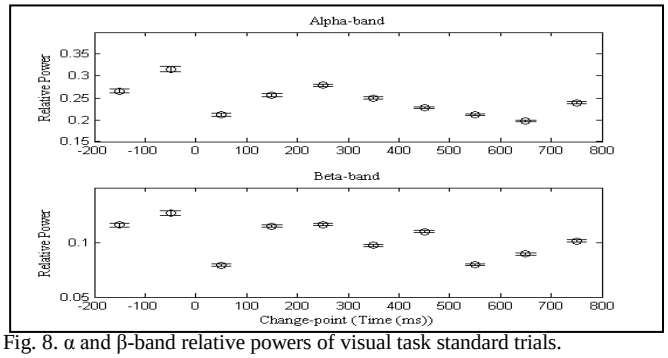

Fig. 8. α and β-band relative powers of visual task standard trials.

The β-band activity is also in agreement with the "maintaining the status quo" hypothesis [4] which states that the β-band power is lower when we expect some cognitive processes happen which change the status quo. Here, in response to the target trials, the frontal cortex, which is the center of executive functions in the brain, gets active to coordinate the proper action.

On the other hand, for auditory and visual standard trials in Figs. 6 and 8 respectively, we observe the opposite trend. Although, they start with relatively high pre-stimulus α and β-band activity, they decrease and again increase around 200 ms to 400 ms post-stimulus which is the time when the brain is already processed the stimulus and the appropriate decision is made. This is again in line with the "inhibition timing" hypothesis for α-band power and the "maintaining the status quo" hypothesis for β-band power; in the standard trials, the frontal cortex is not involved in coordination of any action and it just needs to keep the status quo which is the situation without any behavioral response.

In conclusion, our developed change-point method and frequency-band components' single-trial analysis are able to provide additional evidence for two relevant hypotheses in the literature related to α and β-band activities; they show how the brain rhythms in the task-related region of the cortex coordinate temporally with sub-second resolution.

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