INVESTIGATING NEURAL PATTERNS IN DYNAMIC FACIAL PROCESSING UTILIZING REPRESENTATIONAL SIMILARITY ANALYSIS

by

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This thesis investigates the neural patterns underlying dynamic facial processing using modern functional magnetic resonance imaging (fMRI) analysis. Facial perception is central to everyday social encounters and has been studied extensively. However, I seek to incorporate more naturalistic stimuli and representational similarity analysis (RSA), a more dimensional approach than traditional univariate analysis. Participants were shown short videos of volunteer actors making positive or negative facial expressions either toward or away from the camera. They were instructed to determine the emotional valence of each clip while remaining naive to the true purpose of the study. In this secondary analysis, I reprocessed the fMRI data. Activation patterns were correlated with hypothetical models for each possible driving condition of facial processing using standard RSA methods across 414 brain parcels. Results showed widely distributed, overlapping patterns, particularly in the identity condition, within regions associated with the default mode network. This suggests that facial identity is a primary driver of neural responses and encoding in dynamic facial processing. This factor ought to be carefully considered in the design and analysis of future social cognition experiments.

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Introduction

Imagine the following scenario. You are in the grocery store when you make eye contact with a person you've never met before, and they smile. Though you may not be consciously aware of it, your brain is encoding an array of information. This information forms the basis for your understanding of who this person is, the emotions they may be experiencing, whether those emotions are directed at you, and more. Although awkward to explain, these are trivial daily encounters. Now imagine a similar but different scenario, and a new array is formed, encoding the same types of information, this time with different inputs. Understanding how that array is formed and what key conditions drive its design is of growing interest within the field of cognitive neuroscience.

Humans encode an endless array of co-occurring information. As a result, our brains have adapted to use complex representational systems to store information that can be decoded and accessed in future encounters. These systems form the link between stimuli and the appropriately evoked responses, both cognitive and physical, that support our social abilities. Often, neural representations of these stimuli overlap significantly, working together to provide a cohesive experience. Disentangling these systems is essential for understanding how specific conditions may operate as drivers (Berkman et al., 2014; Chavez et al., 2024). This disentanglement requires careful thought, balancing ecological validity with increased variability. In other words, the balance between whether the experiment validly investigates the social event in question and the reliability of the measurement, given the inherent variability of dynamic social processes. The purpose of this research is to determine what drives neural patterns formed by dynamic facial processing. More specifically, it aims to uncover these patterns and their spatial relationships in ways that are both ecologically and experimentally valid.

Literature Review

A History of fMRI Analysis Methods Through the Lens of Facial Processing

Univariate Analysis

Facial processing guides our day-to-day interpersonal interactions and has thus been of special interest in social and cognitive neuroscience. The advent of functional magnetic resonance imaging (fMRI) enabled a shift from simply viewing anatomical brain regions to assessing function. Blood oxygen level-dependent (BOLD) signals became a secondary but reliable predictor of brain activation (Ogawa et al., 1992). These levels are measured relative to baseline activation. Increasing BOLD levels indicate increased activity, and vice versa. A common fMRI experimental design is the block design. It consists of alternating "on" blocks, during which a stimulus is presented, and "off" blocks, during which no stimulus is presented. Using a statistical model, changes in activation magnitude are correlated with time points of interest. Changes are calculated per voxel, the smallest 3-dimensional neural unit, measuring approximately 1 mm^3. This is the basis of univariate analysis of fMRI data, which measures gross changes in BOLD signals as a proxy for neural activity and compares neural activity during "on" and "off" blocks at the voxel level (Friston et al., 1994). Researchers may then map the cognitive processes targeted during each block to corresponding functionally active voxels, a principle known as localization of function. Nancy Kanwisher and colleagues used these univariate analysis methods to confirm that activation levels were consistently elevated in the fusiform face area (FFA; a specialized region within our visual system) when participants viewed faces rather than common objects (1997). Thus, our understanding of the FFA as our hub for facial processing was born.

One problem with using univariate analyses for dynamic processes such as facial perception is that they focus on narrow regions that show gross changes in activation magnitude, implying that the brain is a one-to-one function-to-voxel-area processing unit. Everything below a statistically relevant baseline is counted "inactive." While useful in some cases, such as localization, this type of analysis overlooks the less active yet vital contributions of other brain regions that together paint the full picture of our cognitive experience. Thus, the brain is *not* a one-to-one mapping and processing unit.

FMRI studies are also prone to another conundrum, namely the inability to make a reverse inference. Researchers may reasonably predict that when presented with a face, participants will show increased activation in the FFA. Making the reverse inference would imply that FFA activation consistently represents facial processing rather than the numerous other neural processes that overlap with the region. This claim cannot be supported using univariate analysis. The question also remains which of these processes (social attention, emotion, facial identity, etc.) is most influential in shaping how the brain represents the information required for dynamic facial processing (i.e., neural patterns).

Multivariate Pattern Analysis

Computational neuroscientists have since developed more complex analytical methods to account for the intricacies of neural connectivity. Again, traditional univariate methods are limited to measuring gross activation levels above threshold. Results paint a picture of artificially isolated areas in which the brain decodes social processes. Multivariate pattern analysis (MVPA) reveals how social processes are represented throughout the brain, capturing additional regions with lower activation levels. Haxby and colleagues employed MVPA to assess Kanwisher's claim, finding that encoded information about faces and objects is represented in widely

distributed, overlapping patterns (Haxby et al., 2001). Patterns of both maximally and minimally responsive brain areas were predictive of stimulus type (Haxby et al., 2001). This supported the notion that results from minimally responsive brain regions should not be discounted, as is common in univariate analysis. Using MVPA-generated data, represented in multidimensional space, we can more precisely determine whether a particular activation pattern reliably predicts a specific social process. While univariate analysis may tell us which few brain regions decode the difference between a brain and a house, MVPA can reveal how these regions work together to produce our comprehensive understanding of each. With this combination of information, computer models can be trained to effectively decode various neural patterns and their associated cognitive processes.

This dramatic increase in information underscores the importance of studying patterns alongside gross activation levels to enhance ecological validity. With MVPA, we can also come closer to making the reverse inference. Gross activation in the FFA may reflect facial identification, emotion, or numerous other overlapping cognitive processes. Now, the nuances within brain activation patterns reveal signatures specific to neural processes, allowing their differentiation. MVPA's sensitivity to distributed information may be better suited to the naturalistic, more variable stimuli inherent in social neuroscience (Weaverdyck et al., 2020).

Representational Similarity Analysis

Since its inception in 2001, MVPA has grown within fMRI research, and researchers have continued to improve its decoding ability. In 2008, Kriegeskorte developed a branch of MVPA known as representational analysis (RSA) (Kriegeskorte et al., 2008). Like MVPA, RSA relies on transforming data into a multidimensional space, which allows measurement of the distances between data points. There are a variety of ways to measure this distance, such as the distance

between means, Euclidean (physical) distance, and correlational distance. Correlational distance is the most popular because it ignores the mean, focusing on correlations in pattern data (i.e., does this pattern look like the other pattern?), rather than on more traditional questions, such as whether this average activation is close to the other average. RSA quantifies similarities among multiple generated activation patterns using representational dissimilarity matrices (RDMs). Essentially, this is a matrix in which each condition is compared with every other. The values inside represent a measure of the similarity between that condition and the others. For RDMs, the higher the value, the more *dissimilar*.

These RDMs can be correlated with RDMs generated from any other data set. For example, one may compare EEG data in monkeys to human fMRI data. Within their respective spaces, these data are incompatible with one another for comparison. However, by transforming the data into a multidimensional space and establishing RDMs, you create a new language in which these data can be compared. The concept of comparing data across modalities revolutionized fMRI analysis and led to the investigation of hypothetical RDM models. A simple example of the logic behind RDMs and RSA is provided below and compared to univariate and MVPA in Figure 1.

Researchers may hypothesize that neural representations of sad faces will be most similar to other sad images (dissimilarity = 0) and most dissimilar to happy images (dissimilarity = 1). They may then create a hypothetical RDM model that conveys that information in a simple binary format. A different model can be created for any hypothesis (ex. faces vs animals) following the same basic principle that similar categories will have a dissimilarity of 0 and dissimilar categories will have a dissimilarity of 1 (Fig. 1). The RDM derived from real data will be far more complicated, as it is generated by comparing

experimentally derived BOLD activation patterns. Researchers can then compare the experimentally derived RDM against the hypothetical models to determine which categories drive our neural representation and in which brain regions (Chavez et al., 2024). For example, if the hypothetical model based on angry/happy faces were most similar to the experimental model, we could conclude that valence drives our neural responses to this stimulus.

RSA allows brain activation, or more specifically, similarity of neural patterns, to be studied as an independent variable rather than a dependent variable, inching researchers closer to making valid reverse inference. The reverse inference in this case would be that a specific neural pattern elicited corresponds to a specific cognitive process. Though still an impossible claim to make definitively, this is a much more specific claim than those of univariate analysis. RSA's sensitivity to noise and distortion is a concern, given the volume of neural information required for accurate analysis. However, the flexibility and ability to reliably depict how information is constituted in the brain reassert the validity of this methodology (Popal et al., 2019).

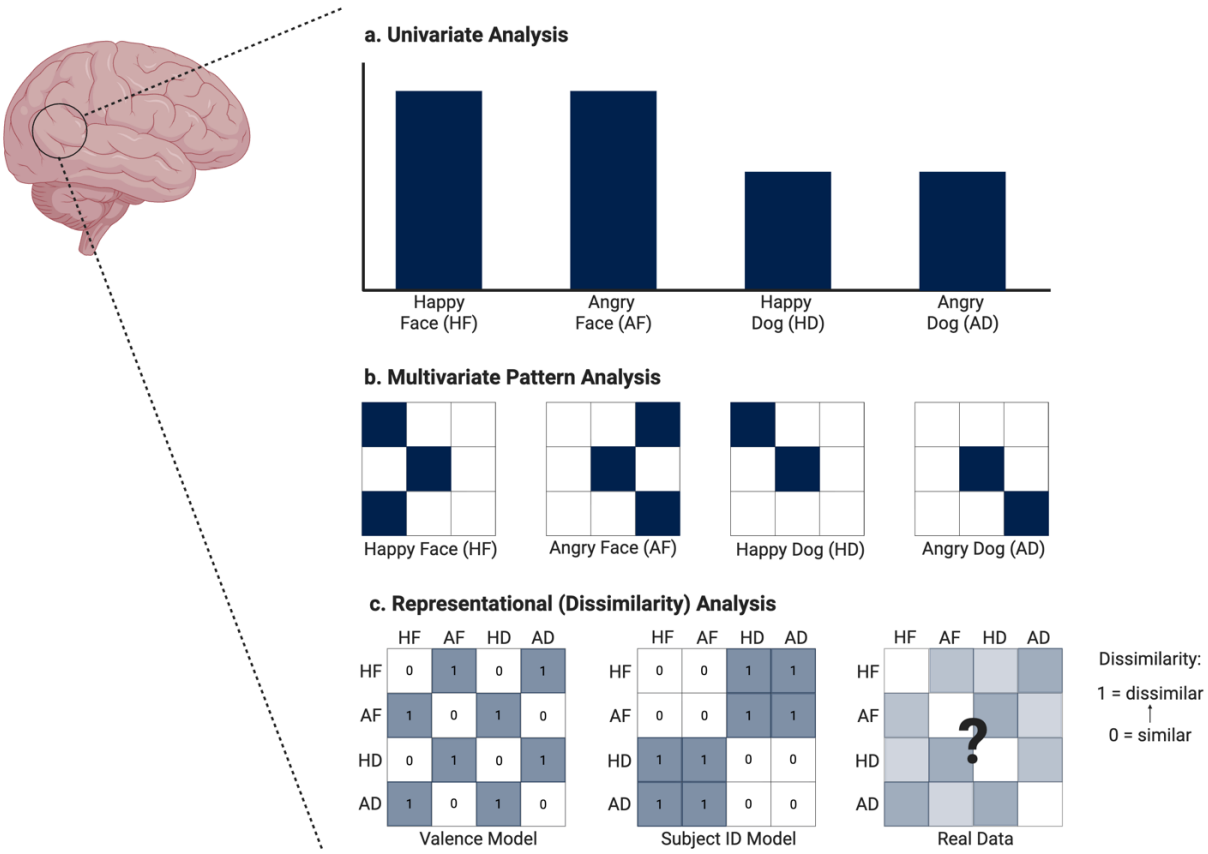


Figure 1: A Comparison of Univariate, Multivariate, and Representational Similarity Analysis.

Hypothetical example for analyzing neural responses to visual social stimuli. (a) Univariate Analysis illustrates the average activation level across four conditions: Happy Face (HF), Angry Face (AF), Happy Dog (HD), and Angry Dog (AD). (b) Multivariate Analysis displays activation patterns for each condition, highlighting distinct spatial distributions despite similar average activation levels. (c) Representational (Dissimilarity) Analysis compares the observed neural patterns against theoretical models. The Valence Model predicts similarity based on emotional affect, while the Stimulus Model predicts similarity based on stimulus type (ie. human vs. dog face) using a simplified binary. The RDM of the real data captures the observed dissimilarity (1 = dissimilar, 0 = similar) and is therefore computed over the full range of outcomes rather than as a simple binary. These results are used to determine which theoretical model best fits.

Social Attention & Expression as Additional Drivers of Facial Processing

Facial perception is one of the most studied drivers of facial processing, but conditions such as social attention and expression are key additional influences. A review of past studies reveals that impairments in one's ability to process eye gaze and its direction may lead to difficulty in recognizing facial identities and emotions, tasks central to social interactions (Itier & Batty, 2009). Early methods relied on cartoon drawings of faces with circles for eyes, shifting pupil placement to change where the cartoon is "looking." Others used images of arrows. Results show that both eye gaze and arrow cues can direct participant gaze and, thus, attention (Ristic et al., 2002). Recently, some have adopted real still images of human faces, though these are often cropped in somewhat unnatural ways and lack the dynamics of most everyday encounters. Researchers also began incorporating animated faces modeled after realistic images, finding that manipulating participants' social attention caused increased brain activation in regions that play a central role in social cognition (Schilbach et al., 2011). The neural regions involved in decoding eye gaze overlap widely with many others associated with social cognition. Therefore, the question is in which regions does eye gaze act as a driver of our neural representation? Nonetheless, there is still much progress to be made in studying more ecologically relevant stimuli (i.e., real human faces).

Researchers have since challenged Kanwisher's original findings that the FFA is solely responsible for facial identity as opposed to expression (Fox, Moon, et al., 2009). In fact, one study found activity in the FFA increased when participants attended to facial expression rather than identity (Ganel et al., 2005). Subsequent studies have identified additional brain regions involved in processing facial expressions, including many that overlap in processing multiple emotions (Fusar-Poli et al., 2009). Dynamic facial processing is most likely not entirely encoded

within the FFA. Rather, encoding this information would create an expansive map not captured by facial identity or expression alone. The indicated level of interdependence is yet another reason to shift from univariate analysis to pattern analysis methods such as RSA.

Research Goal

The goal of this research is to expand understanding of the factors that drive the neural representation of dynamic facial perception using naturalistic stimuli and RSA methodology. The following research focuses on three possible conditions: action as a proxy for social attention, emotional valence, and stimulus facial identity. Participants viewed short clips of volunteers making happy or angry faces, acting toward or away from the camera. Hypothetical models were based only on each of the above conditions. By comparing neural patterns recorded from individual participants during the experiment, we can determine which (if any) models are similar. This information can then be used to determine in which areas of the brain our three conditions act as drivers of representation patterns. Ultimately, we may also infer the socio-cognitive information encoded in said patterns. I hypothesize that a blend of information from the three conditions above will be distributed throughout neural space in largely overlapping patterns. Participants attended to the emotional valence of the target stimuli. Thus, valence may have more distributed driving effects due to this design.

Methods

Participants

I am utilizing secondary data from a 2015 study. Thirty-three right-handed participants were recruited from the Dartmouth College community in Hanover, New Hampshire. All were right-handed and had no known pre-existing psychiatric or neurological disorders. Demographic information was self-reported as follows: age (range = 18–19, M = 18.09, SD = ±0.29), sex (Female = 22, Male = 11), race (American Indian or Alaskan Native = 1, Asian = 5, Black or African American = 2, White or Caucasian = 19, multiple = 4), and ethnicity (Hispanic = 3, Non-Hispanic = 30). After quality control, inspecting for excessive head motion, distortion, and misalignment, all 33 participants were included in the analysis portion of the study. Participants provided informed consent in accordance with guidelines from the Committee for the Protection of Human Subjects at Dartmouth College and were compensated either with course credit or payment.

Naturalistic Stimuli

A total of 16 volunteers, evenly split between males and females (9 White, 2 Asian, 2 Hispanic/Latino, 1 Black, and 2 other), created the stimulus videos. Figure 2 shows an example from one such volunteer. Each two-second video featured a single volunteer performing one of the following: a happy face while facing away from the participant, a happy face while turning toward the participant, an angry face while facing away from the participant, or an angry face while turning toward the participant. All videos were filmed with volunteers starting 45° away from the camera, so emotional valence couldn't be inferred from body placement alone. This resulted in four conditions for each of the 16 targets, yielding 64 naturalistic video stimuli.

Researchers have found that naturalistic stimuli provide more robust signaling information, capturing more facial processing regions of interest than static stimuli (Fox, Iaria, et al., 2009). Using naturalistic stimuli rather than static images or drawings, as some other research has done, also yields more ecologically relevant results (Berkman et al., 2014).



Figure 2. Still images, illustrating the video clips.

Task and Procedure

Participants completed four runs (A, B, C, D) during an fMRI session. They viewed video stimuli on a screen via a mirror attached to their head coil. Within each run, all 64 video stimuli were presented in a randomized order, so they weren't clustered by emotional valence, action (away vs. turn), or volunteer identity. Once randomized, the order of video stimuli within each run remained consistent (i.e., all run As were identical to each other, run Bs to each other, etc.). The order of each run was also counterbalanced across participants. Essentially, each participant viewed the same four runs, albeit in different orders. Participants knew they would

view videos of people making facial expressions and were tasked with classifying each clip's emotional valence as positive or negative.

Image acquisition

Magnetic resonance imaging was performed on a Philips Achieva 3.0 Tesla scanner with a 32-channel phased-array coil. Structural images were acquired with a T1-weighted MP-RAGE protocol (220 sagittal slices; TR: 8.176 ms; TE: 3.72 ms; flip angle: 8°; 1 mm isotropic voxels). Functional images were acquired with a T2*-weighted echoplanar sequence (TR: 2000 ms; TE: 35 ms; flip angle: 90°). For each participant, four runs of 168 whole-brain volumes (35 axial slices per whole-brain volume, 3x3x3.486 voxel size) were collected.

Data Processing & RSA

FMRI data were analyzed using FSL (Smith et al., 2004). Data were preprocessed according to the following standard procedures. First, magnetic field distortion was corrected using a generated field map. Next, slice-time correction accounted for errors introduced by differences in slice acquisition times. Images were smoothed using a 4.0 mm FWHM Gaussian kernel. We used a lower smoothing kernel to account for RSA's reliance on fine-grained pattern analysis (Kriegeskorte et al., 2008). FSL brain extraction was also performed. Finally, images underwent a two-step normalization process. Each participant's functional images were linearly registered with FLIRT to their anatomical images, then nonlinearly registered with FNIRT to the MNI template (standard space).

The resulting data was analyzed using a multi-level modeling approach. First-level analyses were conducted for each participant to assess neural responses to each condition over the duration of each run, and the data underwent standard Pearson-correlation-based RSA (Fig. 3). A second-level analysis combined data across each of the four runs to generate an average

neural response per individual over the duration of the experiment. A group-level analysis was performed to identify patterns consistent across participants for population-level inferences about the representation of facial processing in the brain.

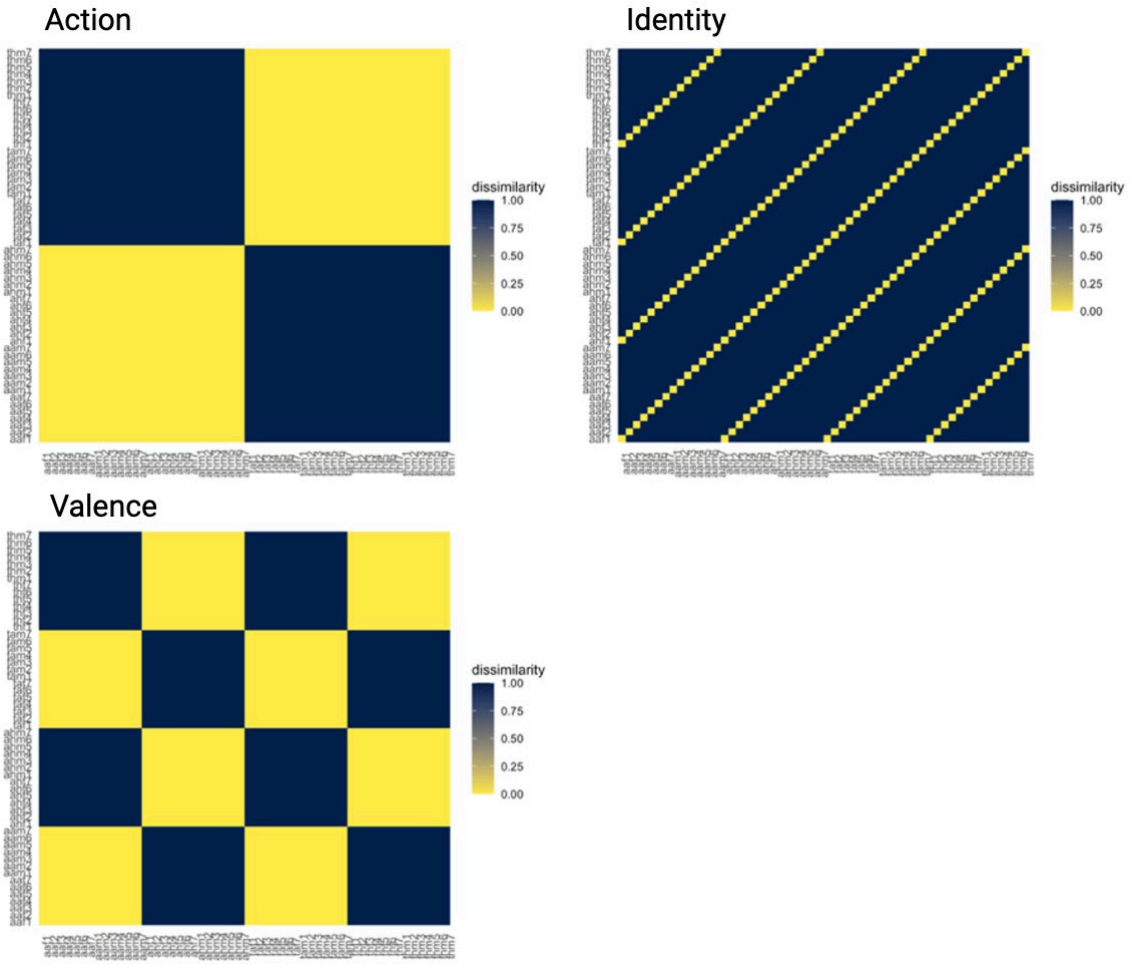


Figure 3. RDMs for Action, Valence, and Identity Models.

Theoretical RDMs representing distinct hypotheses for neural encoding. The action model predicts neural similarity based solely on the direction of gaze (toward self vs. away from self). The valence model predicts that stimuli with similar emotional affect (positive vs. negative) will elicit similar neural patterns, regardless of other conditions. Finally, the identity model predicts neural similarity based on target identity alone. Dissimilarity is represented on a scale from 0 (yellow: identical patterns) to 1 (navy: maximally dissimilar patterns). These models serve as the computational framework against which recorded neural data is compared using RSA.

Results

MVPA of fMRI data was conducted independently across 414 parcels. The goal of the RSA was to determine where patterns of activity most closely matched the RDM models generated for each condition (action, valence, target identity), while controlling for the other two. Thus, revealing where each condition acts as a driver for our neural representation of facial perception. The results of the analysis are shown in Figure 4. The resulting patterns are minimally overlapping, with the most widespread effects occurring within the identity category. Tables 1-3 show a complete list of the significant parcels. Importantly, these results do not tell us whether a region is more or less active. Rather, the data show the regions that encode necessary information related to each condition, which is integrated with information from other regions that contribute to our ability to process facial information.

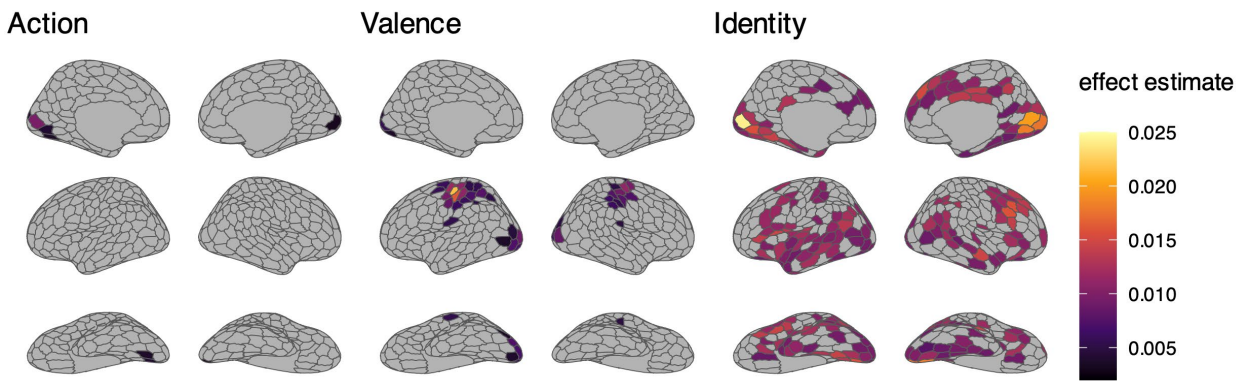


Figure 4. Anatomical Distribution of Representational Patterns.

Mapping of representational networks for social stimuli. The action map illustrates regions where the neural pattern similarity is significantly driven by gaze direction. The valence map illustrates regions that are significantly predicted by the emotional affect of the stimuli. The identity map highlights cortical areas where representational patterns differentiate between the identities of individual stimuli. The effect estimate is provided.

Action

RSA revealed several parcels of interest that store our neural representation of action (ie. look vs away). All parcels fell within the primary visual cortex (V1) of the occipital lobe, which is associated with early, simple visual processing. A summary of such brain regions is provided in Table 1.

Brain region	Peak coordinates (x, y, z; MNI)	Schaefer Parcel	Estimate	*P*-value (corrected for multiple comparisons)
L primary visual cortex	(-5, -75, -5)	185	0.004	<0.001
L primary visual cortex	(-21, -75, -10)	180	0.004	0.001
L primary visual cortex	(-3, -75, 1)	194	0.010	<0.001

Table 1. Brain regions where representational patterns most correlated with the action model.

This table lists regions, their corresponding peak coordinates, and the Schaefer parcel for which neural activation patterns were most significantly predicted by gaze direction. Peak coordinates are presented in MNI space, and the *P*-values have been corrected for multiple comparisons.

Valence

Results in the valence condition partially overlap the look category. However, several parcels extend beyond early V1 and begin to enter more specialized visual system regions (Fig. 4). We also observe highly statistically significant input from both the right and left somatosensory networks (b=0.012, P <0.001; b=0.010, P <0.001). The primary task required participants to code the stimuli valence, thereby contributing to this effect. Notably, we do not see a significant contribution from the limbic system, the brain's center for emotional processing.

Brain region	Peak coordinates (x, y, z; MNI)	Schaefer Parcel	Estimate	*P*-value (corrected for multiple comparisons)
L somatosensory network	(-28, -17, 71)	149	0.012	<0.001
R somatosensory network	(28, -11, 71)	329	0.010	<0.001

Table 2. Brain regions where representational patterns most correlated with the valence model.

This table lists regions, their corresponding peak coordinates, and the Schaefer parcel for which neural activation patterns were most significantly predicted by emotional affect. Peak coordinates are presented in MNI space, and the *P*-values have been corrected for multiple comparisons.

Identity

The identity condition resulted in the most widely distributed representation of facial processing. Results included several parcels that overlapped both the look and valence conditions. Consistent with prior research, the activation patterns within the fusiform face area are predictive of facial identity (b=0.009, P=<0.001). Most interesting is the number of parcels within the default mode network (DMN), a network of brain regions that is consistently suppressed during goal-directed tasks. These regions include the right dorsal medial prefrontal cortex (R dmPFC) and R posterior cingulate cortex (R PCC) (b=0.015, P=<0.001; b=0.013, P=0.001). A summary of select DMN and supporting regions is in Table 3.

Brain region	Peak coordinates (x, y, z; MNI)	Schaefer Parcel	Estimate	*P*-value (corrected for multiple comparisons)
L dorsal medial prefrontal cortex	(-3, 48, 36)	23	0.010	0.015
R dorsal medial prefrontal cortex	(6, 48, 36)	269	0.015	<0.001
L posterior cingulate cortex	(-3, -39, 25)	76	0.013	0.015
R posterior cingulate cortex	(3, -33, 26)	271	0.013	0.001
L temporoparietal junction	(-50, -51, 13)	108	0.011	0.005
R temporoparietal junction	(50, -44, 16)	344	0.010	0.008
L amygdala	(-25, -11, -21)	405	0.010	<0.001
R amygdala	(25, -11, -21)	412	0.009	0.001
L fusiform face area	(-40, -61, 13)	138	0.010	0.018
R fusiform face area	(40, -61, 13)	375	0.009	<0.001

Table 3. Brain regions where representational patterns most correlated with the identity model.

This table lists regions, their corresponding peak coordinates, and the Schaefer parcel for which neural activation patterns were most significantly predicted by target identity. Peak coordinates are presented in MNI space, and the *P*-values have been corrected for multiple comparisons.

Discussion

Effective social interaction requires the use of overlapping, widely distributed representational systems, several of which contribute to our dynamic facial processing ability. This research used naturalistic stimuli to determine which aspects of stimuli drive our encoded neural patterns. We focused on three possible conditions as drivers: action (as a representation of social attention), valence, and stimulus facial identity. Using RSA of fMRI data, we compared hypothetical models of neural patterns with real, experimentally derived patterns to begin disentangling the conditions. Analysis showed that each of the three proposed conditions plays a role in driving our neural representations across more than one brain parcel. Thus, supporting the conjecture that the brain is not a one-to-one processing unit, but rather stores information in diffuse patterns. Results show that facial identity, as a driver, is encoded in the most widely distributed pattern across all conditions. Others have also found similar results within the ventral stream, anterior temporal lobe, and anterior fusiform gyrus (Goesaert & Op De Beeck, 2013; Nestor et al., 2011). Regions identified in this experimental context (Fig. 4) reveal that identity is organized more globally by the brain.

Action

Areas of significance within the active condition included V1, the early visual cortex responsible for lower-level visual processing. An initial interpretation of this data is that stimuli that are actively turning appear more similar, not because of the overall perceived image, but because of a simple identifier, such as the observed lines or sharp corners. All stimuli were recorded at 45°, so placement alone did not indicate whether the stimuli would face away from or turn toward the camera. The early visual cortex is one such area where the action and identity conditions overlap, indicating that they act independently as significant drivers of facial

perception. One subset of facial perception is facial recognition, the ability to differentiate between two distinct faces. The consensus has long been that holistic processing, or processing of the face as a single, integrated whole, is an accurate predictor of facial recognition. Evidence now suggests that feature-based processing may be a more accurate predictor of early facial recognition (Goesaert & Op De Beeck, 2013). New findings, together with our results, may explain why action, as a driver of facial processing, appears to be confined to these early visual areas.

Valence

Results revealed two main regions in which valence drove our neural representation: V1 and the primary sensorimotor cortex (SM1), a broad area spanning the central sulcus responsible for both sensory and motor functions. The parcels within V1 were slightly past the early visual cortex, now entering ventral temporal areas and partially overlapping the fusiform gyrus. As discussed, this brain region plays a central role in encoding our neural representation of faces (Fusar-Poli et al., 2009; Ganel et al., 2005; Kanwisher et al., 1997). However, because RSA captures multidimensional neural patterns, our results indicate the FFA is not the only region contributing to any of the three conditions. Valence also drove neural representation within SM1, likely due to the scanner task. Participants were instructed to code each stimulus for valence using a button placed in their right hand, thereby reinforcing neural dissimilarities between happy and sad faces. This likely explains why we see significant results within SM1, a confound of the experimental design.

It is surprising to see a lack of subcortical representation from regions within the limbic system. This may be because some structures, such as the amygdala, habituate quickly to emotion-based tasks (Breiter et al., 1996). Suggesting that there was no significant change in

neural patterns between happy and sad stimuli. Without change, happy stimuli will look the same as sad stimuli, at least within the amygdala, which is incompatible with the hypothetical model generated.

Identity

As mentioned, the most numerous and distributed effects were observed in the target condition. It is clear from these results that more areas of the brain are involved in our neural representation of facial perception, particularly when considering identity alone. Unsurprisingly, there is some overlap with the fusiform face area. However, there are also several midline cortical regions, such as the medial prefrontal cortex (mPFC), posterior cingulate cortex (PCC), and the temporoparietal junction (TPJ). These regions are included in the DMN. Originally discovered due to its inactivity during goal-directed tasks (Raichle et al., 2001), further research has confirmed that the default mode is not simply our "baseline." Rather, these brain regions are imperative for our understanding of the self *and* others (Schilbach et al., 2008). Essentially, when our brains are not actively processing external stimuli, these regions enter a self-referential, daydreaming state.

Several significant parcels overlap with the mPFC, and recent research shows that this region serves as a hub of the DMN (Li et al., 2014). The ventral mPFC connects to emotional processing regions, such as the amygdala, working with the PCC to formulate our empathy response. Meanwhile, the anterior and dorsal mPFC primarily help us delineate self from others (Li et al., 2014). The mPFC and TPJ appear to be the primary regions involved in global switching between social and non-social cognitive processes, as well as in more specific theory of mind tasks—though their exact roles are the subject of much debate among social neuroscientists. Theory of mind is our ability to interpret another person's cognitive state based

just on their behavior, or facial expression, in this case. It is evident from the many cognitive processes contained within the DMN that target identity is an incredibly complex condition. The hypothetical model can only consider stimulus identity at face value. The brain may be encoding more, ascribing mental states, and drawing connections between self and other.

Future Directions

There were several limitations of this experiment due to my use of secondary data. In the future, I might alter the experimental design to more directly target the three proposed conditions (action, valence, and identity). For example, including stimuli designed to elicit a stronger, more varied emotional response from the participant may elicit activity in subcortical and limbic areas. I may also include more sub-conditions within identity that factor in stimulus emotion and action to better tease which aspects of identity drive which areas of the DMN. Finally, one could switch the participant task from categorizing valence to categorizing turning action (none or toward self) to ensure we see a similar pattern of activation as resulted in the present design.

Conclusion

In conclusion, the results of this analysis reveal that determining who you are looking at requires more brain areas than determining the stimulus's emotional valence or social orientation. Our neural representations of facial perception in DMN regions are driven by stimulus identity. In other words, when your eyes catch another's in the grocery store, the activation patterns across your brain store information regarding who that person is in relation to you, considering whether you've seen them before, and ascribing cognitive processes based on their expression. This finding may shape how researchers design and analyze future social perception tasks. If one doesn't adequately account for facial identity you may miss some of what is driving the main effect of the experiment or conflate results.

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