ORIGINAL ARTICLE

The Comparison between Visually and Auditory Oddball Tasks in the EEG Experiment with Healthy Subjects

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Received: 31 August 2020 / Accepted: 25 October 2020

Abstract

Purpose: The purpose of this study is estimating and comparing the three different dimensions of the EEG and studying the trials variability for two auditory and visually oddball tasks in the healthy subjects. They include regional as the region of the brain, longitudinal as the repetition of the stimuli, and functional as whole curve of Evoked Related Potential (ERP), dimensions.

Materials and Methods: The sample size is seventeen, with six females, in this three-trial study with standard and target stimuli per task. The dataset was downloaded from the internet and preprocessed. The Hybrid Principal Component Analysis (HPCA) decomposed the ERPs and estimated eigen components of three dimensions. The 95% Bayesian credible sets and trial effects as random effects of the first eigen component of each dimensions studied with the Generalized Additive Mixed Model (GAMM).

Results: The p-values of the interaction effects between time and stimuli, repeats and stimuli and regions and stimuli are <0.05 for three dimensions, except in auditory task of longitudinal dimension and in visual task of regional dimension that are >0.05. The p-value of trial effects are <0.05 and for auditory task in the longitudinal dimension is borderline.

Conclusion: The HPCA methodology decompose the time-domain ERPs to the functional-longitudinal and regional dimensions. The first eigencompments capture the most variations of every dimensions and we study the behavior of three-dimensions with them. We conclude that the repeating of the stimuli has a positive effect on the visual tasks. We also study the variability between trials with GAMM that are statistically significant.

Keywords: Electroencephalography; Functional Data Analysis; Bayesian Data Analysis; Attention; Evoked Related Potential.

DOI: https://doi.org/10.18502/fbt.v7i4.5322

Frontiers in BIOMEDICAL TECHNOLOGIES

1. Introduction

The standard statistical multivariate models such as Independent Component Analysis (ICA), Principal Component Analysis (PCA), etc. were used for analyzing the Electroencephalography (EEG) datasets [1]. They work with the summary of statistics like averages on all Evoked Related Potential (ERP) on each sensor and sometimes on the whole brain or only the amplitude and latency of the waves. The summary statistics pool the information and destroy some aspects of the dataset. For example, the averaging along each ERP on the sensors destroys the longitudinal dimension, the effects of repeating the stimuli, meanwhile averaging along each sensor destroys the region of the brain dimension. But the recent advances in the statistical methods, Functional Data Analysis (FDA), consider the underlying curves of data and the derivatives of the functions [2]. We can count the Bayesian fully Spatio-temporal multivariate autoregressive time series models [3], Bayesian Functional data analysis [4], the modified functional PCA [5], the multi-dimensional FPCA [6], and Hybrid PCA (HPCA) [7] among them. They consider the ERP as curves in the analysis and extract some new effects such as spatial, regional, longitudinal, etc. from them.

The P300 ERP was studied for more than 50 years [8] for detecting concealed information and deception [9], their role in the auditory [10], emotions [11], visually task [12], rapid statistical learning, memory, and novelty processing with two subcomponents P3a for novelty and distracting novelty and P3b for target detection [13] and its relation to the physical activity and cardiorespiratory [14], their role in the language comprehension [15] and its development by age [16]. Many Brain-Computer Interfaces (BCI) [17] and EEG-fMRI papers for studying internal attentions [18] considered this phenomenon.

In this study, we analyze the EEG datasets from an EEG-fMRI study which was gathered and published for understating and exploring the mechanism of attention in the brain with two tasks; Auditory and Visually Oddball tasks [19-23]. First, we estimate the longitudinal, regional, and functional effects, second, we calculate the 95% Bayesian credible set among three trials and finally we investigate the stimuli and trial effects with a generalized additive mixed model [7].

2. Materials and Methods

2.1. Dataset

The dataset is an EEG-fMRI [21] experiment to study the internal attentions in the brain with 17 participants (6 females, mean age is 27.7 years). There are three trials and two tasks for each experiment including auditory and visual stimuli. And there are two stimuli in each task (each has 125 stimuli); standard stimuli that must be ignored (80% most of the time) and target stimuli in which participants must push the button to the responde (most of the time 20%).

The auditory task includes standard stimuli (390 Hz tone) and target stimuli (laser gun sound). The visual task includes standard stimuli (small green circle on isoluminant grey background, 1.5-degree visual angle) and target stimuli (large red circle on isoluminant grey background, 3.45-degree visual angle). The stimulus duration is 200 ms and the ITI (inter-trial-interval) is 2-3 seconds which is uniformly distributed. The first two stimuli are standard.

The sampling rate is 1000 Hz with 49 channels. The custom cap configuration were bipolar electrode pairs and twisted leads. We use the re-referenced electrode space. Therefore, there are 1 to 34 electrodes. The dataset is downloaded from the openNeuro website [24].

2.2. Data Preparation

We clean each trial dataset separately by removing the artifacts, filtering, epoching, and using baseline correction with R, version 4.0.2 [25], which was validated with EEGLAB Toolbox outputs [26]. We average the signals from sensors based on their locations on the scalp head into six regions: Frontal, Central, Occipital, Parietal, Left Temporal and Right Temporal. We estimate the ERP wave for each participant in each trial for each region of the brain.

2.3. Statistical Modeling

2.3.1. The HPCA Decomposition

We assume that $Y_{diq}(r,t,s)$ is an ERP wave, which contains regional-longitudinal-functional-trial ERP wave for subject i, $i = 1,\dots,17$, from group d, $d = 1$ $(Standard\ Stimuli), 2\ (Target\ Stimuli)$, in region r, $r = 1,\dots,6$, at time t, $t \in [0{,}800]ms$ for the functional part and s, $s \in [1{,}25]$ for the longitudinal part, and q, $q = 1{,}2{,}\text{and}\ 3$ for trial number. The HPCA was used to estimate the regional, longitudinal, and functional effects for each trial separately, as stated in [7]:

$$Y_{diq}(r,t,s) = \mu_q(r,t) + \eta_{dq}(r,t,s) + \sum_{k=1}^{R=6}\sum_{l=1}^{\infty}\sum_{m=1}^{\infty}\xi_{diq,klm}v_{dkq}(r)\phi_{dlq}(t)\psi_{dmq}(s) + \epsilon_{diq}(r,t,s)$$

The $\mu_q(r,t)$ is an overall mean function. $\eta_{dq}(r,t,s)$ is group-region shifts. $\xi_{diq,klm}$ is the subject-specific score. The $v_{dkq}(r)$ are common eigenvectors for the regional marginal covariance matrix. The $\phi_{dlq}(t)$ and $\psi_{dmq}(s)$ are common eigenfunctions for functional and longitudinal marginal covariance surfaces. Therefore, we have the following estimations for each trial:

Trial 1: $\hat{Y}_{di1}(r,t,s) = \hat{\mu}_1(r,t) + \hat{\eta}_{d1}(r,t,s) + \sum_{k=1}^{R=6}\sum_{l=1}^{\infty}\sum_{m=1}^{\infty}\hat{\xi}_{di1,klm}\hat{v}_{dk1}(r)\hat{\phi}_{dl1}(t)\hat{\psi}_{dm1}(s) + \epsilon_{di1}(r,t,s)$

Trial 2: $\hat{Y}_{di2}(r,t,s) = \hat{\mu}_2(r,t) + \hat{\eta}_{d2}(r,t,s) + \sum_{k=1}^{R=6}\sum_{l=1}^{\infty}\sum_{m=1}^{\infty}\hat{\xi}_{di2,klm}\hat{v}_{dk1}(r)\hat{\phi}_{dl2}(t)\hat{\psi}_{dm2}(s) + \epsilon_{di2}(r,t,s)$

Trial 3 $\hat{Y}_{di3}(r,t,s) = \hat{\mu}_3(r,t) + \hat{\eta}_{d3}(r,t,s) + \sum_{k=1}^{R=6}\sum_{l=1}^{\infty}\sum_{m=1}^{\infty}\hat{\xi}_{di3,klm}\hat{v}_{dk1}(r)\hat{\phi}_{dl3}(t)\hat{\psi}_{dm1}(s) + \epsilon_{di3}(r,t,s)$

The number of eigenvector and eigenfunctions are estimated by the total fraction of variance explained (FVE_{dKMLq}) which is greater than 90% of FVE. In this study, we only estimate and use the first eigenfunctions of functional dimeson $(\hat{\phi}_{111}(t),\ \hat{\phi}_{211}(t),\ \hat{\phi}_{112}(t),\ \hat{\phi}_{212}(t),\ \hat{\phi}_{113}(t),\ \hat{\phi}_{213}(t))$ with $t \in [0{,}800]ms$ and longitudinal dimension $(\hat{\psi}_{111}(s),\ \hat{\psi}_{211}(s),\ \hat{\psi}_{112}(s),\ \hat{\psi}_{212}(s),\ \hat{\psi}_{113}(s),\ \hat{\psi}_{213}(s))$ with $s \in [1{,}25]$ and the first eigenvector of the regional dimension $(\hat{v}_{111}(r),\ \hat{v}_{211}(r),\ \hat{v}_{112}(r),\ \hat{v}_{212}(r),\ \hat{v}_{113}(r),\ \hat{v}_{213}(r))$ for each stimulus and in each trial, because most of the total variations are explained by the first of them.

2.3.2. The 95% Bayesian Confidence Bands

We estimate the 95% Bayesian confidence bands for the first eigenfunction of functional and longitudinal dimensions in three trials. Therefore, we have an estimate based on three trials and their variabilities. For simplicity of the analysis, we do not consider the time correlation within curves and between trials in this calculation and we assume that observations distribute independently. This may cause to estimate of the higher variance in the estimations.

The $(t_i,\hat{\phi}_i),\ \{\hat{\phi}_i, 1 \le i \le (800\times 3) = 2400\}$ are estimated eigenfunction values for functional dimension and $\{t_i, 1 \le i \le 2400, 1 \le t \le 800\}$ are observed times in each stimulus. And $(s_j,\hat{\psi}_j), \{\hat{\psi}_j, 1 \le j \le (25\times 3) = 75\}$ are estimated eigenfunction values for longitudinal dimension and $\{s_j, 1 \le j \le 75, 1 \le s \le 25\}$ are repeats in each stimuli [27].

The first eigenfunction of the functional dimension model is:

$$\hat{\phi}_i|\boldsymbol{\beta},\boldsymbol{u},\sigma_\varepsilon^2 \sim N(\beta_0 + \beta_1 t_i + \sum_{k=1}^{K} u_k z_k(t_i), \sigma_\varepsilon^2) \quad (ind)$$

$$\boldsymbol{u}|\sigma_u \sim N(0,\sigma_u^2 I)$$

$$\beta_0,\beta_1 \sim N(0,\sigma_\beta^2)$$

$$\sigma_u \sim Half-Cauchy\ (A_u)$$

$$\sigma_\varepsilon \sim Half-Cauchy\ (A_\varepsilon)$$

The $\beta_0,\beta_1,\sigma_u,\sigma_\varepsilon$ are random effects and the hyperparameters $\sigma_\beta > 0, A_u > 0, A_\varepsilon > 0 = 10^5$.

The first eigenfunction of the longitudinal dimension model is:

$$\hat{\psi}_j|\boldsymbol{\beta},\boldsymbol{u},\sigma_\varepsilon^2 \sim N(\beta_0 + \beta_1 s_j + \sum_{k=1}^{K} u_k z_k(s_j), \sigma_\varepsilon^2) \quad (ind)$$

$$\boldsymbol{u}|\sigma_u \sim N(0,\sigma_u^2 I)$$

$$\beta_0,\beta_1 \sim N(0,\sigma_\beta^2)$$

$$\sigma_u \sim Half-Cauchy\ (A_u)$$

$$\sigma_\varepsilon \sim Half-Cauchy\ (A_\varepsilon)$$

The $\beta_0,\beta_1,\sigma_u,and\ \sigma_\varepsilon$ are random effects and the hyper-parameters $\sigma_\beta > 0, A_u > 0, A_\varepsilon > 0 = 10^5$.

We use the MCMC (Monte Carlo Markov Chain) method with 15000 iterations. The first 5000 of them are warm-ups and the thin factor is 2. The estimation

is done in RStan [28]. The MCMC samples were checked with four plots: A time series or a trace plot, a lag-1 plot, an autocorrelation function plot, and a kernel density estimation of the posteriors density function of parameters. Therefore, the 95% credible set for the first eigenfunctions of functional and longitudinal dimensions in three trials and each group was estimated.

The first and second eigenvectors of the regional dimension were estimated by averaging over the three runs and plot against each other. The standard deviation of the three trials is also estimated.

2.3.3. The Generalized Additive Mixed Models

The Generalized Additive Mixed Model (GAMM) is a mixed model extension of the GAM and it can model the fixed and random effects together. We treated a group of stimuli as a fixed effect and trials as a random effect in the following models and used a thin plate regression spline for times and repeats in the functional and longitudinal dimensions, respectively [27].

The model of the first eigenfunction of functional effects is:

$$\phi_{1ij} = Trial_i + \beta_1(t_{ij}) \times Stimuli_i + \varepsilon_{ij}$$

$$1 \le j \le 800, \quad 1 \le i \le 3$$

$$Trial_i \sim N(0, \sigma_U^2) \quad (ind), \; \varepsilon_{ij} \sim N(0, \sigma_{U\varepsilon}^2) \quad (ind)$$

The model of the first eigenfunction of longitudinal effects is:

$$\psi_{1ij} = Trial_i + \beta_1(s_{ij}) \times Stimuli_i + \varepsilon_{ij}$$

$$1 \le j \le 25, \quad 1 \le i \le 3$$

$$Trial_i \sim N(0, \sigma_U^2) \quad (ind), \; \varepsilon_{ij} \sim N(0, \sigma_{U\varepsilon}^2) \quad (ind)$$

We also treated the region of the brains as a fixed effect. The model of the first eigenvector of longitudinal effects is:

$$v_{1i} = Trial_i + \beta_1(Reg1_i) + \beta_2(Reg2_i) + \beta_3(Reg3_i) + \beta_4(Reg4_i) + \beta_5(Reg5_i) + \beta_6(Reg6_i) + \beta_7(Reg1_i) \times Stimuli_i + \beta_8(Reg2_i) \times Stimuli_i + \beta_9(Reg3_i) \times Stimuli_i + \beta_{10}(Reg4_i) \times Stimuli_i + \beta_{11}(Reg5_i) \times Stimuli_i + \beta_{12}(Reg6_i) \times Stimuli_i + \varepsilon_{ij}$$

$$1 \le i \le 3$$

$$Trial_i \sim N(0, \sigma_U^2) \quad (ind), \; \varepsilon_i \sim N(0, \sigma_{U\varepsilon}^2) \quad (ind)$$

The above models were fitted for the auditory and visual tasks with the GAMM function in the mgcv package [29] in R separately. The coefficients are estimated and the P-Values are reported. The log-likelihood ($ln(L)$), Akaike information criterion (AIC) ($\mathrm{AIC} = -2\ln(\mathrm{L}) + 2\mathrm{p}$) and Bayesian Information Criteria (BIC) ($BIC = -2\,ln(L) + plog(n)$) were reported for model comparisons, where L is the maximized likelihood function for the estimated model, p is the number of estimated parameters and n is the number of observations.

3. Results

3.1. The HPCA and Their Credible Sets

The HPCA decomposition of ERP waves for each stimulus in each task for three trials is extracted. The first eigenfunctions for functional and longitudinal dimensions and first and second eigenvectors for regional dimensions are estimated and their 95% Bayesian credible sets were reported.

3.1.1. The Functional Dimensions

The 95% credible set of the auditory task in the standard and target stimuli showed that the variability between trials in the standard stimuli is less than target stimuli. Thus the estimated credible set is narrower in the standard stimuli rather than target stimuli. There is a peak between 400 and 600 ms in the target stimuli. On the other hand, the visual tasks have two completely different patterns in the standard and target stimuli. The standard stimuli are almost flat but the target stimuli have a big peak between 400 and 600 ms (Figure 1).

3.1.2. The Longitudinal Dimensions

The standard stimuli in the Auditory have a wider 95% credible set than target stimuli. But both estimated curves have a similar pattern.

The visual tasks have two completely different patterns in the standard and target stimuli. The standard stimuli have a linear positive trend but the target stimuli have a smooth positive trend (Figure 2).

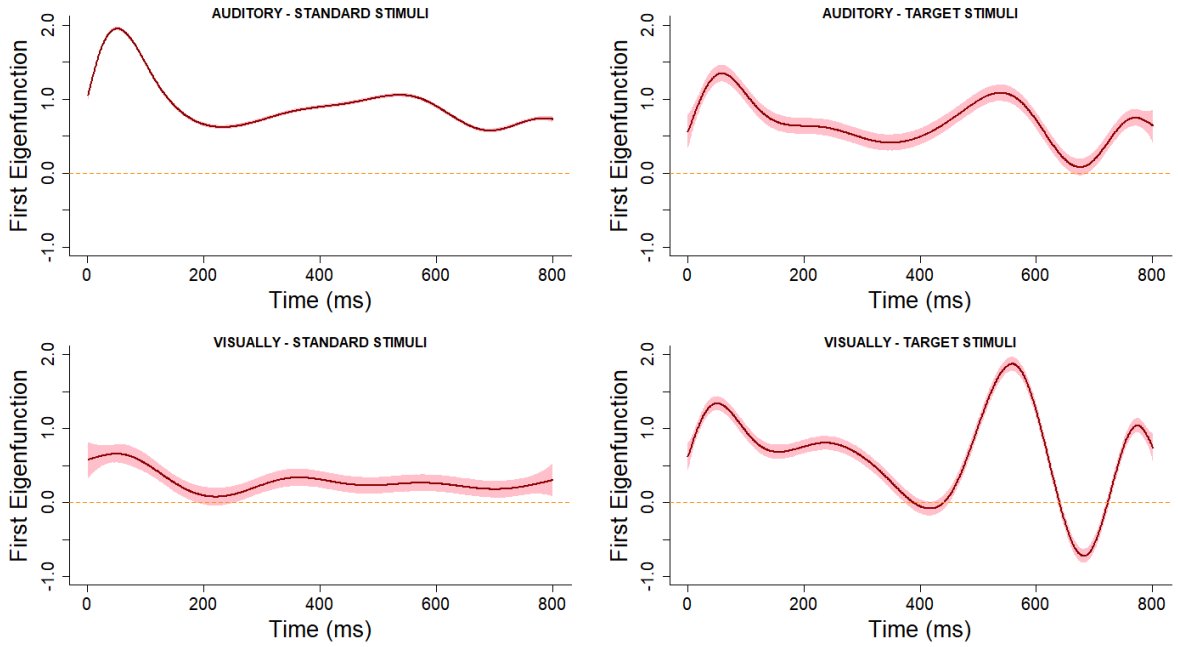

Figure 1. The estimated 95% credible sets for three trials of first eigenfunctions of functional effects (Top left): Auditory task and standard stimuli, (Top right): Auditory task and target stimuli, (Bottom left): Visually task and standard stimuli, (Bottom right): Visually task and target stimuli

3.1.3. The Regional Dimensions

The estimated mean ± standard deviation for three trials for the first and second eigenvectors for six regions of the brain was plotted against each other. In the auditory task with standard stimuli, the occipital and left temporal are far from each other and the other parts but in the target stimuli, these two regions are close to each other. But in the visual task, the pattern of different regions is not changing dramatically in the standard and target stimuli (Figure 3).

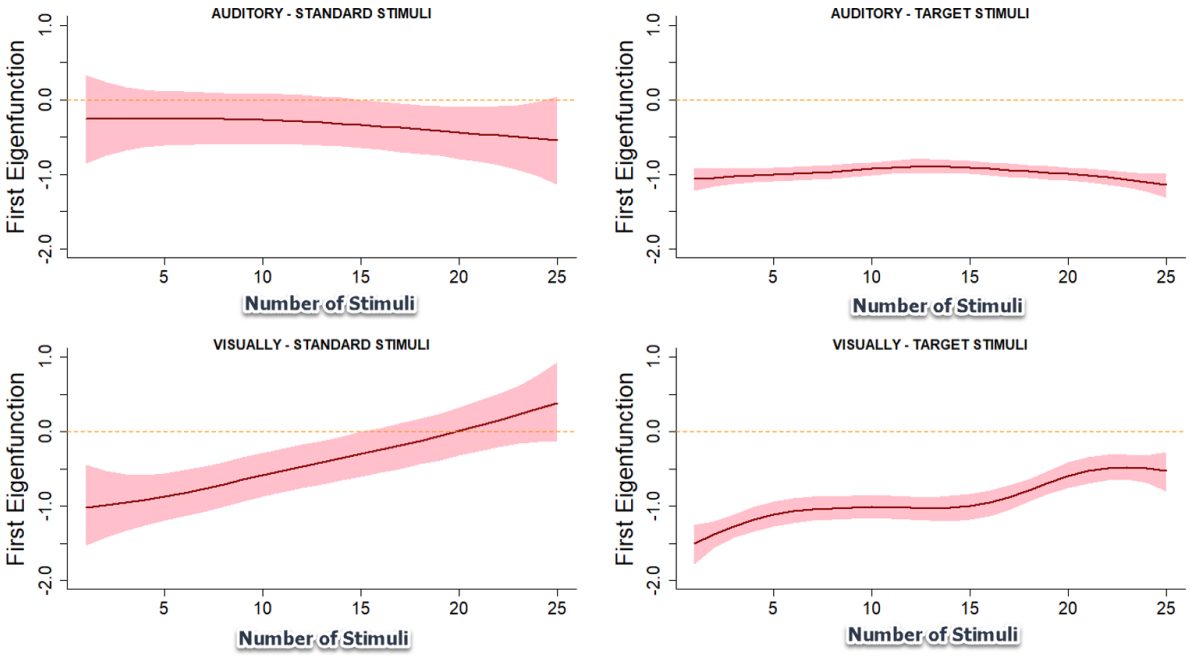

Figure 2. The estimated with 95% credible sets for three trials of first eigenfunctions of longitudinal effects(Top left): Auditory task and standard stimuli, (Top right): Auditory task and target stimuli, (Bottom left): Visually task and standard stimuli, (Bottom right): Visually task and target stimuli

3.2. The GAMM Results

The GAMM results include three-part, the fixed effect estimates, the random effects statistical significance and log-likelihood, AIC, and BIC. The model is estimated for two tasks separately.

3.2.1. The Functional Dimensions

The interaction between the fixed effects of time and stimuli is statistically significant for both tasks (P-values are less than 0.05). The random effects, trial, are also statically significant for both tasks (P-values are less than 0.05) (Table 1).

3.2.2. The Longitudinal Dimensions

The interaction between fixed effects of repeats and stimuli is not statistically significant in the Auditory Task (P-values are not less than 0.05) and are statistically significant in the visually task (P-values are less than 0.05). The random effects, trial, are not significant for the Auditory (P-value: 0.06) but they are significant for the visual task (P-value: <0.00) (Table 2).

3.2.3. The Regional Dimensions

The fixed main effects include statistically significant brain regions (P-value less than 0.05) for both tasks and the main effect of the target stimuli is significant for auditory (P-value: <0.00) and is not significant for the visual tasks (P-value: >0.06). The interaction between target stimuli and the region of the brain is only significant for Occipital, Parietal, and Right Temporal (P-values < 0.05) for the auditory task. The random effects, trials, are significant for both tasks (Table 3).

4. Discussion

The first eigenfunctions of ERP waves for the auditory and visual tasks with standard and target stimuli are different from each other (Table 1). And the different trials produce different first eigenfunctions and are not statistically the same (Figure 1). The functional dimension of the ERPs have a complex structure and we cannot capture all important patterns with the first eigenfunctions. The difference between standard and target stimuli is observed. The first eigenfunction for the target stimuli captures the peak between 400-600 ms for the auditory task and between 500-600 ms for the visual task. The auditory task with oddball target tasks showed a peak around 300-600 ms [30], two peaks between 200-400 ms and 600-800 ms [31], between 500-800 ms [32], around 200 ms and 500 ms [18], around 400 ms [21]. The target stimuli with the visual oddball task have two peaks around 100-200 ms and 200-300 ms [31], between 500-800 ms [32], between 100-400 ms and 600-800 ms [18], around 200 ms and 300 ms [33], between 200-400 ms for stimulus-locked [22] window and around 400 ms [21].

Table 1. The ANOVA table for the first eigenfunction of the functional part by tasks

Functional Part					
Task		**AUD**		**VIS**	
		Estimate	**P-Value**	**Estimate**	**P-Value**
Fixed Effect	*Intercept*	0.806	<0.001	0.465	0.0760
	Standard Stimuli × Time	1.125	<0.001	0.617	0.0196
	Target Stimuli × Time	1.651	<0.001	2.705	0.0000
		F-Value	**P-Value**	**F-Value**	**P-Value**
Random Effect	*Trial*	49.14882	<0.001	29.84901	<0.0001
		Log-likelihood	-3319.323	**Log-Likelihood**	-5034.378
Model		**AIC**	6652.645	**AIC**	10082.76
		BIC	6697.984	**BIC**	10128.09

The dependent variable is the first eigenfunction for the functional part.

The first eigenfunction of the longitudinal effects captures nearly all of the variations in these dimensions. In the auditory task, the longitudinal effects are not statistically significant (Table 2) and they have an almost zero-slop line pattern (Figure 2). It stated that the repeating of the stimuli does not have statistical effects on the ERPs. But in the visual task, the longitudinal effects are statistically significant (Table 2) and their values increase with repeating the stimuli both in the target and standard (Figure 2). The visual task is more complex than auditory tasks and participants need time and repeats to concentrate on them.

The first and second eigenvectors for the regional dimensions for both auditory and visually did not change dramatically in standard and target stimuli (Figure 3). But the frontal, Occipital, Parietal, and Right Temporal regions changed in the target stimuli of the auditory task. In the auditory target stimuli, the frontal, some part of the central and right temporal [30], the right temporal and central [31], the frontal at

Table 2. The ANOVA table for the first Eigenfunction of longitudinal part by tasks

Longitudinal Part					
Task		**AUD**		**VIS**	
		Estimate	**P-Value**	**Estimate**	**P-Value**
Fixed Effect	*Intercept*	-0.670	0.0154	-0.660	0.0075
	Standard Stimuli × Repeats	-0.092	0.2182	0.425	0.0000
	Target Stimuli × Repeats	-0.015	0.8410	0.264	0.0002
		F-Value	**P-Value**	**F-Value**	**P-Value**
Random Effect	*Trial*	2.52	0.06	20.45	<0.0001
Model		**Log-likelihood**	-153.707	**Log-Likelihood**	-140.998
		AIC	321.414	**AIC**	295.996
		BIC	342.347	**BIC**	316.9291

The dependent variable is the first eigenfunction for the longitudinal part.

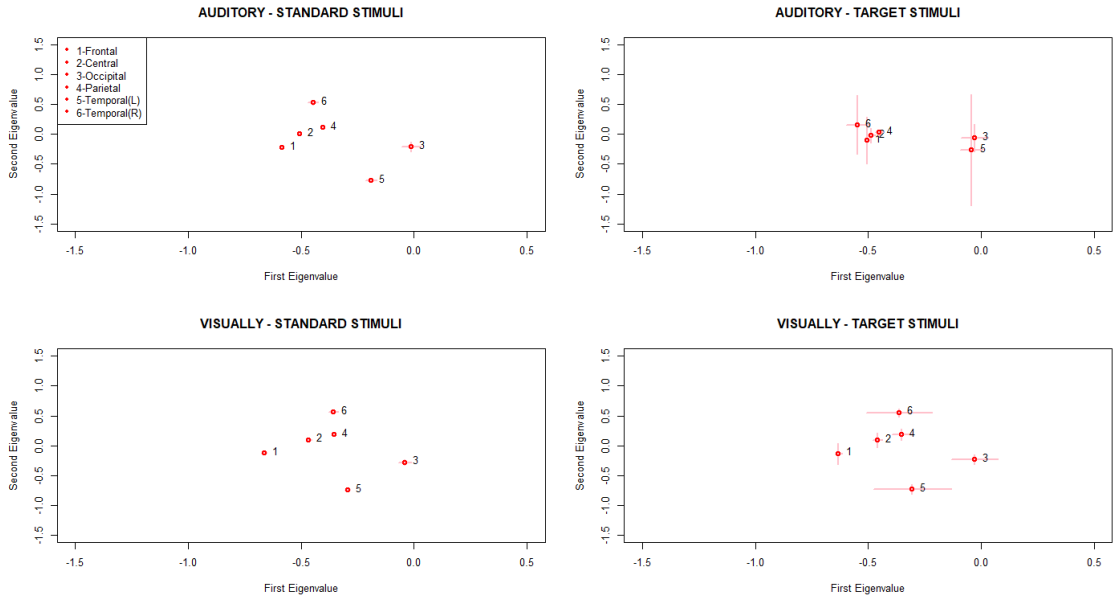

Figure 3. The estimated mean ± standard deviation for three trials of first and second eigenvectors of regional effects (Top left): Auditory task and standard stimuli, (Top right): Auditory task and target stimuli, (Bottom left): Visually task and standard stimuli, (Bottom right): Visually task and target stimuli

200 ms to some part of the left and right temporal and occipital and parietal from 350 ms to 600 ms [32] and in the visual target stimuli, occipital [31], occipital and left temporal from 300 ms to the whole brain except some part of frontal at 450 ms [32], frontal at 225 ms to 250 ms [22] have higher values than other regions. One reason for the non-significance of regions in the visual tasks is that all regions are activated and the difference between regions are not statistically significant.

The EEG data structure is complex and standard statistical methods cannot capture them. The HPCA methodology extracts functional, longitudinal, and regional dimensions simultaneously [7]. The between trial variability is another dimension that we introduce in this research and model them as random effects in the regular GAMM. The future direction of this research is to incorporate this dimension into the HPCA method and estimate its effect simultaneously. The Bayesian credible set is a useful method for EEG trials with a few numbers of trials to estimate the variability with the MCMC sampling techniques. There are different Bayesian algorithms, including the BUGS project (Bayesian inference using Gibbs sampling), Integrated and Nested Laplace Approximations (INLA) and we use the No-U-Turn sampler (a variant of Hamiltonian Monte Carlo) with RStan [28] which is very fast [34]. Another point for future research is by comparing different MC algorithms with EEG data. We use GAMM with the thin plate regression spline and random effects to model the between trial variability.

5. Conclusion

We conclude that the functional data analysis provides many statistical methods to analyze the EEG dataset by considering the underlying function of the curves. The HPCA can capture the functional-longitudinal and regional dimensions and we also

Table 3. The ANOVA table for the first eigenfunction of the regional part by tasks

Regional Part					
Task		**AUD**		**VIS**	
		Estimate	**P-Value**	**Estimate**	**P-Value**
Fixed Effect	*Intercept*	-0.584	< 0.00	-0.664	< 0.00
	Central	0.077	0.01	0.198	< 0.00
	Occipital	0.572	< 0.00	0.622	< 0.00
	Parietal	0.181	< 0.00	0.309	< 0.00
	Left Temporal	0.396	< 0.00	0.370	< 0.00
	Right Temporal	0.137	< 0.00	0.306	< 0.00
	Target Stimuli	0.080	< 0.00	0.032	0.60
	Target Stimuli ×Central	-0.058	0.13	-0.025	0.77
	Target Stimuli × Occipital	-0.095	0.02	-0.019	0.83
	Target Stimuli × Parietal	-0.127	< 0.00	-0.029	0.74
	Target Stimuli × Left Temporal	0.068	0.08	-0.042	0.63
	Target Stimuli × Right Temporal	-0.179	< 0.00	-0.036	0.67
		F-Value	**P-Value**	**F-Value**	**P-Value**
Random Effect	*Trial*	401.20	<.0001	88.95	<.0001
Model		**Log-likelihood**	79.92	**Log-likelihood**	48.88
		AIC	-131.85	**AIC**	-71.75
		BIC	-109.68	**BIC**	-49.59

The dependent variable is the first eigenfunction for the longitudinal part. The base region is frontal and the base stimuli is standard**.**

study the new dimension, trials with GAMM. We estimate the credible sets with the Bayesian data analysis.

The different regions of the brain have not the same activity in these two tasks. The repeating of the stimuli has a positive effect on complex tasks such as visual tasks. The first eigenfunction of the functional effect cannot capture all variabilities of this dimension and we need more eigenfunctions to study N1, P1, N2, and P3. The between trial variability is statistically significant, and we suggest studying this effect to show the stability of the trials. Although this EEG-fMRI data previously was analyzed [19-23, 35], the longitudinal effects within a trial were studied statistically [36, 37], and we study the between trials effects with random effects and estimate 95% Bayesian credible sets for the first time.

Acknowledgments

We thank Turin Cloud Services, Iran National Cloud, IPM for computation server (https://turin.ipm.ir/en/), and National Brain Mapping Lap (http://nbml.ir/EN).

References

1- T. Hastie, R. Tibshirani, and J. Friedman, "The elements of statistical learning: data mining, inference, and prediction". *Springer Science & Business Media*, 2009.

2- J. Ramsey, B. W. Silverman, "Functional Data Analysis," *Springer*, 2005.

3- P. A. Valdes-Sosa, "Spatio-temporal autoregressive models defined over brain manifolds," (in eng), *Neuroinformatics*, vol. 2, no. 2, pp. 239-50, 2004, doi: 10.1385/ni:2:2:239.

4- C. M. Crainiceanu and A. J. Goldsmith, "Bayesian functional data analysis using WinBUGS," *Journal of statistical software*, vol. 32, no. 11, 2010.

5- Z. Lin, L. Wang, and J. Cao, "Interpretable functional principal component analysis," (in eng), *Biometrics*, vol. 72, no. 3, pp. 846-54, Sep 2016, doi: 10.1111/biom.12457.

6- K. Hasenstab *et al.*, "A multi-dimensional functional principal components analysis of EEG data," (in eng), *Biometrics*, vol. 73, no. 3, pp. 999-1009, Sep 2017, doi: 10.1111/biom.12635.

7- A. Scheffler *et al.*, "Hybrid principal components analysis for region-referenced longitudinal functional EEG data," (in eng), *Biostatistics*, vol. 21, no. 1, pp. 139-157, Jan 1 2020, doi: 10.1093/biostatistics/kxy034.

8- J. Polich, "50+ years of P300: Where are we now?," *Psychophysiology*, vol. 57, no. 7, p. e13616, 2020.

9- J. P. Rosenfeld, "P300 in detecting concealed information and deception: A review," *Psychophysiology*, vol. 57, no. 7, p. e13362, 2020.

10- R. J. Barry, G. Z. Steiner, F. M. De Blasio, J. S. Fogarty, D. Karamacoska, and B. MacDonald, "Components in the P300: Don't forget the Novelty P3!," *Psychophysiology*, vol. 57, no. 7, p. e13371, 2020.

11- G. Hajcak and D. Foti, "Significance?... Significance! Empirical, methodological, and theoretical connections between the late positive potential and P300 as neural responses to stimulus significance: An integrative review," *Psychophysiology*, p. e13570, 2020.

12- E. M. Bernat, J. S. Ellis, M. D. Bachman, and B. M. Hicks, "P3 amplitude reductions are associated with shared variance between internalizing and externalizing psychopathology," *Psychophysiology*, p. e13618, 2020.

13- Y. M. Fonken, J. W. Kam, and R. T. Knight, "A differential role for human hippocampus in novelty and contextual processing: Implications for P300," *Psychophysiology*, p. e13400, 2019.

14- S. C. Kao *et al.*, "A systematic review of physical activity and cardiorespiratory fitness on P3b," *Psychophysiology*, vol. 57, no. 7, p. e13425, 2020.

15- M. Leckey and K. D. Federmeier, "The P3b and P600 (s): Positive contributions to language comprehension," *Psychophysiology*, vol. 57, no. 7, p. e13351, 2020.

16- T. Riggins and L. S. Scott, "P300 development from infancy to adolescence," *Psychophysiology*, vol. 57, no. 7, p. e13346, 2020.

17- B. Z. Allison, A. Kübler, and J. Jin, "30+ years of P300 brain–computer interfaces," *Psychophysiology*, vol. 57, no. 7, p. e13569, 2020.

18- V. Salmela, E. Salo, J. Salmi, and K. Alho, "Spatiotemporal dynamics of attention networks revealed by representational similarity analysis of EEG and fMRI," *Cerebral Cortex*, vol. 28, no. 2, pp. 549-560, 2018.

19- B. R. Conroy, J. M. Walz, B. Cheung, and P. Sajda, "Fast simultaneous training of generalized linear models (FaSTGLZ)," *arXiv preprint arXiv*:1307.8430, 2013.

20- B. R. Conroy, J. M. Walz, and P. Sajda, "Fast bootstrapping and permutation testing for assessing

reproducibility and interpretability of multivariate fMRI decoding models," *PloS one*, vol. 8, no. 11, 2013.

21- J. M. Walz, R. I. Goldman, M. Carapezza, J. Muraskin, T. R. Brown, and P. Sajda, "Simultaneous EEG-fMRI reveals temporal evolution of coupling between supramodal cortical attention networks and the brainstem," *Journal of Neuroscience*, vol. 33, no. 49, pp. 19212-19222, 2013.

22- J. M. Walz, R. I. Goldman, M. Carapezza, J. Muraskin, T. R. Brown, and P. Sajda, "Simultaneous EEG–fMRI reveals a temporal cascade of task-related and default-mode activations during a simple target detection task," *Neuroimage*, vol. 102, pp. 229-239, 2014.

23- J. M. Walz, R. I. Goldman, M. Carapezza, J. Muraskin, T. R. Brown, and P. Sajda, "Prestimulus EEG alpha oscillations modulate task-related fMRI BOLD responses to auditory stimuli," *NeuroImage*, vol. 113, pp. 153-163, 2015.

24- "https://openneuro.org/." [Online]. Available: https://openneuro.org/.

25- R. C. T. (2020), " R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria." [Online]. Available: https://www.R-project.org/.

26- A. Delorme and S. Makeig, "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis," *Journal of neuroscience methods*, vol. 134, no. 1, pp. 9-21, 2004.

27- J. Harezlak, D. Ruppert, and M. P. Wand, Semiparametric regression with R. *Springer*, 2018.

28- S. D. Team, "RStan: the R Interface to Stan. R package version 2.17. 3," ed, 2018.

29- S. Wood and M. S. Wood, "Package 'mgcv'," *R package version*, vol. 1, p. 29, 2015.

30- J. I. Padilla-Buritica, J. V. Hurtado, and G. Castellanos-Dominguez, "Supervised piecewise network connectivity analysis for enhanced confidence of auditory oddball tasks," *Biomedical Signal Processing and Control*, vol. 52, pp. 341-346, 2019.

31- A. Modirshanechi, M. M. Kiani, and H. Aghajan, "Trial-by-trial surprise-decoding model for visual and auditory binary oddball tasks," *NeuroImage*, vol. 196, pp. 302-317, 2019.

32- A. S. Dizaji and H. Soltanian-Zadeh, "A change-point analysis method for single-trial study of simultaneous EEG-fMRI of auditory/visual oddball task," *bioRxiv*, p. 100487, 2017.

33- L. Hong, J. M. Walz, and P. Sajda, "Your eyes give you away: prestimulus changes in pupil diameter correlate with poststimulus task-related EEG dynamics," *PLoS One*, vol. 9, no. 3, p. e91321, 2014.

34- M. A. A. Turkman, C. D. Paulino, and P. Müller, Computational Bayesian Statistics: An Introduction. *Cambridge University Press*, 2019.

35- X. Qi and R. Luo, "Function-on-function regression with thousands of predictive curves," *Journal of Multivariate Analysis*, vol. 163, pp. 51-66, 2018.

36- K. Hasenstab, C. A. Sugar, D. Telesca, K. McEvoy, S. Jeste, and D. Şentürk, "Identifying longitudinal trends within EEG experiments," *Biometrics*, vol. 71, no. 4, pp. 1090-1100, 2015.

37- E. Campos *et al.*, "Principle ERP reduction and analysis: Estimating and using principle ERP waveforms underlying ERPs across tasks, subjects and electrodes," *NeuroImage*, vol. 212, p. 116630, 2020.