Applying time-frequency and generalized eigendecomposition analyses on oddball effects

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Psychology 5621

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11 December 2019

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Introduction

The Oddball Effect and the Event-Related Potentials

Cognitive and attention tasks have been measured in a variety of ways over the course of history with modern approaches including electroencephalography (EEG), essentially a measure of electrical activity in the brain. Through EEG experiments, researchers and clinicians gain a better understanding of the human brain and behavior and have, in more recent years, established replicable and reliable results for various types of paradigms. One such paradigm, the Oddball Paradigm, has been studied since the early 1970s (Squires, 1975), and has shown effects on specific neural locations and temporal windows. These measured brain responses, or Event-Related Potentials (ERP), allow for a non-invasive assessment of brain activity following a stimulus. Regardless of using an auditory or visual stimulus, the oddball effect has been consistently replicated over time, as well as further expanded, giving insight into how the human brain functions.

Pre- and Post-Stimulus Time-Frequency Analysis of Visual Stimuli and their Relationship to the ERP

Previous research has demonstrated that the observed increase in ERP P300 amplitude in auditory oddball stimuli compared to common stimuli is associated with power increases in three separate frequency bands: delta (< 3 Hz), theta (3 – 8 Hz), and alpha (8 – 13 Hz) (Başar-Eroglu, Başar, Demiralp, & Schürmann, 1992; Kolev et al., 1997). While cortical EEG has provided some insight into the localization of these signals, research from human electrocorticography and animal research suggests that the origins of the P300 response are not purely neocortical signal, but rather reflective of hippocampal-cortical communication (Başar-Eroglu, Başar, Demiralp, & Schürmann, 1992). These authors define the P300 response generally as prompted by unexpected but highly task-relevant stimuli that requires a motor or cognitive response (Başar-Eroglu, Başar, Demiralp, & Schürmann, 1992). However, if the basis of these signals is reflective of hippocampal-cortical dynamics, then it is possible that other hippocampal task-relevant oscillations are present as well, such as interactions between endogenous alpha, theta and delta, post-stimulus behavioral performance, and ERP components.

Resting state EEG is dominated by these spontaneous alpha band oscillations; one study found an increase in pre-stimulus alpha power was associated with decreased ability to discriminate visual stimuli in the parietal and occipital regions (van Dijk, Schoffelen, Oostenveld, & Jensen, 2008). The authors propose that this parieto-occipital alpha power represents inhibitory processes of higher-level cognitive function. Additionally, in an auditory oddball paradigm, pre-stimulus alpha power at Pz and Cz were significantly correlated with post-stimulus ERP amplitudes (Barry, Kirkaikul, & Hodder, 2000), and furthermore, waxing and waning alpha phase states at stimulus onset differentially affected the subsequent post-stimulus ERP components in an oddball paradigm (Barry et al., 2004). Importantly, it is yet unclear whether the brain adapts to this state during the task given that no change in pattern was observed from the first block to the last.

Given the breadth of research demonstrating not only that the amplitude of the ERP response is dependent on power and phase of pre-stimulus alpha, but also the evidence that pre-stimulus alpha is reflective of domain-general and spontaneous brain activity, the current study attempts to generalize these findings to the visual domain in an oddball paradigm.

Prediction 1: Time-frequency analysis of the post-stimulus time window will reveal increases in theta, alpha and delta power in oddball trials compared to common trials.

Prediction 2: Prestimulus alpha in visual trials will mediate the post-stimulus ERP amplitude and time-frequency response.

Previous literature has examined these questions using standard approaches of time-frequency analysis at the level of individual trials and averaged responses. In one study, rather than simply extracting average frequency power information in a task-relevant time window, the authors use a principal component analysis technique to extract time-frequency components in an oddball paradigm. Using this technique and comparing it to a traditional time-frequency analysis, they were able to identify increases in delta and theta activity (Bernat, Malone, Williams, Patrick, & Iacono, 2007). However, PCA proved to be more sensitive to parsing signal from noise and was able to account for more overall variance than the analysis of time-frequency condition averages (Bernat, Malone, Williams, Patrick, & Iacono, 2007).

Advanced Decomposition of EEG Signal Using Generalized Eigendecomposition

In a recent study on steady-state evoked potentials (SSEPs), Cohen and Gulbinaite (2017) used generalized eigendecomposition to facilitate the time-frequency analysis on neural responses to rhythmic sensory stimulation. Eigendecomposition is the main idea underlying principal component analysis (PCA), where the eigenvector pointing to the direction of the maximal variance of the data is found by examining the covariance matrix. Previous studies have used different source separation techniques, including PCA (Bernat et al., 2007; Bernat, Williams, and Gehring, 2005). However, PCA has its bad performance in source separation in neural signals. While most brain dynamics are not in an orthogonal pattern, PCA is a blind source separation technique that produces pairwise orthogonal eigenvectors. Studies have shown that principal component analysis gives poor results compared to other procedures that do not require orthogonality (e.g., Delorme et al., 2012; Dien et al., 2007).

One way to overcome this constraint is to use generalized eigendecomposition (GED). GED first creates two covariance matrices for two features, one serving as the signal and one as the reference, and uses eigendecomposition to find out a set of eigenvectors that maximally differentiate activity between these two different features, which can be used as spatial filters to increase the signal-to-noise ratio. Therefore, for our final analysis, we attempted to use GED to isolate alpha-band activity and compare between different experimental conditions (i.e. oddball vs common).

Prediction 3: Generalized eigendecomposition serves as a more sensitive tool for separation of signal from noise and will allow us to examine more closely the characteristics of specific frequency band between different conditions.

Methods

Data collection and Preprocessing

The EEG experiment follows the conventional oddball paradigm setup with four visual color blocks and four auditory sound blocks. Each block contains 40 trials where 8 of them are oddball trials and 32 of them are common trials. On each trial, a fixation is present for 500ms, following by the stimulus presented for 200ms. The intertrial interval (ITI) is 1.5-2 seconds after the response is made. EEG data were continuously recorded with a sampling rate of 1000 Hz.

The EEG data were first bandpass filtered using a finite impulse response (FIR) filter with a range of 0.5 to 30 Hz. Then bad channels were removed and all responses at individual electrodes were referred to the montage reference value. The EEG data was then epoched and baseline-corrected from 500ms pre-stimulus onset to 1000 post-stimulus onset. Trials that were contaminated by head movement noises were visually inspected and rejected. To get rid of the eye-blink noise, independent components that were sensitive to eye blinks were identified and removed from the EEG data with the Independent Component Analysis (ICA) approach. All the above preprocessing steps were supported by the modules in EEGLAB, a MATLAB-based toolbox. Finally, Surface Laplacian was conducted to filter out the low-frequency spatial components from the EEG data. Trials from each condition of each subject were aggregated for further analyses.

Event-related Potentials

Before computing ERPs, all error trials were removed in order to ensure that all task stimuli were properly encoded by participants. We first calculated ERPs by averaging trials at several channels including P3, P4, Pz, Fz, and Cz that were originally found to reveal oddball effects. To observe the spatial localizations of oddball effects, we made topographical plots of whole-scalp channel ERPs that compare common versus oddball conditions.

Time-Frequency Analysis of Pre and Post-stimulus Time Windows

The EEG data were re-preprocessed for time-frequency analysis using the Fieldtrip software (Oostenveld et al, 2011). The data were segmented using the stimulus onset as the 0-time point. Pre-stimulus trials were epoched to be 3 seconds pre-stimulus and 1 second post-stimulus and post-stimulus trials were epoched to be 1 second pre-stimulus and 3 seconds post-stimulus. All trials were notch filtered at 58-60Hz, re-referenced to the average signal from the left and right mastoid (TP9 & TP10), and bandpass filtered between .5 and 40 Hz. Though a wavelet analysis was used and essentially acts as its own bandpass filter, visual inspection of the quality of the data suggested the data may benefit from repeated temporal filtering. The data was down sampled to 250 Hz, and Independent Components Analysis was performed to remove artifactual EOG and EMG signal.

To perform the time frequency analysis for the post-stimulus time window, a wavelet convolution using a hanning window was performed to extract power information on the time period of interest, -1 seconds to 1 seconds in .01 second increments between .5 and 12Hz with a .001Hz resolution. Visual and auditory trials were analyzed, though our primary hypotheses concerned only the visual trials. The trials were sorted into oddball and common trials and a grand average across participants was calculated in the following electrodes: P3, P4, Pz, Cz, and Fz. A similar analysis was performed for the pre-stimulus time window on the time period of interest: -2 seconds to .5 seconds in .01 second increments between 2 and 16Hz with a .001Hz resolution. The trials were averaged across participants in electrodes Pz and Cz, based on prior research (see introduction). Trials were baseline decibel corrected and time window was narrowed for aesthetic purposes during plotting.

Generalized Eigendecomposition (GED)

We report the procedure of using generalized eigendecomposition to derive a spatial filter and applying it to the raw data. First, we applied a narrow band-pass filter centered at 7 Hz with a full width at half maximum (FWHM) of 5 Hz. Noticeably, Cohen & Gulbinaite’s (2017) preferred this Gaussian-shaped filter and time-domain covariance because in their study, they used stimuli flickering at different frequencies that will elicit rhythmic brain responses (steady-state evoked potentials), which are not stationary nor sinusoidal. Here we also used a Gaussian filter to account for non-stationarity.

From the filtered data, we constructed two covariance matrices, a pre-stimulus one with a time window from -500 ms to 0 ms and a post-stimulus one with a time window from 0 ms to 500 ms. Then, we performed a generalized eigendecomposition to extract the largest eigenvectors that differentiate pre-stimulus and post-stimulus response. We then multiplied the component weights with the raw data and showed the topographical characteristics of the components. Finally, we applied a Hilbert transformation analysis to the EEG data filtered by the component weights. For the power correction of the result, we used -300 ms to 0 ms as the baseline.

Results

Event-related Potentials

We found a robust P300 effect at electrode P3 and this effect is stable across the five subjects. Figure 1 shows the comparison of common versus oddball conditions (top panel), along with separated comparisons of visual (middle) and auditory (bottom) conditions. The top panel shows a larger amplitude of ERPs for oddball condition relative to common condition at post-stimulus latency around 300 ms, that is also observed for the comparison between visual common and visual oddball condition. Surprisingly, the comparison within auditory condition looks unusual and we did not find clear oddball effects.

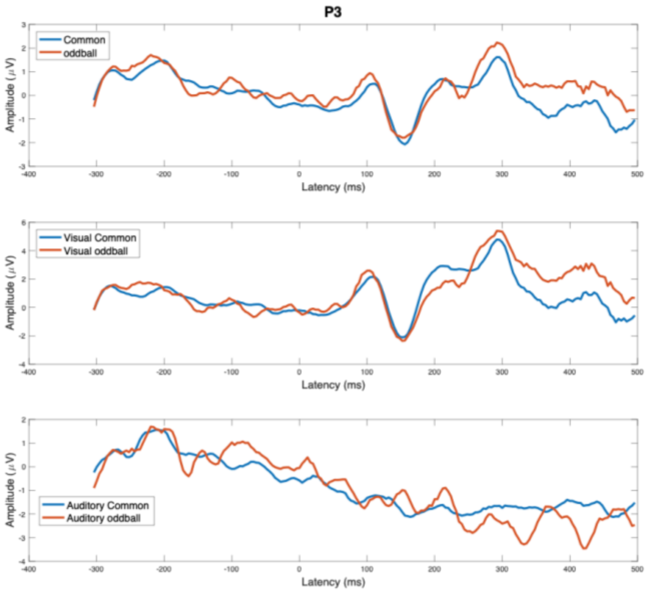


Figure 1: ERP P300 effect identified from electrode P3.

Figure 2 shows the topographical plots of common and oddball conditions under five time windows: -500-0ms, 0-160ms, 160-300ms, 300-500ms, 500-1000ms. Both topographical plots at baseline period (-500-0ms) shows no clear spatial localized effects or difference between oddball and common conditions, which is not surprising. Post-stimulus topographical results show some parietal and frontal activations. We suspect that the frontal activations come from the leftover effects of eye movements, suggesting that some eye movements may not have been completely removed. For parietal activations, we do find a strong difference between oddball and common conditions during time windows 160-300ms and 300-500ms. This parietal result is consistent with the long-held belief of the brain source and timing of oddball effects.

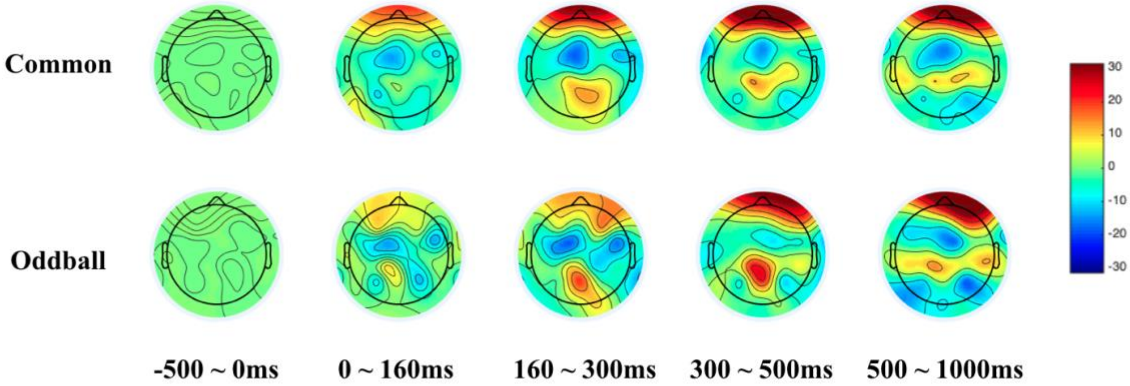
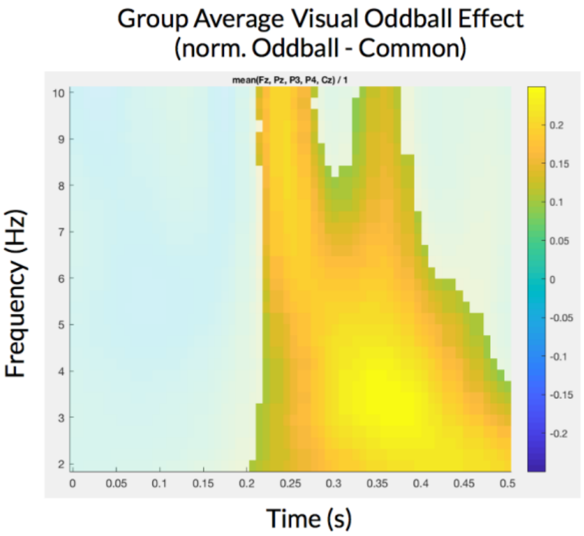


Figure 2: ERP topographical plot of oddball effect.

Time-Frequency Analysis of Post-Stimulus and Pre-Stimulus Time Window

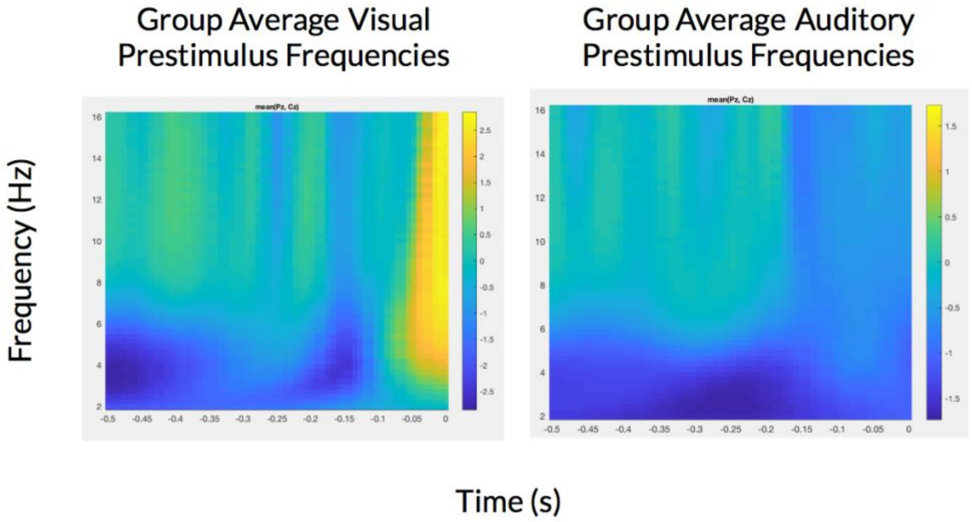
Time-frequency analysis of EEG data during the post-stimulus time window revealed significant increases in delta, theta, and alpha power in visual oddball trials compared to common trials in the 200-500ms time period, all statistics threshold clustered using a monte carlo correction procedure with p-value <.01 and compared to a permutation test of 1000 randomly shuffled data iterations. This was characterized by a particularly large increase in theta activity centered on 350ms, mirroring the ERP results but providing additional information about frequency. This effect was not observed in auditory trials, consistent with what we identified from ERPs result.



Group Average Visual Oddball Effect
(norm. Oddball - Common)

Figure 3: The group averaged normalized subtraction of common trials from Oddball trials in the visual Oddball task, significance highlighted. Significant regions span the 2-10Hz frequency range from 200 to 500 ms after stimulus onset.
[electrodes: mean Pz, Cz, Fz, P3,P4]

In the pre-stimulus time period, no significant alpha increases or decreases were observed, however, significant decreases in delta and theta were observed in both the auditory (-.35 to -.15 ms) and visual (-.5 to -.4 ms) conditions across all trials.



Group Average Visual
Prestimulus Frequencies

Group Average Auditory
Prestimulus Frequencies

Figure 4: The group averaged prestimulus period for visual and auditory trials, respectively, demonstrating a lack of significant alpha activity (plotted with

decibel correction). [electrodes: mean Pz, Cz]

Generalized Eigendecomposition

Figure 5 shows the eigenvalues and first four components from GED analysis. The eigenvalues (denoted by λ) are sorted in descending order. The first component is localized in the medial frontal area and the second component is localized near the eye. We believe that the second component is mostly driven by eye blinking artifact. Also, there is an obvious drop of the eigenvalue from the second component to the third and beyond, so we focused on using the first component as the spatial filter.

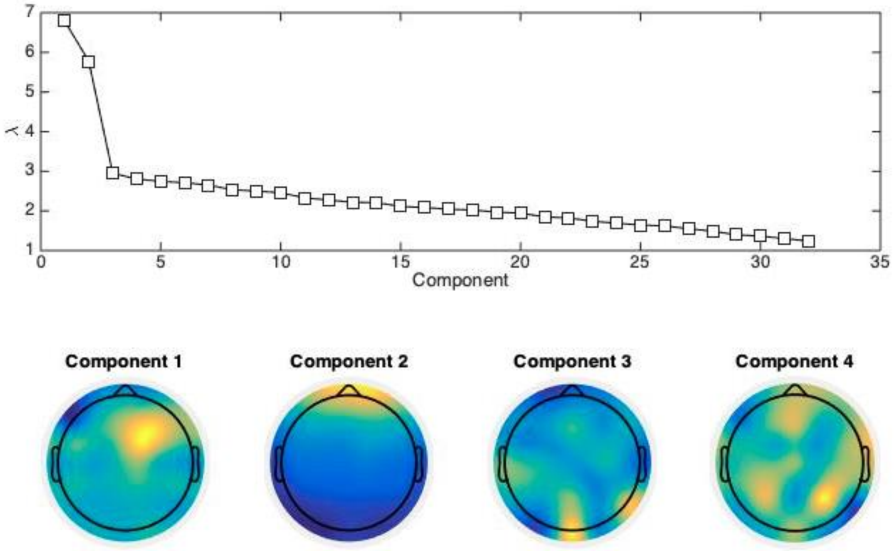


Figure 5: Eigenvalues and topographical component scores from GED

After applying the spatial filter of component weights to the raw EEG data, we observed a suggestive stronger theta-band activation centered at about 600 ms in the oddball trials compared to the common trials (Figure 6). This result is also visible for comparing only visual oddball versus visual common conditions and the effect is stronger (Figure 7).

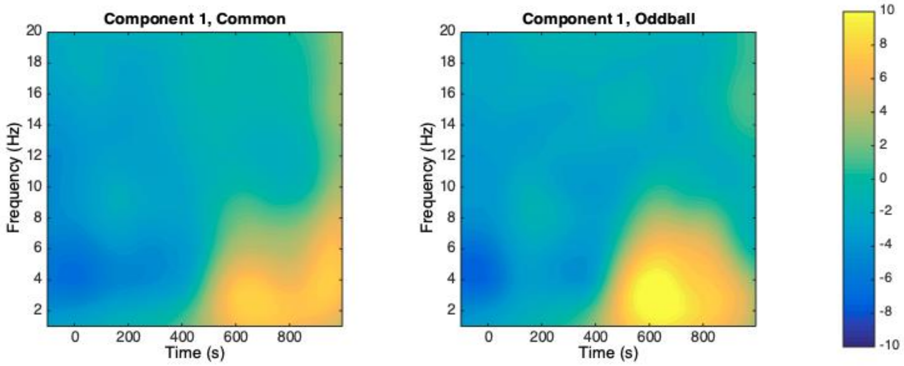


Figure 6: Time-frequency plot with the first GED component weight as a spatial filter for comparing common versus oddball conditions

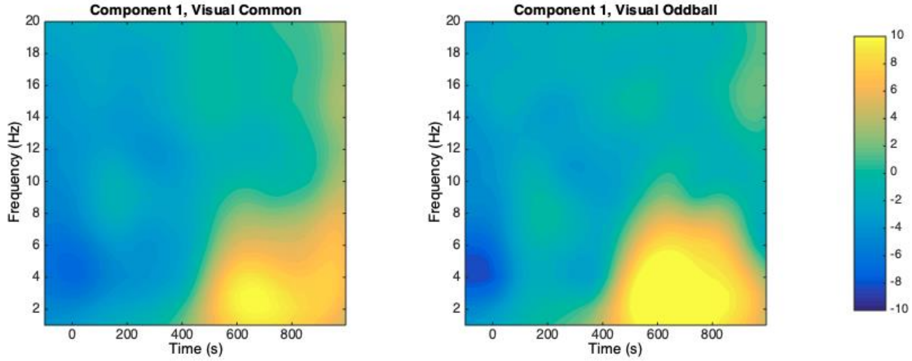


Figure 7: Time-frequency plot with the first GED component weight as a spatial filter for comparing visual common versus oddball conditions

Discussion

Event-Related Potentials

We observed the classic oddball effects at electrode P3, which shows robust effect across subjects. For other electrodes P4, Pz, Fz, Cz that we also examined in the project, Pz also shows group-level effect but this effect is not consistent across subjects. There are a great amount of individual differences in terms of the amplitude, latency and electrodes for the oddball effects. The variation of electrode is reasonable considering the position of electrode placement during the experiment. The different amplitude and latency of ERPs components are worth further investigating in terms of associated underlying cognitive mechanisms.

The spatial localization of the oddball effects investigated in our analysis is by no means a precise localization of brain sources, but rather an attempt with the help of surface laplacian technique. Using surface laplacian for oddball paradigm is debated, as some researchers argue that surface laplacian could remove the P300 effects especially P3b component (Kayser & Tenke, 2015). We surprisingly identified some frontal activations in the EEG spectra and it is very likely that they stand for leftover eye movements. This alerts us to better capture eye movements in the preprocessing step in future practice.

Time-Frequency Analysis

The time-frequency analysis was able to verify the ERP findings described above, where increases in delta, theta and alpha power (in oddball-common trials) were observed at the same time period as the ERP oddball effect. Despite not observing reliable pre-stimulus alpha in the time-frequency analysis, we did observe prestimulus theta and delta power decreases in Pz and Cz. In one relevant study, oddball trials were characterized by increased delta and theta power in the post-stimulus period (250-500ms), but not in a task that periodically omitted an expected auditory stimulus (Başar-Eroglu, Başar, Demiralp, & Schürmann, 1992). Due to these results and the existing literature, the authors suggest there is a dissociation between delta and theta increases: delta responses are involved in “signal matching, decision making, and surprise,” and theta responses are indicative of “focused attention and signal detection.”

In the clinical literature, increases in spontaneous delta activity have been associated with pathology, including ADD and ADHD – generally, an inverse relationship between pre-stimulus activity and post-stimulus activity is observed: in oddball paradigms in those with schizophrenia, it has repeatedly been reported that there is a decrease in delta compared to healthy controls (Güntekin & Başar, 2016). Additionally, in a Go/NoGo paradigm, high pre-stimulus delta power increased the amplitude of post-stimulus ERP components, including the N100 and P300 for Go and NoGo trials. Low pre-stimulus theta power increased the amplitude of post-stimulus P300 Go trials and reduced amplitude of P300 in NoGo trials, suggesting theta, but not delta, is involved in inhibitory control (De Blasio & Barry, 2013).

Together, these findings suggest that a pre-stimulus delta and theta decrease is not an unusual finding, and these endogenous brain rhythms may also be indicative of brain states that predict either superior or inferior performance on cognitive tasks. Future research should attempt to resolve not only the role of pre-stimulus alpha, but also pre-stimulus delta and theta in cognitive processes such as attention, signal detection, and surprise.

Generalized Eigendecomposition

The GED procedure searches for a vector that maximally differentiates two covariance matrices. If we make one of the matrices the covariance of the feature to be maximized and the other one the covariance of the feature to be minimized, then we can get a set of eigenvectors that can serve as weights on aggregated data from all electrodes.

We found a suggestive stronger theta-band power centered around 600 ms after stimulus onset in oddball trials. This is somewhat contrary to what was expected as the oddball effect has previously been seen in an earlier time window in other studies and also by the current study from both ERPs and standard time-frequency analysis. We suspect this unexpected result is due to the following reasons: as suggested in Cohen & Gulbinaite's (2017), selecting the appropriate parameters adds to the subtleties of this method. It is likely that the bandwidth of the spatial filter, reference frequencies, and the time window create covariance matrices that determined the effect we found. It is also possible that the identified late effect from GED reflects other types of cognitive mechanisms that occur in later time course.

Compared with other source separation techniques, GED is a more guided procedure than PCA as it allows flexibility in constructing covariance matrices. Compared with ICA, it is likely that GED involves a more sensitive source separation mechanism so that eye artifacts are still present in the second component from GED, even though we have removed the eye movement component identified from ICA in the preprocessing steps. The small sample size may have been disadvantageous to finding meaningful results using GED; future studies adopting this method are warranted to more robustly contrast different experimental conditions where responses are locked to certain frequencies or localized to particular brain regions.

Conclusion

In the present study, analysis of EEG data of five subjects on a classical oddball paradigm included ERP, time-frequency analysis, and generalized eigendecomposition. We replicated the oddball P300 effects in electrodes including the P3. The time-frequency analysis showed increased alpha, delta, and theta band of oddball versus common conditions at post-stimulus time, and increased delta and theta band at pre-stimulus time. The generalized eigendecomposition was more exploratory, showing theta-band power increase of oddball effects localized to frontal areas. Although the result did not reach the full hypothesized expectations, this has been a worthwhile attempt, and we look forward to conducting further analyses including other source separation methods to investigate the spatial-temporal dynamics of neuroimaging data.

Acknowledgements

The group thanks Dr. Brandon Turner and Jiageng Chen for introducing its members to the world of EEG research and for suggestions provided during the group presentation.

References

Barry, R. J., Kirkaikul, S., & Hodder, D. (2000). EEG alpha activity and the ERP to target stimuli in an auditory oddball paradigm. *International Journal of Psychophysiology*, *39*(1), 39–50. doi.org/10.1016/S0167-8760(00)00114-8.

Barry, R. J., Rushby, J. A., Johnstone, S. J., Clarke, A. R., Croft, R. J., & Lawrence, C. A. (2004). Event-related potentials in the auditory oddball as a function of EEG alpha phase at stimulus onset. *Clinical Neurophysiology*,*115*(11), 2593–2601. doi.org/10.1016/j.clinph.2004.06.004.

Başar-Eroglu, C., Başar, E., Demiralp, T., & Schürmann, M. (1992). P300-response: possible psychophysiological correlates in delta and theta frequency channels. A review. *International Journal of Psychophysiology*, *13*(2), 161–179. doi.org/10.1016/0167-8760(92)90055-G.

Bernat, E. M., Malone, S. M., Williams, W. J., Patrick, C. J., & Iacono, W. G. (2007). Decomposing delta, theta, and alpha time–frequency ERP activity from a visual oddball task using PCA. *International Journal of Psychophysiology*, *64*(1), 62–74. doi.org/10.1016/j.ijpsycho.2006.07.015.

Cohen, M. X., & Gulbinaite, R. (2017). Rhythmic entrainment source separation: Optimizing analyses of neural responses to rhythmic sensory stimulation. *Neuroimage*, 147, 43-56. doi.org/10.1016/j.neuroimage.2016.11.036

De Blasio, F. M., & Barry, R. J. (2013). Prestimulus delta and theta determinants of ERP responses in the Go/NoGo task. *International Journal of Psychophysiology*, *87*(3), 279–288. doi.org/10.1016/j.ijpsycho.2012.09.016.

Delorme, A., Arnaud, D., Jason, P., Julie, O., Robert, O., Scott, M., 2012. Independent EEG sources are dipolar. PLoS One 7, e30135.

Dien, J., Khoe, W., & Mangun, G. R. (2007). Evaluation of PCA and ICA of simulated ERPs: Promax vs. Infomax rotations. Human brain mapping, 28(8), 742-763.

Güntekin, B., & Başar, E. (2016). Review of evoked and event-related delta responses in the human brain. *International Journal of Psychophysiology*, *103*, 43–52. doi.org/10.1016/j.ijpsycho.2015.02.001.

Kayser, J., & Tenke, C. E. (2015). Issues and considerations for using the scalp surface Laplacian in EEG/ERP research: a tutorial review. *International Journal of Psychophysiology*, *97*(3), 189-209.

Kolev, V., Demiralp, T., Yordanova, J., Ademoglu, A., Isoglu-Alkac, U. (1997). Time-frequency analysis reveals multiple functional components during odball P300. Neuroreport 8, 2061-2065.

Robert Oostenveld, Pascal Fries, Eric Maris, and Jan-Mathijs Schoffelen. FieldTrip: Open Source Software for Advanced Analysis of MEG, EEG, and Invasive Electrophysiological Data. Computational Intelligence and Neuroscience, vol. 2011, Article ID 156869, 9 pages, 2011. doi:10.1155/2011/156869.

Squires NK, Squires KC, Hillyard SA. (1975) Two varieties of long-latency positive waves evoked by unpredictable auditory stimuli in man. Electroencephalogr Clin Neurophysiol. 38(4):387-401.

van Dijk, H., Schoffelen, J.-M., Oostenveld, R., & Jensen, O. (2008). Prestimulus Oscillatory Activity in the Alpha Band Predicts Visual Discrimination Ability. *Journal of Neuroscience*, *28*(8), 1816–1823. doi.org/10.1523/JNEUROSCI.1853-07.2008.