Introduction to Cognitive Science

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Assignment 1

Phase One

(1) Introduction Facial recognition is a fundamental aspect of social cognition, and our brains have an incredible capacity to process and extract various features from faces, including identity, expression, and emotion[3, 4, 2]. However, there are still many unknowns about the mechanisms behind this process. In this assignment, we will explore the relationship between different spatial frequencies and facial identity. By applying filters to images of various characters, we will create new images that selectively remove specific spectral data, resulting in images that appear either smoother or less textured than the original. Using these filtered images, we will investigate how the removal of different spatial frequencies affects our ability to recognize facial identity. Through this assignment, you will gain a deeper understanding of the complex processes involved in facial recognition and the specific role of spatial frequencies in this cognitive task. [7, 8]

Keywords: cognitive task, spatial frequency, cognitive science, neuroscience, face processing, face identity

(2) Task Description To investigate the effects of spatial frequency on identity detection, we designed an identity detection psychophysics task. The task includes two pairs of images; two male and two female faces. Each pair of the male and female faces were morphed separately in seven levels, with the first and last levels being two of the four primary images. This resulted in a total of 14 images with various levels of morphing. We also applied low and high spatial frequency filters to each of the 14 images, resulting in 42 stimuli for the task in three levels of spatial frequency (intact, high, and low).

Before the start of the task, participants are given time to get familiar with the names associated with each face. The task is divided into three blocks, with each block containing images only from one of the groups of spatial frequency. There is also an additional fourth block at the end of each session in which images from all groups of spatial frequencies are presented. The order of these three blocks is randomized for each subject. Each block consists of two parts, each of which must be performed with either the right or the left hand. The order of hands within each block is also randomized. Participants must complete a training phase before the task begins to ensure they can recognize the names of the faces correctly. The training stage involves four images from the extremes of the morph spectrum, i.e., the primary faces. The spatial frequency of the images used in the training corresponds to the spatial frequency of the pertinent block. Once a participant detects the identity of each face correctly three times in a row, their performance is displayed on the screen. They can then choose to repeat the training phase or proceed to the task.

We have a total of 1344 (42 images x 32 repetitions) trials divided in 4 blocks. Each trial within each block entails a face presentation followed by a go cue presentation. During each trial, one of the 42 stimuli is presented at the center of the screen for 400 milliseconds. This is followed by two options on the left and right sides of the screen, representing the names of the faces. Participants have three seconds to decide which identity the presented image is most similar to. Since the morphed faces are gender-controlled, the two options are always both male names or female names. The order of the options within each block is fixed.

(3) Data Format We will be using a dataset provided in both CSV and MAT formats, which includes a table of subject-specific variables called "subjectInfo". This table contains information about the subjects' age, gender (as denoted by "sex"), and dominant hand (as denoted by "dom"). The dataset also includes a table of

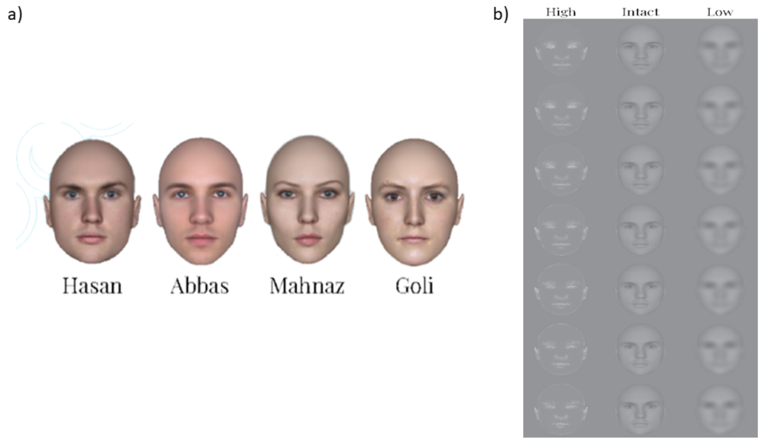

Figure 1: a) Characters' faces and names used in the study, b) Example of different morph and spatial frequency levels between a pair of identities.

per-trial information called "data", which contains details that differentiate each individual trial.

- **trialKeys**: "MahGol" for trials in which the subject is choosing an image in the Mahnaz-Goli spectrum, and "AbHa" for trials in which the subject is choosing an image in the Abbas-Hasan spectrum.
- **levelFreq**: spectral frequency level of presented stimulus (IF: intact, LF: low, HF: high)
- **levelFace**: morph level, ranging from -3 to 3. Negative extremes show Abbas and Mahnaz, positive extremes show Ali and Goli for different pairs.
- **lCueName**: the option showed to the subject on the left side of the screen.
- **rCueName**: the option showed to the subject on the right side of the screen.
- **srespLoc**: the key pressed by subject in this trial.
- **srespChoice**: selected face ID.
- **RT**: subject's reaction time in this trial.
- **Hand**: the hand that subject used in this particular trial.
- **blockType**: the type of block: The first three blocks of each subject are named "same" because all stimuli in these trials are from the same spectral frequency level. The fourth block is named "mix" because the trials are randomly selected from a pool of all images.
- **subjectID**: a unique identifier for each subject.

(4) Problem Description

For this homework assignment, all analyses will be performed separately on each individual subject, and then tested for significance on the population as a whole. We will not pool all trials of all subjects together, although you are welcome to explore this on your own.

1. Psychometric Fitting (40) In this section, we will fit a sigmoidal psychometric curve to the behavioral data by counting the number of subject-rated "Hasan"s and "Goli"s for each level of morphings. For each pair, we will create a scatter plot and then evaluate the psychometric function by minimizing the least square error of a parametrized sigmoid function. The sigmoid function is formulated as in formula :

$$\sigma(x) = \frac{\alpha}{1 + exp(-\beta x)}$$

However, there are other families of models that can be fitted to this type of data, such as the Gaussian CDF function. We can also add parameters to the sigmoid function, resulting in a more generalized sigmoidal function described by formula:

$$\sigma(x) = \frac{\alpha}{1 + exp(-\beta(x-y))} + \lambda$$

To compare these models, we need a metric function. Using mean squared error would not be preferable, as it would be biased toward choosing a model with more parameters. Therefore, scores like Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are more suitable for this task. We will compare sigmoidal functions and Gaussian CDFs for fitting curves to subjects' data points by choosing one of these metrics. Note that there are several blocking variables, such as stimulus's spatial frequency, block type, and trial key, upon which the data shall be stratified. We will visualize the results and describe which model is more suited for data fitting. We will provide examples of fitted curves along with the corresponding data points in the report.
For the rest of this assignment, we will focus on fitting a simple sigmoidal function of formula (1) to the data. We will call the β variable sensitivity (s_σ) and compare results between groups. We will test several hypotheses, including the following:

- whether sensitivity to detecting identity from different spatial frequency bands differs.
- whether people are more adept at identifying images of their conspecific or hetero-specific gender.
- whether subjects can better detect identities in a specific spectral band if they use their left hand.
- whether subjects can better detect identities in a specific spectral band if they use their dominant hand.
- whether women are significantly better than men in the task of identity detection.

We will focus on trials of "same" block types (first three blocks of each subject), and use appropriate statistical tests to test each hypothesis. We will provide informative visualizations for each result and explain our reasoning for choosing each statistical test.

2. Evaluation of Subject Sensitivity using Receptive Operating Curve (ROC) (40) Another approach to comparing the sensitivity of subjects is by using the area under the receptive operating curve (AuROC). In psychophysics, a receptive operating curve (ROC) is a graphical representation of the relationship between stimulus intensity and the probability of a participant's response. It is a plot of the hit rate (the proportion of "yes" responses for a signal-present trial) against the false alarm rate (the proportion of "yes" responses for a signal-absent trial) for different stimulus intensities. The ROC is a valuable tool for assessing the sensitivity of an observer to a particular stimulus or feature, as well as for comparing the performance of different observers or experimental conditions. The shape of the ROC can provide insight into the observer's decision-making process, as well as the reliability and discriminability of the stimulus. In this context, we define the area under the curve as the metric of separability (s_{ROC}). Test all the hypotheses from the previous question using this new metric.

3. Make a Hypothesis! (20) Lastly, formulate a new hypothesis that has not yet been explored in this assignment. Clearly define the problem as a hypothesis, describe the method of estimation, and fully describe the results of hypothesis testing. This is an opportunity to use your creativity and explore different aspects of the dataset. This is a place for your creativity, so don't be afraid to dive into the depths of the dataset!

Phase Two (30 bonus [1])

(5) Introduction

1. Overview of System Behavior Analysis Systems often display complex behaviors, especially when their internal dynamics are not fully understood. Understanding these systems requires observing their responses to various inputs and disturbances to identify patterns, relationships, and governing principles. Analyzing system behavior involves examining how different systems process feedback and adapt to changing conditions.
Open-loop systems operate without feedback, offering insight into initial behavior but not adaptation. Example: a manually adjusted irrigation system where the water flow is set without considering the moisture of the soil. In contrast, closed-loop systems use feedback to dynamically adjust output, which makes them valuable for studying unknown dynamics. Example: a thermostat-controlled heating system that continuously regulates temperature based on real-time feedback.
For example closed-loop neuro-stimulation techniques, such as trans-cranial magnetic stimulation (TMS) combined with EEG, allow modulation of brain activity based on instantaneous feedback, uncovering insights into neural plasticity and functional connectivity[1].
In the context of visual perception, closed-loop systems provide a structured way to investigate how humans perceive and navigate identity transitions in faces. By leveraging Active Appearance Models (AAMs) as generative models, which will be discussed completely in the next section, we can systematically generate controlled variations in facial features, allowing us to study the perceptual trajectory from one identity to another. This approach transforms the process into a dynamic feedback-driven system, where each selection made by a subject refines the pathway through the latent space of the AAM. Specifically, the task involves the transition from one identity to another within the latent space of AAM in a finite number of steps. At each step, a target (goal) face is presented along four generated images, and the subject selects the image they perceive as most similar to the target. This selection serves as feedback, guiding the system's movement in the latent space. Based on this feedback, four new images are generated around the selected image, and the subject is again supposed to select the image closest to the target. This iterative process continues, with each selection refining the trajectory toward the goal face. In essence, the AAM serves as a tool for generating and adapting images based on feedback, mirroring the principles of closed-loop system behavior in the study of human perception.

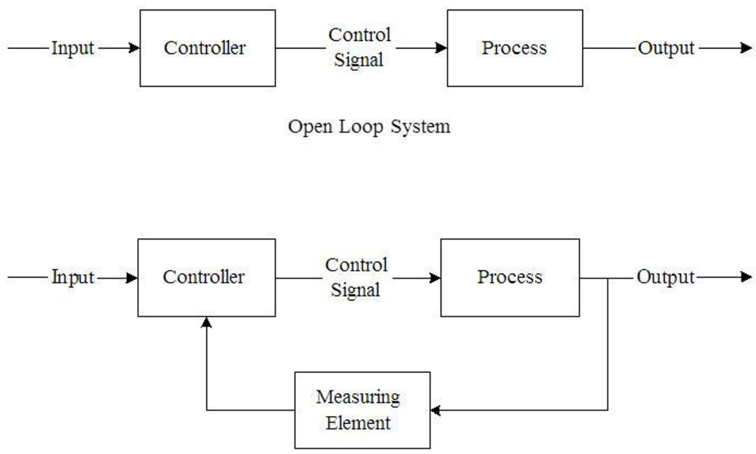

Figure 2: Overview of open and closed-loop systems

2. Modeling Faces Using Active Appearance Models The human face plays a central role in social interaction and cognition, making it an important focus in neuroscience. From an evolutionary perspective, the ability to perceive and interpret faces is essential for recognizing individuals, understanding emotions, and interpreting intentions—key skills for survival and navigating complex social environments. This significance is reflected in the specialized mechanisms of the human brain for face processing, such as the fusiform face area

[1] Applied beyond this assignment to overall assignments grade.

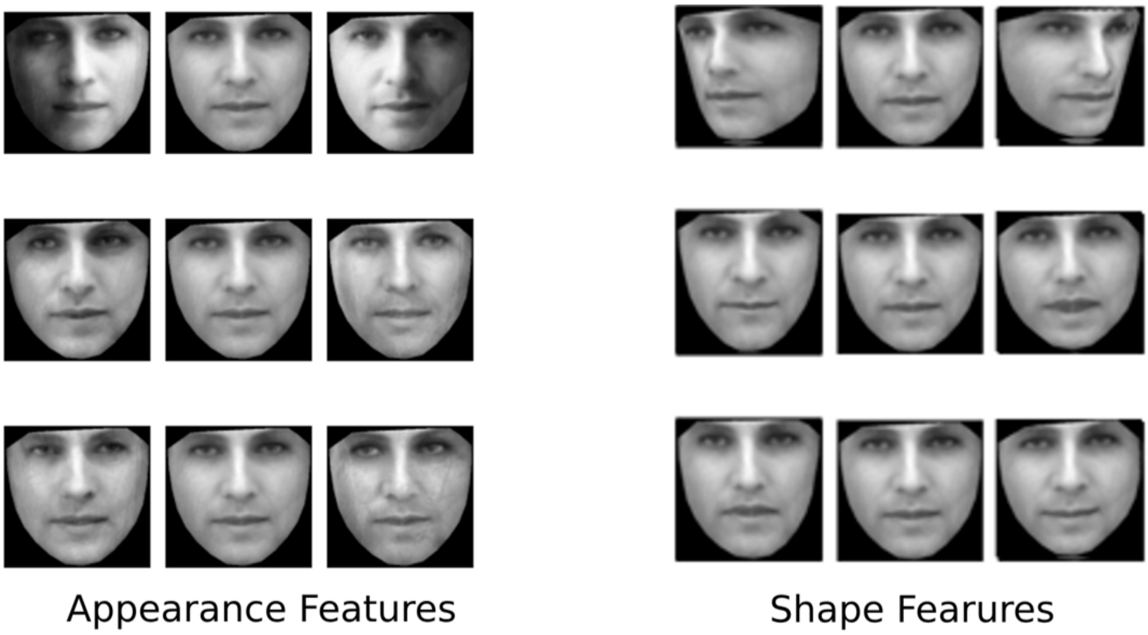

Figure 3: Outputs of an Active Appearance Model (AAM). Each row illustrates the effect of varying a single shape or appearance feature relative to the mean representation.

(FFA), located in the fusiform gyrus. The FFA is highly specialized for facial recognition and collaborates with other regions, such as the occipital face area (OFA) and the superior temporal sulcus (STS), to analyze facial identity, expressions and gaze direction. These neural specializations highlight the evolutionary and cognitive importance of the face [3, 4].
For analyzing this important cognitive stimulus from a computer vision perspective, the face can be seen as a deformable object. Deformable objects are entities that can undergo significant changes in shape and appearance due to factors such as external forces, internal dynamics, or environmental conditions. The human face, for example, constantly changes due to expressions, head movements, and lighting conditions. These variations in geometry and texture make the face a prime example of a deformable object and present unique challenges for modeling and analysis.
To address these challenges, Active Appearance Models (AAMs) provide a powerful tool for studying deformable objects such as the face. By combining statistical representations of shape and appearance, AAMs capture complex variations in a compact and efficient framework. In this homework, we will use AAMs to model and analyze the human face, leveraging their ability to capture and manipulate its variations. AAMs achieve this by modeling the face through two distinct types of features:

- **Shape Features**: These define the geometric structure of the face using specific landmarks, such as the corners of the eyes, the tip of the nose, the edges of the mouth, and the contour of the jawline. Adjusting these features allows for manipulation of the face's geometry, such as altering its width or repositioning facial landmarks.

- **Appearance Features**: These describe the texture and visual details of the face, such as skin tone, wrinkles, freckles, and shadowing. Modifying these features adjusts finer details, like the smoothness of the skin or the effect of lighting.

For further details on how AAMs are trained and represent facial features, refer to [5, 6]. Notably, recent work has shown that the neural codes for facial identity in primate cortex can be well explained by generative models that separate shape and appearance [7, 8]. Additionally, Figure 2 illustrates how independently modifying shape and appearance features affects the generated images, demonstrating the model's ability to effectively capture and manipulate facial variations.

(6) Task Description

1. Objective: Design and implement a psycho physical experiment using PsychoPy to investigate perceptual sensitivity using morphed face images.

2. Materials Provided: You are given two main folders of morphed images, app/ and sha/, Each contains 20 subfolders, named f0, f1, ..., f19. Each fX folder contains 100 images, representing a morph continuum between two extreme face identities.

3. Student-Specific Feature Assignment: Use the last digit of your student number to determine your assigned features For example: If your student number ends in 0, you will work on features f0 and f10. If it ends in 7, you work on f7 and f17.
You must use these two feature folders from both app/ and sha/, totaling four folders: app/fX, app/fX+10, sha/fX, sha/fX+10.

4. Image Selection: From each selected folder, choose 10 images at equal intervals along the morph continuum (e.g., image 10, 20, ..., 100).

5. Trial Design: Present each image 10 times, in a randomized order. On each trial, show one image and ask participants to choose which of the two original faces the image is more similar to. You may choose any keys for response collection, but clearly define them in your instructions (e.g., 'A' = Face 1, 'L' = Face 2).

6. Data Analysis: For each feature and folder, calculate the proportion of responses choosing one face as a function of morph level. Plot psychometric curves (e.g., sigmoid or cumulative Gaussian fits). Calculate and report the Just Noticeable Difference (JND) for each condition.

7. Deliverables:

- PsychoPy experiment code (.py or .psyexp).
- Raw and cleaned data files.
- Psychometric function plots with fitted curves.
- Calculated JND values.
- A brief report (1–2 pages) summarizing methods, results, and interpretation of findings.

References

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Final Notes

- All analysis for this assignment must be completed using R, Python, or MATLAB. The choice of programming language will not affect the assignment grade and is solely based on the student’s preference.
- In addition to the analysis scripts, a well-styled PDF report must be submitted for grading. The report should not include detailed explanations of the code, as it is focused on reasoning and discussing the results.
- Students may not write report or develop the analysis scripts in groups.
- When referencing figures, tables, or formulas in the report, they should be referred to by their unique label.
- The submitted file should be a ZIP file containing a PDF named "report.pdf" and a folder named "scripts" that includes the analysis codes.

Happy Nowruz 1404, May your curiosity & efforts lead to great success!
Your Teaching Team