Quantitive Methods II Proposal

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Introduction

The N170 component from the EEG Signals plays an important role in understanding human cognitive processing of visual cues, specifically in faces and objects. The N170 is crucial for facial recognition and reacts to complex visual objects. Such differential neural responses to objects versus textures, as revealed by fluctuations in the N170 amplitude, indicate that distinct cognitive mechanisms are at play depending on the stimulus type. We hypothesize that the N170's amplitude within the 150-200 milliseconds timeframe after stimulus onset, will be significantly greater for objects versus textures. This suggests a neural preference for object recognition, underscoring the brain's perceptual and cognitive focus on distinguishing between different kinds of visual information. To test this, first, we preprocessed the N170 data from the ERP Core dataset[1], using the MADE pipeline[5]. The dataset includes observations from 40 participants who were tasked with identifying whether the displayed stimulus was an object (face or car) or a texture (altered version of the stimuli). Following preprocessing, we will undertake a series of statistical analyses to test our hypothesis such as linear regression and ANCOVA.

Hypothesis

Question: does exist any difference in the N170 amplitude when participants are watching textures compared to objects?

Hypothesis: The N170 component average amplitude(in a 150-200 ms time window) will be significantly greater when participants are exposed to object stimuli in comparison to texture stimuli

To test this hypothesis, we will run methods below in R and compare them:

- **Linear Regression**

  To test the hypothesis that the N170 amplitude differs between object and texture stimuli we want to use linear regression while age, sex, and handedness are controlled.

  Formula:

  $$\boldsymbol{Avg\ N170\ Amplitude = b_0 + \beta_1(stimulus\ type) + \beta_2(Age) + \beta_3(Sex) + \beta_4(handedness) + \epsilon}$$

  Description of variables:

  - **Stimulus Type (object = 1, texture = 0):** independent variable showing if the stimulus is an object or a texture.(binary and independent variable)
  - **Average N170 Amplitude:** representing the mean amplitude of the N170 component within a window which is 150-200 ms post-stimulus(dependent variable).
  - **Age:** representing the participant's age(continuous independent variable).

- **Sex (female = 1, male = 0):** binary independent variable indicating the participant's sex.
- **Handedness (right-handed = 1, left-handed = 0):** indicating the participant's handedness, included to control for potential effects on N170 amplitude(binary independent variable).
- $\boldsymbol{b_0}$**:** indicating the expected value of the N170 amplitude when all predictors are zero(Intercept).
- $\boldsymbol{\beta_1 \dots \beta_4}$**:** The coefficients for each predictor showing the expected change in N170 amplitude with a one-unit change in the predictor, when all other predictors constant.
- **ε:** The error term accounting for the variance in N170 amplitude which is not explained by the model.

- **Mixed Effects Models**

The Mixed-Effects Model is a good option for applying this method on ERP core dataset[1] to consider correlations within individuals and handle non-independence of observations.
Formula:

$$\boldsymbol{Avg\ N170\ Amplitude_{ij} = b_0 + \beta_1(stimulus\ type_{ij}) + \beta_2(Age_i) + \beta_3(Sex_i) + \beta_4(Handedness_i) + u_{0i} + \epsilon_{ij}}$$

Description of variables:

- $\boldsymbol{Avg\ N170\ Amplitude_{ij}}$: representing the average amplitude of the N170 component for the j^{th} observation in the i^{th} participant(dependent variable,).
- $\boldsymbol{b_0}$**:** The intercept, the expected value of the N170 amplitude when all predictors are zero.
- $\boldsymbol{stimulus\ type_{ij}}$**:** indicating the type of stimulus presented to the i^{th}participant at the j^{th} observation(0 for texture and 1 for object)(categorical independent variable)
- $\boldsymbol{Age_i}$**:** representing the age of the i^{th}participant(continuous independent variable).
- $\boldsymbol{Sex_i}$**:** representing the sex of the i^{th}participant(0 for male and 1 for female)(categorical independent variable)
- $\boldsymbol{Handedness_i}$**:** representing the handedness of the i^{th} participant (0 for left-handed and 1 for right-handed)(categorical independent variable)
- $\boldsymbol{\beta_1 \dots \beta_4}$: The fixed effect coefficients for each predictor, quantifying the association between the predictor and the average N170 amplitude.
- $\boldsymbol{\epsilon_{ij}}$**:** The residual error for the j^{th} observation in the i^{th} participant, showing the variability in N170 amplitude not explained by the model or the random intercepts.
- $\boldsymbol{i}$: Index for participants
- $\boldsymbol{j}$: Index for observations per participant

- $\boldsymbol{u_{0i}}$**:** The random intercept for the i^{th} participant, accounting for the individual-specific random variation in N170 amplitude that is not captured by the fixed effects.

- **ANCOVA**
  we use ANCOVA to know the effect of visual stimuli type (object vs. texture) on the N170 amplitude while controlling for covariates such as age, sex, and handedness
  Formula:

$$\boldsymbol{Avg\ N170\ Amplitude_{ij}} = \boldsymbol{\mu} + \boldsymbol{\tau_i} + \boldsymbol{\beta_1}(\boldsymbol{Age_{ij}}) + \boldsymbol{\beta_2}(\boldsymbol{Sex_{ij}}) + \boldsymbol{\beta_3}(\boldsymbol{handedness_{ij}}) + \boldsymbol{\epsilon_{ij}}$$

  Description of variables:

  - **Avg N170 Amplitude$_{\mathbf{ij}}$**: it shows us the N170 component amplitude for the j^{th} participant who was exposed to the i^{th} type of stimulus (object or texture)(dependent variable).
  - $\boldsymbol{\mu}$: The average amplitude of the N170 component across all participants and conditions.
  - $\boldsymbol{\tau_i}$: The effect of the i^{th} stimulus type (texture or object) on the N170 amplitude.
  - $\boldsymbol{Age_{ij}}$: age of the j^{th} participant who was exposed to the i^{th} type of stimulus(continuous covariate).
  - $\boldsymbol{Sex_{ij}}$**:** The sex of the j^{th} participant (0 for male and 1 for female)(binary covariate).
  - $\boldsymbol{handedness_{ij}}$**:** handedness for the j^{th} participant (0 for left-handed and 1 for right-handed)(binary covariate).
  - $\boldsymbol{\beta_1} \dots \boldsymbol{\beta_3}$:coefficients for the covariates, showing change in the N170 amplitude with a one-unit change in age, changing male to female for sex, and changing from left-handed to right-handed for handedness, respectively.
  - $\boldsymbol{\epsilon_{ij}}$: error term for the j^{th} participant which was exposed to the i^{th} type of stimulus, accounting for variability in N170 amplitude not explained by the model.

Methods

- **Participants**

In this research, we employed the ERP Core dataset [1], which comprises data from 40 individuals, including 25 females and 15 males, aged between 18 and 30 years (mean age 21.5). Of these participants, 38 were right-handed, and all were affiliated with the University of California, Davis community. The participants were proficient in English, had normal or corrected-to-normal vision, normal color perception, and no history of neurological injury or disease.

- **Task and Stimuli**

Two primary sets of stimuli were utilized, each containing 43 colored photographs. The first set featured 43 full-frontal face images, including 21 males, while the second set consisted of 22 car photographs, as illustrated in Figure 1A. The face images were specifically chosen to exclude glasses facial hair, makeup, and to display neutral expressions. Additionally, we created two more stimulus sets by scrambling the original face and car images using a Fourier phase randomization procedure (Figure 1B). This process, involved randomizing the phase spectrum while maintaining the amplitude spectrum of the images. This method preserved key global properties like luminance, contrast, color, and spatial frequency amplitude spectrum, but significantly altered the shape of the images. The presentation of all stimuli maintained visual angles of approximately 3.72° by 4.24°. To ensure consistency in visual stimulation, both the original and scrambled faces and cars were placed against a darker grey background than the general background of the monitor, guaranteeing uniformity in the overall size of the visual stimulus.,

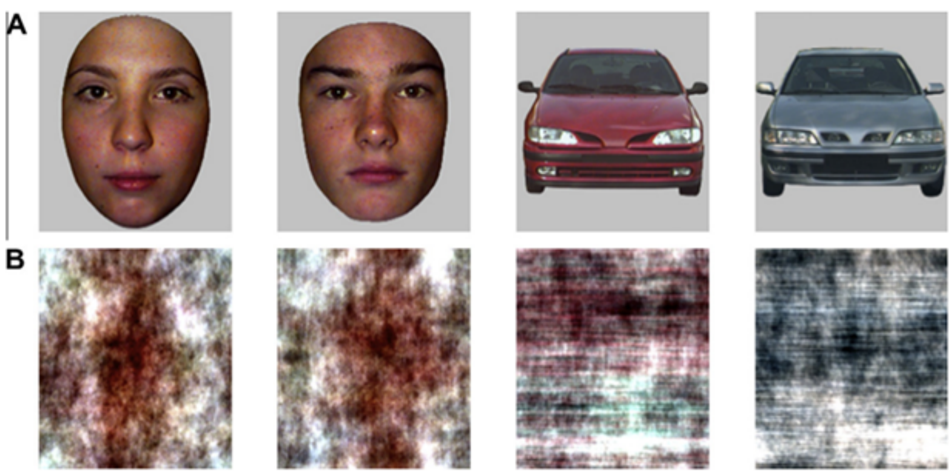

Figure 1
Illustrations of stimuli employed in the experiment. Depictions of face and car stimuli (A) alongside their corresponding Fourier phase-scrambled versions (B) adapted from Ref. [4]

The methodology employed involved several carefully designed steps [1,4]. Participants, after having the electrode cap placed, were seated in a light- and sound-attenuated room at a distance of 100 cm from a computer monitor. The stimuli were displayed on a light grey background using E-prime 1.1 software. Each trial commenced with a fixation point at the center of the screen, visible for 100 ms. This was followed, after a randomized interval of 200 to 400 ms, by a test stimulus which appeared for 300 ms. Subsequently, an inter-trial interval of approximately 1700 ms (ranging from 1600 to 1800 ms) was observed.

Participants were instructed to discern whether the stimulus presented was an object (either a face or a car) or a "texture" (scrambled versions of the stimuli) and respond by pressing one of two keys with their dominant hand. This task, though unrelated to the experiment's primary goals, was intended to keep the participants' attention level consistent. Unbeknownst to the participants, half of the phase-scrambled stimuli were derived from faces and the other half from cars. None of the participants recognized any relationship between these scrambled stimuli and the intact ones.

- EEG Processing

for preprocessing EEG data we used MADE pipeline [5], which is a comprehensive pipeline using MATLAB and the EEGLAB toolbox, in addition we use plugins such as MFFMatlabIO, FASTER, and an adjusted version of ADJUST. Corrections for anti-aliasing filters and task-related time offsets were applied. EEG data were then imported, and channel locations were assigned. To reduce noise and artifacts, a high-pass filter of 0.1 Hz and a low-pass filter of 50 Hz were applied. then we did downsampling the data to 256 Hz for computational efficiency. Channels identified as outer layers, generally containing more noise and artifacts, were excluded from the analysis. Then specific event markers were used to segment the data into epochs which is 1-second segments synchronized with the stimulus (ranging from -200 ms to 800 ms), and a baseline correction was applied. Voltage threshold-based artifact rejection was implemented to remove epochs with extreme EEG values between -125 to 125. Interpolation for Epoch-level channel was conducted for epochs with artifacts. Further, bad channels identified through the FASTER algorithm were eliminated, and an Independent Component Analysis (ICA) was run to identify and exclude components associated with artifacts. Post-ICA, the EEG data were segmented into fixed-length epochs, and a final artifact rejection step was done. for the deleted channels we used interpolated to reconstruct the original channel layout. The data were re-referenced to a common average reference to enhance comparability across recordings. This preprocessing steps ensured us about reliability and validity of our EEG data for subsequent analyses.

- ERP Quantification:

Event-related potentials (ERPs) were quantified to examine neural responses within a specific time window after the stimulus. EEG data was processed using MATLAB (The MathWorks, Inc.). We focused on a time window of 150-200 milliseconds after the stimulus on set, which is crucial for capturing the N170 component. we classified the Event types and epochs which not meeting our criteria (e.g., incorrect responses, latencies outside the ±100 ms range) were excluded. we built a matrix that is in it The ERP data was loaded into a multi-dimensional array, with dimensions corresponding to participants, conditions, channels, and time points. For each participant and condition, we extracted the amplitude within the 150-200 ms window from the averaged ERP data. This matrix served as the basis for subsequent analyses to investigate the neural correlates of the task.

References

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