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UNIVERSITY OF CALIFORNIA, SAN DIEGO

Lateralization of Categorical and Coordinate Stimuli: A Differential
Encoding Account

A Thesis submitted in partial satisfaction of the requirements for the degree
Master of Science

in

Computer Science

by

Vishaal Prasad

Committee in charge:

Professor Garrison W. Cottrell, Chair
Professor Manmohan Chandraker
Professor Virginia de Sa

2017

The Thesis of Vishaal Prasad is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

Chair

University of California, San Diego

2017

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Chapters 2-4, in part, have been submitted for publication of the material as it may appear in Proceedings of Cognitive Science Society, 2017, Prasad, Vishaal; Cipollini, Ben; Cottrell, Garrison W., London, UK, 2017. The thesis author was the primary investigator and author of this paper.

ABSTRACT OF THE THESIS

Lateralization of Categorical and Coordinate Stimuli: A Differential Encoding Account

by

Vishaal Prasad

Master of Science in Computer Science

University of California, San Diego, 2017

Professor Garrison W. Cottrell, Chair

Categorical and coordinate stimuli were proposed by Kosslyn (1987) as a set of lateralized visual tasks with a left hemisphere advantage for categorical and right hemisphere advantage for coordinate. A categorical task uses relative positioning to make a judgment, such as the statement that a glass of water is on a table; a coordinate task uses absolute positioning to make a judgment, such as the statement that the glass of water is 3 inches from my hand. Kosslyn hypothesized that categorical tasks depended on low spatial frequencies and coordinate were preferentially processed in higher spatial frequencies (e.g.

Baker et al. 1999); however, the literature in subsequent years was inconclusive on this hypothesis (Jager and Postma 2003). Slotnick et al. (2001) directly tested Kosslyn's hypothesis and also arrived at conflicting results. By stratifying by difficulty, they showed that Kosslyn's hypothesis holds only when tasks are difficult enough. Our Differential Encoding (DE) model is a three layer neural network that accounts for lateralization of visual processing via the biologically and developmentally plausible mechanism of differences in the connection spread of long-range lateral neural connections. We first establish certain frequency-encoding properties of the DE model. We then show that our model accounts for Slotnick's psychological data and show Slotnick's analysis does not convincingly explain the conflicting results. Instead, we propose that Kosslyn's initial hypothesis was incorrect: categorical and coordinate stimuli are not differentiated solely by spatial frequencies, which is why lateralization has been inconclusive in the past. These results therefore cannot be captured by models such as Ivry and Robertson's (1998) "Double Filtering by Frequency" model, which is driven directly by lateralization in spatial frequency processing.

Chapter 1

Introduction

In 1977, Navon published a seminal work on the "global precedence effect" – a phenomenon where humans notice global, higher level-patterns in a scene or stimulus before perceiving finer levels of discrimination (Navon, 1977). One experiment in this work focused on hierarchical letters, such as a large, "global" T composed of small, "local" F's. Through these stimuli, he showed that humans displayed an advantage for the global level stimulus, i.e. the T in the above example, which he dubbed the "global precedence effect." Five years later, Sergent (1982) noted a peculiar phenomenon: the strength of the global precedence effect varies by hemisphere. That advantage was stronger in the right hemisphere (RH) than in the left hemisphere (LH). Sergent reduced this advantage to differences in frequency processing between the two hemispheres, and this assumption has guided much of the psychological research on visual lateralization thereafter (e.g. Kosslyn et al. 1992; Okubo & Michimata, 2001; Hsiao et al., 2013).

Cognitive models have become an increasingly used tool to test psychological hypotheses that cannot be tested directly in humans. For example, Kosslyn et al. (1992) use cognitive models to test their supposition that categorical and coordinate stimuli are, in fact, qualitatively distinct, as well as to explain objections raised by Sergent (1991). Furthermore, they use a neural network cognitive model to show that the categorical and coordinate

distinction can be explained by lateralized frequency processing, as suggested by Sergent (1982) (Baker, Chabris, & Kosslyn, 1999). Similarly, Ivry and Robertson (1998), lacking a way to test their theorized explanation for the effects observed in Sergent (1982) among other work, used cognitive models as the primary evidence for their model (Ivry & Robertson, 1998). In short, cognitive models allow researchers to test hypotheses that are impossible or unfeasible to test on humans.

However, one must eventually be able to relate the cognitive model back to some neurological basis in the brain – a model that accounts for the data but is biologically implausible has limited value as an explanation. In addition, a neurologically plausible explanation is still weak if it is developmentally implausible. There needs to be reason to suspect that the brain actually does develop in accordance with the model. Many of the cognitive models surrounding visual lateralization do not fulfill both of these criteria, but our Differential Encoding model (DE) does. Cognitive modeling allows us to test the capabilities of the DE model, even as the core mechanism proposed in the model – differential connectivity between cortical patches in the two hemispheres – has not been observed yet, though there is reason to suspect it exists (as outlined in Hsiao et al., 2013).

Furthermore, the increased computational power of the modern day affords modern cognitive modelers some additional advantages. Computational models in the 1990s were often analogous implementations of human experiments rather than exact implementations, due to computational limitations. For example, a 2D image used in human experiments may be represented by a similar 1D task for ease of computation. We can now directly test on the exact same stimuli used in human data, allowing for a one-to-one comparison. In addition, we can use more sophisticated models to better represent the proposed cognitive phenomenon in code. As we will see, these two advantages are instrumental in establishing baseline facts to challenge claims made by psychologists.

This thesis is organized as follows. Chapter 2 provides necessary background, both on

the psychological experiments and the relevant cognitive models. Chapter 3 establishes the methods used in the experiments, provides the results, and provides discussion. Chapter 4 provides a conclusion based on these results and outlines future work to be done.

Chapter 2

Background

The human brain is composed of two relatively disconnected hemispheres that communicate via a bridge of fibers known as the corpus callosum. The level of disconnection and redundancy suggests that for at least some cognitive processes, it may be advantageous for each hemisphere to specialize and reduce redundancy. This functional specialization, called "lateralization," occurs for many diverse cognitive facilities in humans (Stephan et al., 2003) and non-humans alike (Rogers & Andrew, 2002). Prominent examples in humans include fine motor skills and language processing, both of which are left hemisphere dominant (Knecht et al., 2000). Of particular interest to us is visual lateralization. Past studies have shown visual lateralization in processing stimuli ranging from frequency gratings to facial recognition (e.g. Sergent, 1985; Ivry & Robertson, 1998).

One such set of stimuli, from Navon (1977), is hierarchical letters, such as a large, "global" T composed of small, "local" F's, depicted in Figure 2.1A. Sergent (1982) showed that the left hemisphere (LH) has an advantage at identifying the local level target (the letter F in the above example), whereas the right hemisphere (RH) has an advantage at identifying the global level target, seen in Figure 2.1B. She concluded that the LH performs better at high-frequency information, whereas the RH does better at low-frequency information. Kitterle, Christman, and Hellige (1990) directly tested this hypothesis with frequency gratings. First,

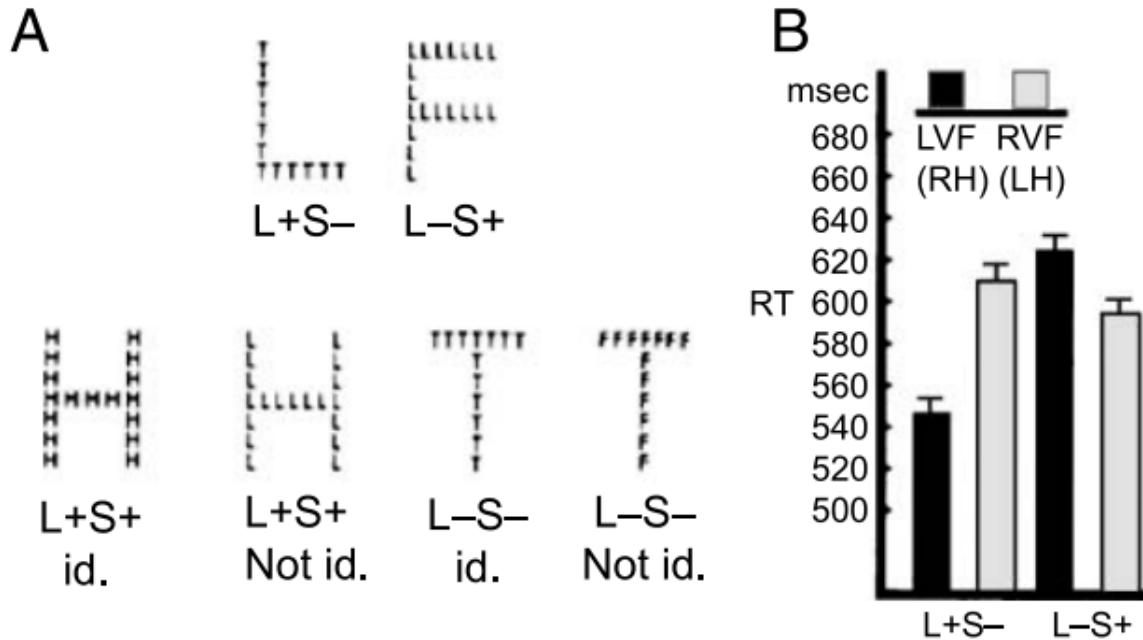


Figure 2.1: Reproduced from Hsiao et al. (2013), itself an adaptation of figures from Sergent (1982), this diagram depicts examples of Navon figures (Navon, 1977) (A) as well as the lateralization results (B).

they tested subjects on whether they detected gratings at two different frequencies when flashed in one visual field. They found no lateralization on this task of detection. They then asked subjects to differentiate between two sets of gratings that varied on frequency, again flashed in one visual field. Lateralization this time did present, even though the same frequency gratings were used. They concluded that frequency lateralization was driven by task demands, rather than purely by stimulus properties.

A year later, the authors further tested the identification task, again using frequency gratings (Christman, Kitterle, & Hellige, 1991). Subjects were asked to distinguish between two sets of stimuli. The first was a baseline stimulus consisting of 0.5 cycles per degree (cpd) and 1 cpd gratings. The second was that same baseline but with a 2 cpd component added in as well. Therefore, the 2 cpd component differentiated the two sets of stimuli. The authors found a LH advantage on recognizing the 2 cpd gratings and a RH advantage on the baseline, as expected. They then repeated the experiment, but this time the baseline

consisted of a 4 cpd and 8 cpd component instead. Therefore, the 2 cpd component was now the low-frequency component rather than the high-frequency component as before. The authors now found a RH advantage on the 2 cpd gratings and a LH advantage on the baseline gratings. The same frequency band lateralized differently based on the particular task. They concluded differences between the hemispheres are not absolute, but instead relative to the frequency band relevant for solving the current task (Christman et al., 1991).

2.1 Categorical & Coordinate Spatial Processing

Kosslyn (1987) and also Kosslyn, Koenig, Barrett, Cave, Tang, & Gabrieli (1989) proposed a new modality of lateralized visual processing, based on the characterization that humans process visual stimuli using two distinct types of spatial relations. Coordinate relations rely on an absolute, metric basis; for example, the statement "the glass of water is 3 inches from my hand" defines a coordinate judgment of one's hand and the glass of water. In contrast, categorical relations rely on abstract, relative terms. The statement "the glass of water is on top of the table" does not tell us exactly where the glass is, only its relative position to a table. Kosslyn argues these are two fundamentally distinct representations. In his 1987 paper, Kosslyn observed a LH advantage for categorical relation judgments and a RH advantage for coordinate relation judgments. He proposed that two different subsystems governed these two relations and that they lateralized based on a "snowball effect" deriving from the LH's known advantage in speech (Kosslyn, 1987). Other work (e.g. Hellige & Michimata, 1989) provided further support for this hypothesis with more varied types of stimuli (e.g., a bar and dot stimulus).

However, in 1991, Sergent found that this lateralization effect presented only when stimuli were degraded, and several analyses have noted that the lateralization only appears in right-handed people (Slotnick, Moo, Tesoro, & Hart, 2001). Other researchers likewise found weak or inconclusive evidence for lateralization of categorical and coordinate stimuli.

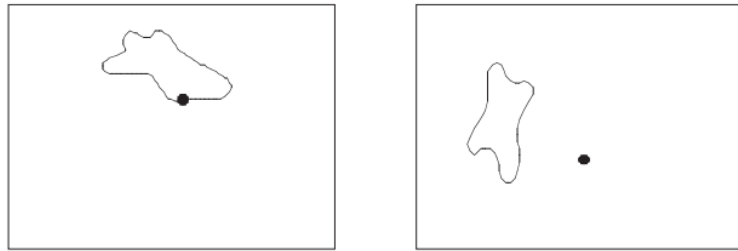
Okubo and Michimata (2002) note that the LH advantage on categorical processing is not always present. Furthermore, the results of Slotnick et al. (2001), detailed below, reveal that the RH advantage on coordinate processing does not necessarily present. Nevertheless, researchers generally agree that a distinction exists, even if it is weaker than originally thought (see Jager & Postma, 2003 for a review).

Noting the inconclusive evidence of whether categorical and coordinate is a meaningful distinction, Slotnick et al. (2001) sought to test Kosslyn's hypothesis directly, using the same class of stimuli used in Kosslyn et al. (1989). These stimuli, shown in Figure 2.2, include coordinate and categorical judgments on blob/dot and plus/minus stimuli. In addition, they added a new stimulus type, paired squares, which was designed to resist "categorization" of coordinate tasks, whereby a subject on later trials during an experiment learns a coordinate task (e.g., is the plus far away from the minus) and turns it into a categorical task (Slotnick et al., 2001). This effect had been proposed to weaken the RH advantage on coordinate stimuli, and so Slotnick et al. (2001) added the paired squares coordinate stimulus, which forces the subject to make a direct metric comparison between the two halves of the stimulus.

They conducted a series of five experiments on 134 subjects, each with one hemisphere temporarily deactivated by an intracarotid injection of sodium amobarbital. This deactivation process removes any interhemispheric interference.

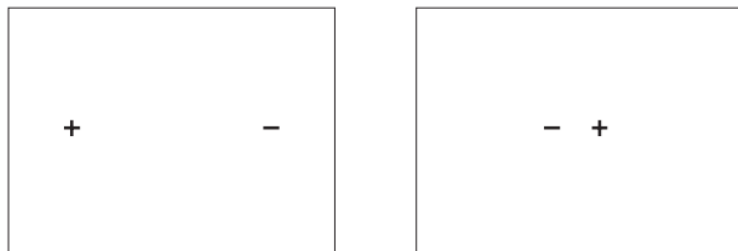
The results were generally in line with Kosslyn's hypothesis. The two categorical experiments showed LH dominance, and coordinate paired squares showed RH dominance. Coordinate plus/minus didn't lateralize, but it also did not show LH dominance. However, the coordinate blob/dot experiment did not show the expected RH dominance, instead showing the opposite lateralization compared to the original paper. The authors noted that distances between components of their figures, such as the plus and minus, were larger in their experiments than in Kosslyn et al. (1989). They suspected this made the task too easy to show proper lateralization.

Blob/Dot



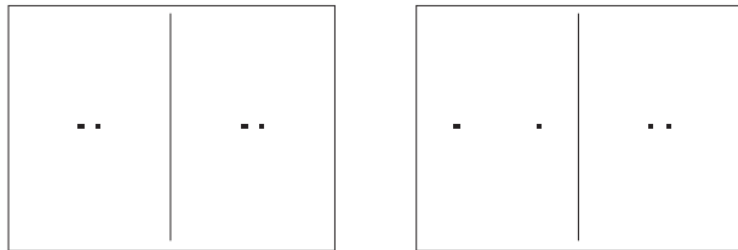
(a)

Plus/Minus



(b)

Paired Squares



(c)

Figure 2.2: This figure was taken directly from Slotnick et al. (2001). Note that paired squares only had a coordinate task, whereas blob/dot and plus/minus have both categorical and coordinate.

Consequently, they ran a post-hoc analysis that stratified the tasks based on difficulty, and suggested that only when a task is made more difficult does lateralization arise on coordinate experiments. Difficulty has been reported to modulate lateralization in other experiments (e.g. Sergent, 1985), so they reasonably concluded that task difficulty is an important factor in the lateralized processing of categorical and coordinate stimuli.

In light of these conflicting data, Kosslyn and colleagues have refined their hypothesis and now argue that lateralization in categorical and coordinate stimuli exists due to a difference in frequency processing, potentially based on hemispheric differences in neuronal receptive fields (see Kosslyn, Chabris, Marsolek, & Koenig, 1992; Baker, Chabris, & Kosslyn, 1998; Chapter 9 of Hugdahl & Davidson, 2003). Cowin and Hellige (1994) tested this hypothesis via low-pass filtered stimuli via blurring, and they failed to find a visual field difference. Okubo and Michimata (2002) note that the LH categorical advantage, ostensibly based on high spatial frequencies, is tenuous to begin with. Instead, they sought to remove low spatial frequency information via a process called contrast balancing. In support of Kosslyn's hypothesis, they showed that the RH coordinate advantage, but not the LH categorical advantage, was eliminated by contrast balancing. Nevertheless, scarce data, beyond Okubo and Michimata's (2002) results, tie together spatial frequency processing and categorical and coordinate lateralization.

2.2 Double Filtering by Frequency Theory

Based on Sergent's (1982) theory, Ivry and Robertson (1998) proposed their Double Filtering by Frequency (DFF) theory to explain the asymmetric spatial frequency processing. The DFF theory is built on the assumption that visual lateralization is driven directly by lateralized spatial frequency processing. In their theory, there are two filtering processes that occur in vision. The first filter, which is identical in both hemispheres, determines the task-specific frequencies of a visual stimulus. The second filtering process leads each

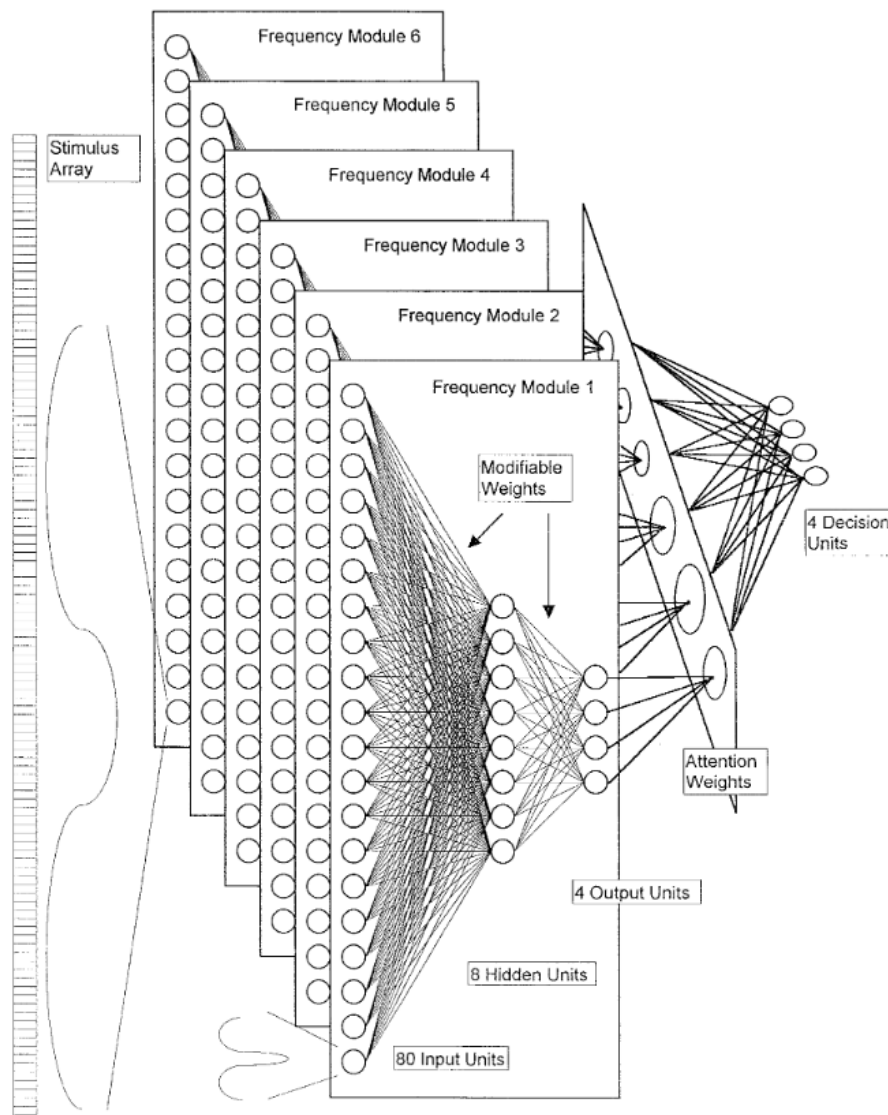


Figure 2.3: Taken directly from Figure 7.3 of Ivry & Robertson (1998), this diagram depicts the computational model of the DFF theory. The frequency modules are the same in both hemispheres, but the attention weights are lateralized such that the LH prioritizes information from higher frequency modules and the RH prioritizes information from lower frequency modules.

hemisphere to "emphasize different aspects of the internal representation of the stimulus" (Ivry & Robertson, 1998).

Figure 2.3, lifted directly from a figure in Ivry & Robertson (1998), is the computational

representation of their theory. The first filter is implemented via a set of six frequency modules, where each neuron encodes information across a large spread of input pixels or across a low spread of input pixels. It is theorized that neurons with large receptive fields encode low-frequency information better (Kosslyn, Chabris, Marsolek, & Koenig, 1992; Ivry & Robertson, 1998) due to the coarse coding effect (Ballard, Hinton, Sejnowski, et al., 1983). Therefore, each of these frequency modules can be seen as capturing specific frequency-based information. Each module then consolidates its output to a single neuron in the next layer. Finally, these six neurons are connected to the decision neurons at the end of the network.

In this way, the DFF theory directly encodes frequency processing lateralization as outlined in Sergent (1982), but it does so in a manner consistent with Kitterle et al.'s (1990) results. The first filter, which can be thought of as a representation of stimulus properties, is where detection of frequency gratings would first occur. In accordance with Kitterle et al. (1990), this filter is the same in both hemispheres. The lateralized second filter, where the system chooses which frequencies to emphasize based on the task, would differentiate between wide and narrow frequency gratings. Therefore, results in this identification task would be lateralized, once again in accordance with Kitterle et al. (1990).

Ivry and Robertson (1998) replicated the results in Sergent (1982) using 1D hierarchical stimuli modeled after the Navon (1977) figures used in Sergent (1982). These 1D stimuli are shown below, in Figure 2.4. Furthermore, the DFF theory accounts for data from Christman, Kitterle, and Hellige (1991). The authors showed that frequency processing differences between the hemispheres are not absolute, but instead relative to the frequency band relevant for solving the current task. The DFF theory hypothesizes that the visual system first chooses the most relevant frequencies, before having different preferences on those frequencies. This allows the model flexibility in capturing the relative frequency effect. Finally, their model accounts for the categorical and coordinate spatial relations.

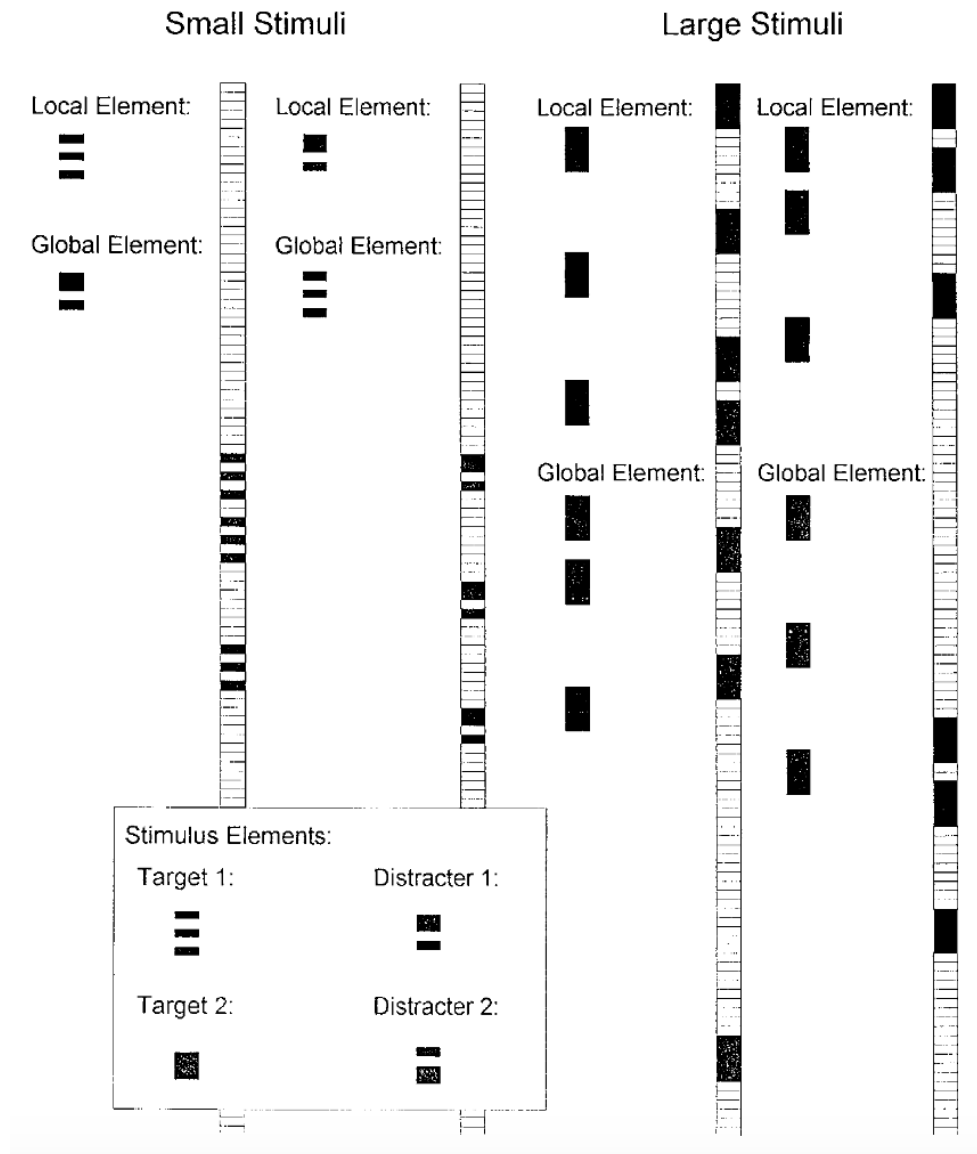


Figure 2.4: Taken from Ivry & Robertson (1998), this diagram shows 1D hierarchical stimuli. Due to computational constraints, the authors used these stimuli in lieu of Navon figures as were used in Sergent (1982).

They showed their computational model (illustrated in Figure 2.3) could account for the bar and dot experiment from Kosslyn et al. (1989), though it is worth noting they encoded this task in 1D rather than encoding the exact psychological task.

The main weakness of the DFF theory is that there is no neurological basis for the core mechanisms of the DFF theory, nor is there a developmental explanation of how or why

this phenomenon would emerge (see Cipollini, 2014 for an in-depth discussion). The DFF theory may account for much of the data, but there is not a reason to believe it actually occurs in the brain.

Competing with the DFF theory is our Differential Encoding (DE) model (Hsiao, Shahbazi, & Cottrell, 2008; Hsiao, Cipollini, & Cottrell, 2013). This model has accounted for many of the same data, but via specific biological mechanisms and a plausible neurodevelopmental cause. We go into more detail below.

2.3 The Differential Encoding Model

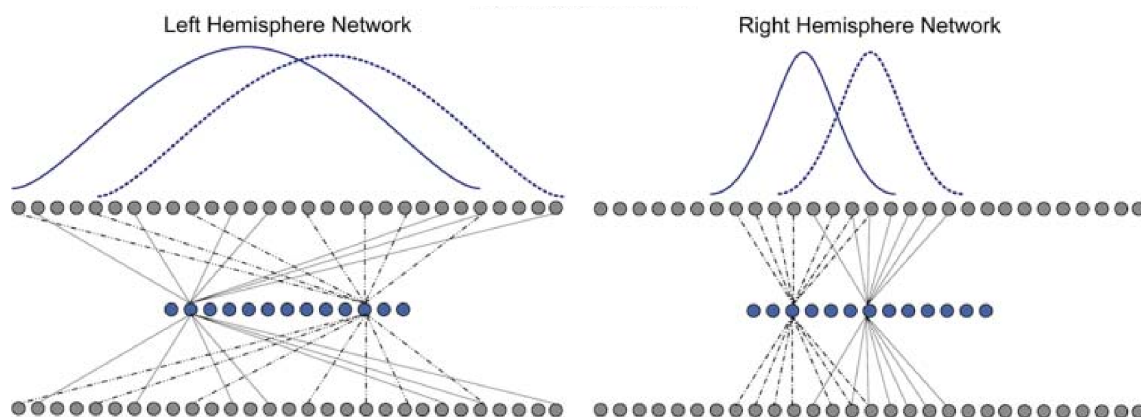


Figure 2.5: Taken from Hsiao et al. (2013), this diagram shows the autoencoder models with varying connection spreads and symmetric connections.

The Differential Encoding (DE) model is another explanation for human visual lateralization (Hsiao et al., 2008; Hsiao et al., 2013). It is inspired by an anatomical difference in the auditory system's long range lateral connections (LRLCs). Similar to that in the visual system, lateralization in the auditory system results in an RH advantage on low-frequency information (prosody) and LH advantage on high-frequency information (content) (Ley & Bryden, 1982; Ivry & Robertson, 1998). On average, a LH neuron connects to neighbors generally farther from itself than the RH neurons do (Galuske, Schlote, Bratzke, & Singer, 2000). This effect occurs in the language-specific processing of auditory signals, rather

than in the primary auditory areas (Galuske et al., 2000), consistent with the task-level, but not stimulus-level, lateralization noted in Kitterle et al. (1990).

The DE model hypothesizes these LRLCs as the driving factor behind visual lateralization as well. Lateralization of LRLCs has not yet been observed in the visual system, but there is reason to believe it exists (as detailed in Hsiao et al, 2013). Compared to the DFF theory, the DE model has the advantage of having neurodevelopmental and neuroanatomical plausibility (Cipollini, 2014).

Computationally, the Differential Encoding model is a standard 3-layer neural network which can be thought of as a recurrent neural network unrolled one step in time. The first set of connections is a sparse autoencoder, trained on natural images, to represent how a stimulus might be represented in the early stages of the brain using low level processing such as Gabor filters. Each neuron in the autoencoder corresponds to a spatial location, and it connects to 5 other neurons generated randomly from a Gaussian centered around the neuron itself. The LH and RH networks vary merely by the standard deviation, or sigma parameter, of the Gaussian, to mimic the lateralized connection spread of the LRLCs, shown in Figure 2.5. Note that this differs from a Gaussian receptive field. The Gaussian controls the location of connections, not their value.

The hidden units are trained to reproduce natural image patches via backpropagation (Williams & Hinton, 1986). Once trained, the hidden units are then connected to separate task-specific output units that are trained by the delta rule to perform some task. In this way, the information represented by the hidden layer is tested as to what tasks it is best at.

2.3.1 Results from Hsiao et al. (2013)

Hsiao et al. (2013) established key properties of the Differential Encoding model. They showed that the model accounts for the same simplified 1D stimuli used in Ivry & Robertson (1998) as well as the full, 2D hierarchical letters used in Sergent (1982). The authors also

compared natural image reconstruction of the RH autoencoder to that of the LH autoencoder. They found that the RH preserves the low spatial frequency information better, whereas the LH preserves high spatial frequency information better. The RH network also reconstructs high-pass filtered stimuli with better performance, whereas the LH network reconstructs low-pass filtered stimuli with better performance. They conclude that the LH autoencoders are biased to reproduce high spatial frequency information; likewise for RH autoencoders and low spatial frequency information. This is consistent with Sergent's (1982) theory that frequency differences underlie this lateralization, though this property arises naturally in the DE model (in contrast, the DFF theory directly incorporates it).

As Kosslyn and colleagues have suggested (e.g. Baker et al., 1999), the distinction between categorical and coordinate stimuli may stem from a difference in frequency information. Therefore, we test the network on Slotnick et al. (2001)'s stimuli to further establish the relationship between our model and frequency lateralization, as well attempt to reach parity with the DFF theory on these stimuli.

Chapter 2, in part, is a reprint of the material as it appears in Vision Sciences Society 2017. Prasad, Vishaal; Cipollini, Ben; Cottrell, Garrison W., St. Pete Beach, FL. The thesis author was the primary investigator and author of this paper.

Chapter 2, in part, has been submitted for publication of the material as it may appear in Proceedings of Cognitive Science Society, 2017, Prasad, Vishaal; Cipollini, Ben; Cottrell, Garrison W., London, UK, 2017. The thesis author was the primary investigator and author of this paper.

Chapter 3

Experimental Methods and Results

The goal of this work was originally to implement the Slotnick et al. (2001) results into the Differential Encoding framework. In the process, we found it necessary to test further frequency encoding properties of the DE, to anchor certain lines of analysis about the Slotnick results. This chapter therefore includes methods, results, and discussion for the Slotnick analysis as well as these ancillary analyses.

3.1 Establishing Crossover Points for the Differential Encoding Model

Hsiao et al. (2013) noted that the RH model encodes more information at lower frequencies, whereas the LH model encodes more at higher frequencies. We empirically tested this by looking at the reproductions of natural images from the autoencoder corresponding to each hemisphere. The natural images were 68 pixels high by 50 pixels wide patches taken from the van Hateren natural images dataset (van Hateren & van der Schaaf, 1998). We would expect that if the RH model encodes more information at lower frequencies, then its noisy reconstruction of the image would lose less information at lower frequencies relative

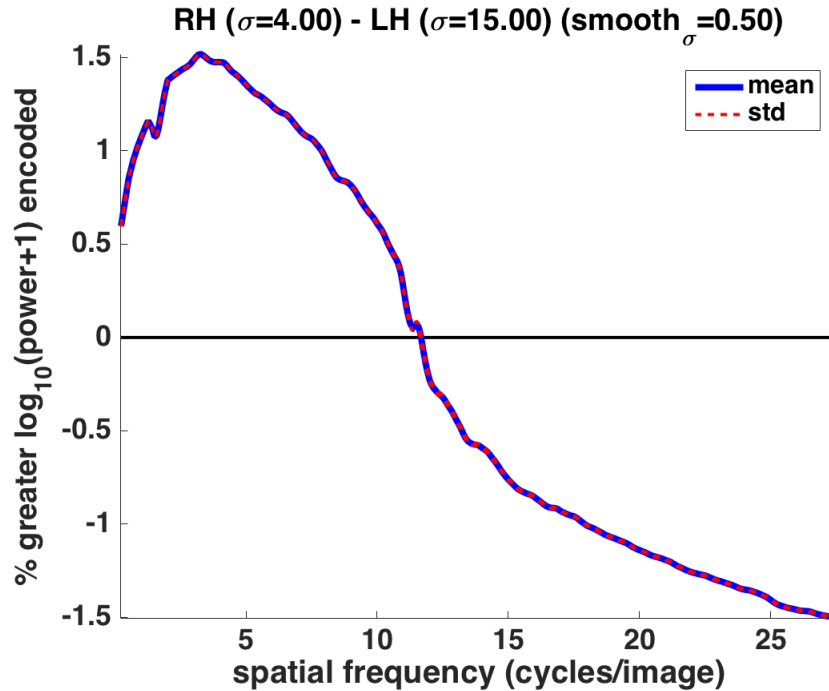


Figure 3.1: In reconstructing the stimulus image, the RH network encodes more information at lower spatial frequencies, whereas the LH encodes more at higher spatial frequencies. This figure is similar to Figure 7b from Hsiao et al. (2013).

to the LH model, and vice-versa at higher frequencies.

Figure 3.1 shows this to be exactly the case, for a network trained on natural images. On the x-axis is the spatial frequency; on the y-axis is the increase in information encoded by the RH versus the LH, in terms of $\log(\text{power}+1)$. At about 10 cycles per image (CPI), the RH encodes about 1% more log power. In Figure 3.1, the solid blue line indicates the mean difference. The dashed red line indicates the standard deviation at each point, but we are simply interested in the trend line as a motivation for this section. Therefore, the standard deviation was Gaussian smoothed with a sigma parameter of 0.50 to keep the figure clean.

From Figure 3.1, we observe the RH model's reconstruction preserves more lower frequency information, based on the positive y-axis value. Similarly, the LH model's reconstruction preserves more higher frequency information. There is a crossover point at about 12-13 CPI where the two models encode about the same data. However, this graph is

for a particular set of sigma values (RH: 4 pixels, LH: 15 pixels) with a particular number of connections (5), for a particular stimulus size (68x50). We might be interested in assessing how these three factors interact.

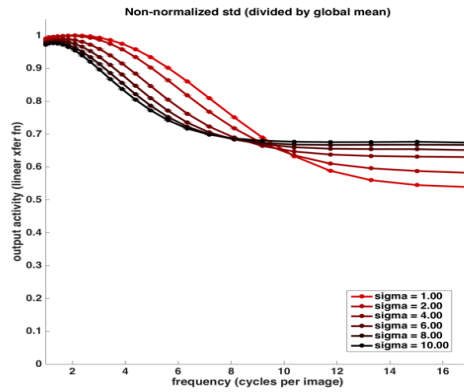
3.1.1 Procedure

To that end, we tested how the crossover point varies across three factors. Specifically, using an autoencoder trained on image patches of van Hateren natural images, we tested its neurons' responsiveness to a set of frequency gratings of 8 orientations, 8 phases, and 24 frequencies (van Hateren & van der Schaaf, 1998). If a neuron is responsive to a specific frequency, then we should observe different output activity for different phases and orientations at a given frequency. In contrast, suppose it provides the same output, strong or weak, to all phases and orientations at a particular frequency. Then, that neuron does not discriminate at that frequency range.

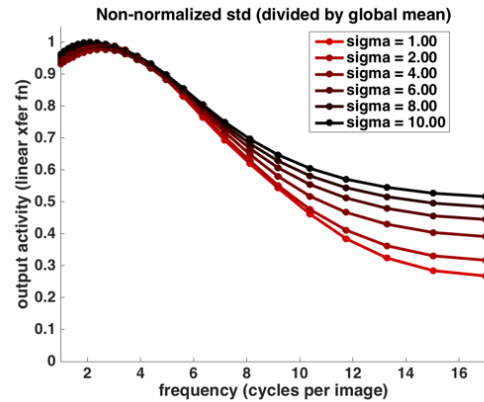
Therefore, we took the standard deviation of each neuron's activations across all 64 gratings of a frequency, as a measure of its responsiveness to that frequency. We then took the mean of all neurons' responsiveness, to represent that network's (i.e. for a particular sigma value) overall responsiveness to a frequency. In this way, we are able to judge how discerning a given model configuration – based on image size, number of connections, and sigma – is at different spatial frequencies.

3.1.2 Results and Discussion

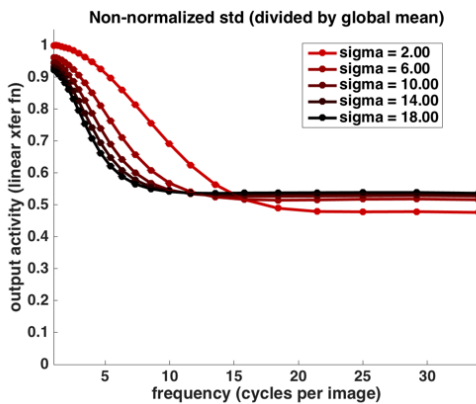
Figure 3.2 provides the results of our experiment. The upper and lower rows correspond to 34x25 and 68x50 image sizes, respectively; the left and right columns correspond to networks with 5 and 20 connections respectively. For a given plot, the x-axis is the spatial frequency in cycles per image (CPI), and the y-axis is the output activity (as described in Chapter 3), scaled so that the highest value is 1. Lighter/ redder lines correspond to smaller



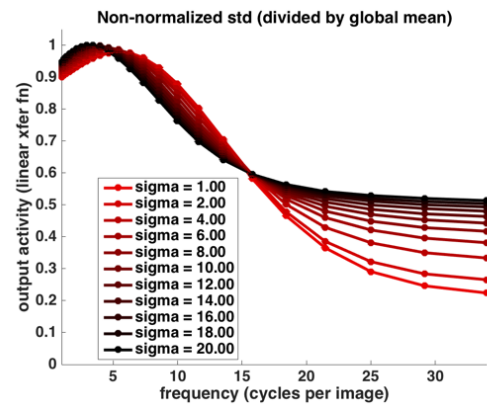
(a) 34x25 image size, 5 connections



(b) 34x25 image size, 20 connections



(c) 68x50 image size, 5 connections



(d) 68x50 image size, 20 connections

Figure 3.2: There are four plots shown here, each corresponding to a different number of connections and image size. Within a plot, there are a number of sigma values chosen. Each curve represents the network's scaled output activity on gratings at that spatial frequency.

sigma networks (i.e. RH networks), and blacker lines correspond to larger sigma networks (i.e. LH networks).

We can see a few trends across the four plots. As expected, the larger sigma networks (LH) encode more information at higher spatial frequencies. Interestingly, however, as the number of connections increases, the RH advantage at lower frequencies decreases (and even reverses for very low frequencies) – for this reason, we chose 5 connections in our results for the Slotnick et al. (2001) replication experiments.

Notably, the crossover point location shifts from about 9 CPI on 34x25 images to about

15 CPI on 68x50 images. This result is interesting, because it in effect encodes the relative frequency effect as outlined in Christman, Kitterle, and Hellige (1991) and coded into the DFF theory (Ivry & Robertson, 1998). Stimulus size can, in effect, be thought of as visual acuity. Higher visual acuity means that more information in a scene can be represented. This is analogous to a larger stimulus size, which provides more space to encode images. Higher levels of the visual processing system decrease in visual acuity, which suggests that the relative frequency effect may reduce to the location wherein the visual processing is occurring (Sergent, 1983; Hopf et al., 2006).

3.2 Replicating Slotnick et al. (2001)

3.2.1 Stimuli

The stimuli used in the 2001 study are reproduced in Figure 3.3 for convenience. To recap, there are three types of stimuli: blob/dot, plus/minus, and paired squares. All three stimulus types involve coordinate tasks. Blob/dot requires an evaluation of how far apart the blob and dot are, and plus/minus likewise requires an evaluation of how far apart the plus and minus are. The paired squares task, in contrast, requires judging whether the two sets of paired squares are equidistant or not. The former two stimulus types also have categorical tasks. The blob/dot categorical task requires evaluating whether the dot is on the blob or off of it, and the plus/minus categorical task requires evaluating whether the plus is on the right or the left. There is no categorical task for paired squares.

Our implementation of the stimuli is shown in Figure 3.4. They were implemented as bitmaps, following the images published in the original paper as best possible. In accordance with the methods laid out in Hsiao et al. (2013), the stimuli were implemented as 34 pixels high by 25 pixels wide. However, an issue emerged. A 34x25 pixel image simply did not afford us enough space to accurately recreate the irregular surface of the blob. Therefore,

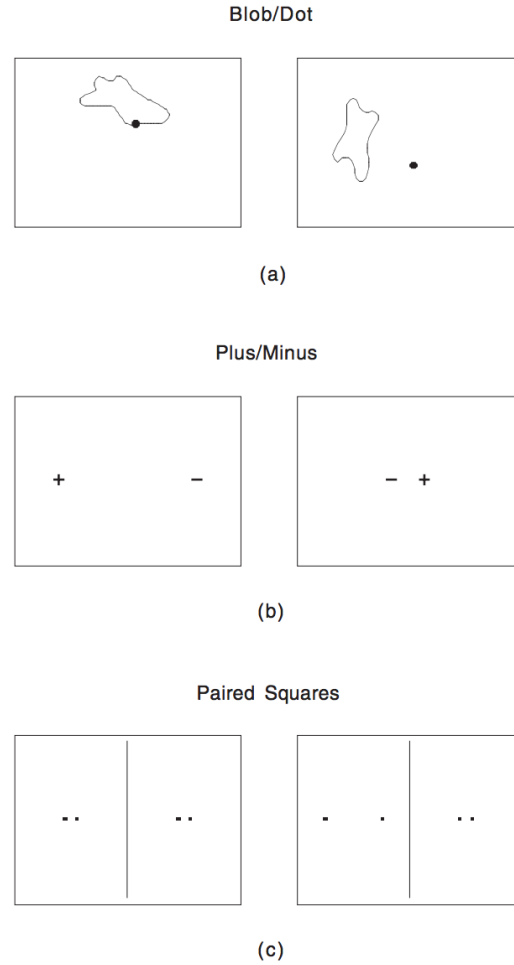


Figure 3.3: This figure was taken directly from Slotnick et al. (2001). Note that paired squares only had a coordinate task, whereas blob/dot and plus/minus have both categorical and coordinate.

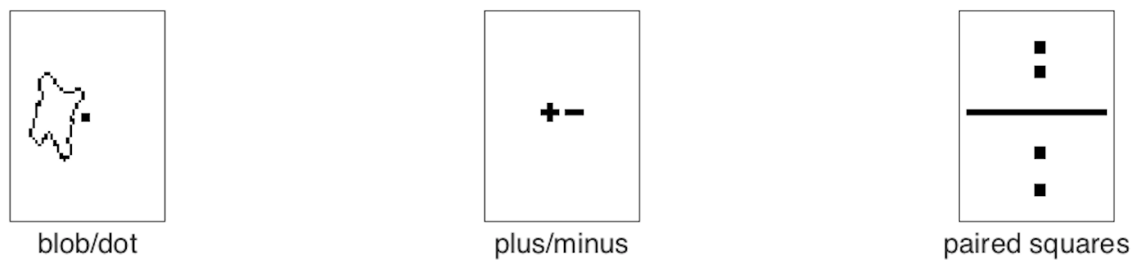


Figure 3.4: This figure illustrates our implementation of the Slotnick et al. (2001) stimuli.

we simply implemented this stimulus to be twice as large in each dimension – 68 pixels high by 50 wide.

The paired squares stimulus had a similar problem: the squares of interest were simply too small. Not only was performance very poor, in later experiments involving bandpass filtering on the stimuli (detailed below), the squares would disappear. It became apparent that they needed to be of larger size. Consequently, we modified the stimulus such that the bar was horizontal, and the squares varied on the y-axis rather than the x-axis. This ameliorated the issue of stimulus degradation without fundamentally altering the task.

The simulation was implemented in MATLAB. All code is open source¹.

3.2.2 The Computational Model

The DE computational model consists of two parts, as detailed in Chapter 2. In the first part, a sparse autoencoder learns to create noisy reconstructions of van Hateren natural images (van Hateren & van der Schaaf, 1998). This step transforms the stimulus in a manner similar to how higher levels of visual processing may represent a stimulus. In the second part, a perceptron is trained to distinguish a task – for example, whether the dot is on the blob or off of it. The stimulus, e.g. of a blob and dot, is noisily reconstructed by the autoencoder before being fed into the perceptron.

The train set and the test set for the perceptron were both the same. Consequently, high levels of regularization are used, as detailed in the next subsection. Error was given by the sum-squared error (SSE) between the perceptron output (real-valued between 0 and 1) and the true label (0 or 1). As in past experiments (e.g. Dailey, Cottrell, Padgett, & Adolphs, 2002; Hsiao et al., 2013), this error can be thought of as the uncertainty of the network and compared to human reaction time.

¹<https://github.com/guruucsd/DifferentialEncoding/releases/tag/slotnick>

3.2.3 Model Parameters

Due to the varying resolutions, the experiment sizes had different hyper-parameters. Of particular interest, the 34x25 images had a RH and LH standard deviation (σ) of 4 and 10 pixels respectively; the 68x50 had 4 and 15. Results were stable across the choice of σ , provided a large enough difference in the two σ values. For both image sizes, each neuron had five connections per hidden unit, with one hidden unit per pixel of the image. We used dropout of 0.7 (Srivastava, Hinton, Krizhevsky, Sutskever, & Salakhutdinov, 2014) and introduced Gaussian noise, with $\sigma = 0.5$ and $\text{mean} = 0$, on the input, to avoid overfitting on these smaller datasets. A relatively high dropout was used as the model otherwise performed exceedingly well on the plus/minus tasks. Results were stable among reasonable configurations of all of these parameters, so we believe our results are general to the task and not specific to our setup.

The human experiment used 100 LH subjects and 124 RH subjects; however, 54 hemispheres of patients deemed abnormal or otherwise compromised (e.g. those with parietal lobe tumors) were excluded (Slotnick et al., 2001). We followed the same analyses done in the human experiment, and in an attempt to roughly match statistical power, we instantiated each hemisphere in our computational model 100 times.

3.2.4 A Key Methodological Difference from Hsiao et al. (2013)

There is one noteworthy methodological difference between the analyses carried out in Hsiao et al. (2013) and the analyses done here. In the former, the authors used an early stopping criterion based on objective error to avoid overfitting on the data. In this work, the DE model incorporates regularization in the form of dropout and in noise (see Bishop, 1995, for an exploration of noise as a regularizer). Consequently, instead of using training loss as the stopping criterion, we train both networks for the same amount of iterations. The autoencoder ran for 50 iterations to minimize the difference between the original image and

its reconstruction. The perceptron ran for 100 iterations, minimizing the error between the true label (e.g. a 1 indicating that the plus is on the right of the minus) and its prediction, a real-valued number in $[0, 1]$.

3.2.5 Results and Discussion

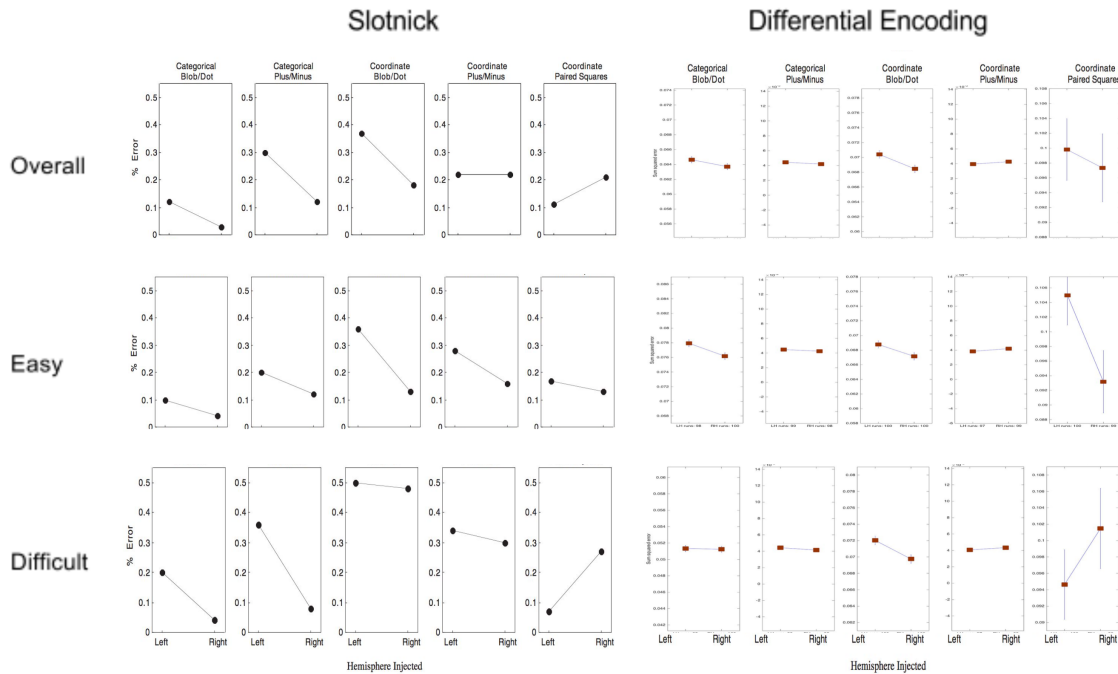


Figure 3.5: Differential Encoding results follow the overall Slotnick et al. (2001) results for task x hemisphere interactions. Note that the left/right labels refer to the hemisphere deactivated, and lower is better. Hence, for example, the first graph in the first row shows that the left hemisphere is better at the Categorical blob/dot task. Also note that hemispheric performance, not absolute performance, was relevant, so y-axes were re-scaled to emphasize slope.

We now look to compare the performance of the Differential Encoding model to the human results on the stimuli presented in Slotnick et al. (2001). Figure 3.5 compares the performance of the Differential Encoding model to the human data. Error is given by the sum-squared error (SSE) between the perceptron output (real-valued between 0 and 1) and the true label (0 or 1). The DE results in Figure 3.5 are scaled so each figure has a y-axis of

range 0.01. This allows for slope – the measure of lateralization and the result of interest – to be compared visually.

It may appear that the DE results do not follow the human data perfectly, but the key concepts are hit. Categorical blob/dot, coordinate blob/dot, and categorical plus/minus all showed the LH advantage as in the original paper. Note that categorical blob/dot shows weak lateralization, yet among every configuration and in every instance tested, the LH lateralization remains. Figure 3.6 shows categorical blob/dot run with 200 (instead of 100) instantiations; we see that with enough statistical power, the LH advantage on this stimulus from the Slotnick paper is, in fact, replicated. Crucially, the anomalous result in the original paper is maintained: categorical blob/dot is not more LH-dominant than coordinate blob/dot. Running a repeated-measures ANOVA gives an F-score of 1.200 ($p > 0.25$). This is the result that contradicts Kosslyn's hypothesis.

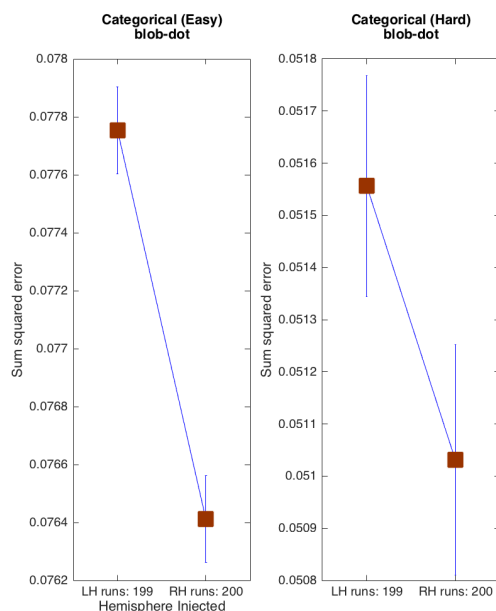


Figure 3.6: With more statistical power via 200 runs, we see from the standard error bars that the LH advantage on categorical blob/dot is in fact significant across both easy and hard configurations.

Coordinate plus/minus shows no lateralization, as in the original paper. Further-

more, categorical plus/minus has a stronger LH lateralization than coordinate plus/minus ($F=12.96$, $p<0.001$). These results all follow the human data laid out in Slotnick et al. (2001).

Paired squares on first glance appears to have reverse lateralization as in the human data. However, paired squares was extremely volatile across small changes of parameters, showing large error bars, and that advantage disappears or reverses spontaneously. This is made clear by the large standard error bars in the plots. Slotnick et al. (2001) reported RH lateralization on this stimulus had only marginal statistical significance ($p<0.1$) in their results as well. Therefore, while we will look to investigate this stimulus further, that it did not show LH dominance suffices for now.

The middle and bottom rows in Figure 3.5 show the results of the human data and the DE model for easy and hard subsets respectively. Our model replicates the results fairly well. But before further analyzing the results, we take a closer look into Slotnick et al.'s (2001) difficulty stratification, in order to understand which relationships across difficulty are crucial to replicate.

3.2.6 Revisiting Slotnick's Stratification

Slotnick et al. (2001) directly measured lateralization in a subject by having them perform the task after one hemisphere had been temporarily deactivated as part of a routine presurgical evaluation for treatment of intractable epilepsy. This meant the authors could only run their experiments once. When their data did not align with Kosslyn's hypothesis, they conducted a post-hoc analysis of the data to explain the results. The crucial conclusion of this analysis is that lateralization follows prevailing wisdom only if the task is difficult enough.

We find reasons to doubt Slotnick et al.'s conclusions. First, there are critical inconsistencies in their figures. If the easy and hard instances of a task both lateralize in the same

direction, then combining all trials together should as well. Yet, as shown in Figure 3.5, coordinate plus/minus overall does not lateralize, though its easy and difficult subsets did. In particular, for the left hemisphere injected results, both the easy and the hard results are greater than the overall result.

In addition, most of the stratifications between easy and hard were not built in a principled manner and therefore lack validity. Slotnick et al. (2001) state that the stratification of the paired squares task was simply an empirical heuristic, as there was no fundamental way of differentiating easy and hard stimuli. They instead chose "easy" to be the stimuli where the distances between the two pairs of squares are different. Likewise, they chose "hard" to be the stimuli that had the equal distances. As these were the two categories the subjects were differentiating between (i.e., "different" vs. "same"), this stratification is ill-conceived. Similarly, they note that no analogous concept of difficulty really exists for categorical stimuli, so they simply used the same division as their coordinate counterparts.

The coordinate blob/dot methodology is well-principled and the results are internally consistent. Yet the other tasks are not, and if we are to take difficulty stratification as the explanation for coordinate blob/dot results, we expect that effect to carry over to all stimuli. This was not convincingly shown. Consequently, we search for an alternate explanation for these results.

We suggest the original assumption from Kosslyn et al. (1992) is incorrect. If the general RH-dominance of coordinate stems from known spatial frequency patterns, then the anomalous coordinate blob/dot result is perplexing. Spatial frequency lateralization is well-established, and the coordinate and categorical judgments are certainly task-based. But if coordinate and categorical judgments are not beholden to specific spatial frequencies profiles, then it can simply be that something else drives lateralization in coordinate and categorical stimuli, and that factor is absent in coordinate blob/dot. Therefore, we look to empirically test the connection between spatial frequencies and categorical and coordinate

relations.

3.3 Bandpass Filtering the Slotnick Stimuli

Kosslyn et al. (1992) argued that lateralization in categorical and coordinate processing can be reduced to lateralization in spatial frequency processing, via neuronal receptive fields. However, scarce data directly supports the assertion that spatial frequencies drive performance on categorical and coordinate stimuli. With the DE model, we can test this assertion directly. We have shown that the DE model accounts for several spatial frequency properties. Therefore, if spatial frequencies truly drive performance, we expect for this fact to be reflected in the performance of the DE model.

For example, consider the claim that a categorical task contains more task-relevant information at high spatial frequencies than a coordinate task does. We run a stimulus (e.g. blob/dot) through a bandpass filter at lower spatial frequencies (e.g. [0 CPI, 8 CPI]). According to Kosslyn et al. (1992), the categorical version of this task ("Is the dot on or off of the blob?") lost more-task relevant information than the coordinate version ("Is the dot more than 3 pixels away from the blob?"). Therefore, we also expect performance of the perceptron on categorical to suffer more on this particular bandpass window. The opposite should be true at a window centered at a higher frequency: coordinate should suffer more if the bandpass filter is at higher spatial frequencies.

It is important to contrast this procedure to the work done in Cowin and Hellige (1994) and Okubo and Michimata (2002). In those works, the authors manipulated spatial frequencies to test how lateralization on coordinate and categorical processing is affected. In contrast, this procedure tests the interaction between spatial frequencies and network performance on coordinate/categorical stimuli in general. While the choice of hemisphere may change the absolute performance on a given task, we expect that the task-specific frequencies remain constant. Our goal, therefore, is to assess whether there are patterns of

network performance degradation across categorical and coordinate stimuli consistent with Kosslyn et al.'s (1992) hypothesis. Specifically, we look for a greater drop in performance on categorical stimuli with bandpass windows centered at lower frequencies, compared to the drop in performance on coordinate stimuli. We expect the opposite at higher frequencies.

3.3.1 Procedure

We test Kosslyn et al.'s (1992) hypothesis by bandpass filtering the Slotnick et al. (2001) stimuli and seeing how performance varies based on frequency window. We train the autoencoder on the full broadband van Hateren natural images as usual (van Hateren & van der Schaaf, 1998). However, we do not train the perceptron on the full broadband Slotnick et al. (2001) stimuli. Instead, we use a bandpass filter on the stimuli and feed the filtered stimuli into the autoencoder. The perceptron is the same as always: it learns to distinguish, for example, between the dot being on the blob or off of it. However, the autoencoder's reconstruction of the blob/dot image will be different due to the bandpass filter. After a particular configuration finishes running, we run slide the window over into a new frequency window and re-run the same process.

We chose a bandpass width of 4 CPI for 34x25 stimuli and 8 CPI for 68x50 stimuli and used bandpass step of 1 CPI and 2 CPI respectively. Therefore, the 34x25 experiments (paired squares, plus/minus) had windows of [0 CPI, 4 CPI], [1, 5], etc. all the way to [13, 17]. The 68x50 experiments (blob/dot) had windows [0, 8], [2, 10], etc. all the way to [26, 34]. For each experiment, we measured the average network performance for each bandpass window and plotted the results. Therefore, each experiment had a graph where an (x, y) pair corresponds to the center of the bandpass filter and the SSE of the model respectively.

Results were agnostic to a host of parameter choices, including bandpass width (within reason) and dropout. As mentioned earlier, we used a bandpass width of 4 CPI and 8 CPI for 34x25 and 68x50 images respectively. We let dropout = 0.7, as with the previous

experiments. As hypothesized, results were also agnostic to our choice of sigma. We chose $\sigma = 4$ for these experiments.

3.3.2 Results and Discussion

Our results in Figure 3.7 contradict Kosslyn et al.'s (1992) hypothesis. Each graph in Figure 3.7 corresponds to a specific stimulus and task. The x-axis corresponds to the center of the bandpass window – 2 CPI corresponds to a [0 CPI, 4 CPI] window for a 34x25 image, and 4 CPI corresponds to a [0 CPI, 8 CPI] window for a 68x50 image. The y-axis corresponds to the performance (in SSE) of the DE model at that particular bandpass window. The data points are linearly interpolated.

Coordinate paired squares is almost parabolic with a minimum around 10 CPI. Coordinate plus/minus is largely agnostic to frequencies, whereas categorical shows a bimodal preference, with the stronger one at higher spatial frequencies. Categorical blob/dot performed equally well at the windows centered from 10 to 18 CPIs, whereas coordinate performed best in the window centered at 10 CPIs and was locally parabolic around that area. Outside of these frequency ranges, critical image features are lost and both networks perform similarly poorly.

From Figure 3.7, it is clear that there is no unifying trend in these results. We expected to see that categorical stimuli, compared to coordinate stimuli, would see a greater drop in performance at bandpass windows centered around lower frequencies. Coordinate stimuli, compared to categorical stimuli, should see a greater drop in performance at higher frequencies. Neither of these is the case. In fact, it is not clear that there is any clear trend among the two categorical experiments or the three coordinate experiments. For example, both coordinate plus/minus and categorical blob/dot (in relevant ranges) show no little difference in performance in all frequency ranges where image features are retained. These results dispute the notion that categorical stimuli and coordinate stimuli are differentiated by their

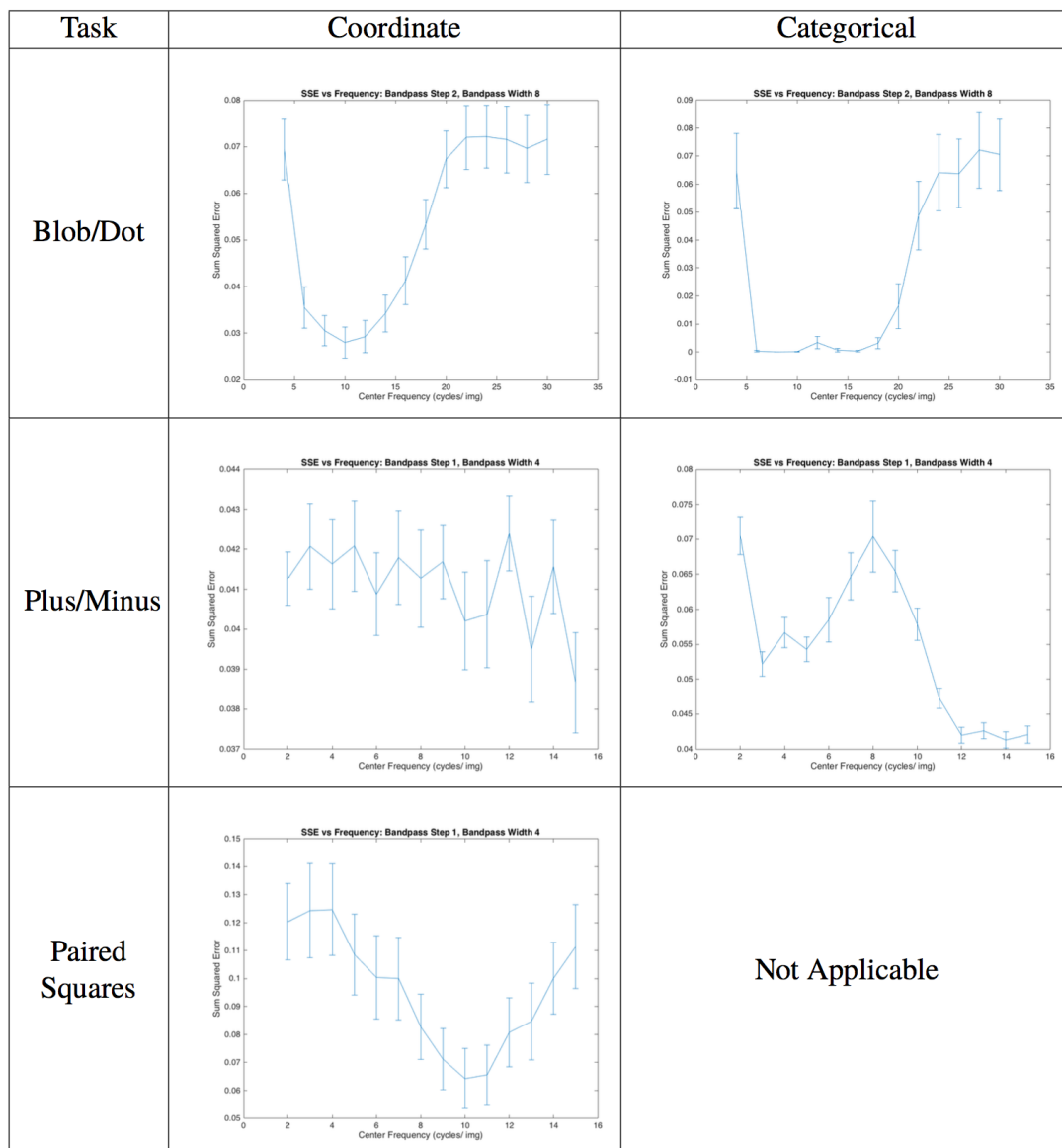


Figure 3.7: A comparison of the Differential Encoding network's frequency preferences, based on network accuracy on a task using bandpasses centered around a certain frequency. We would expect, if categorical and coordinate processing were based on spatial frequency profiles, for there to be a consistent pattern between increased performance on categorical in HSFs and increased performance on coordinate in LSFs. We do not see this pattern.

task-relevant frequencies.

An image consists of more than simply spatial frequencies. From these results, we cannot rule out that Kosslyn and his colleagues were correct about spatial frequencies

partly driving lateralization in coordinate and categorical processing. However, our results lead us to question spatial frequencies as the sole explanation for this dichotomy. If they were, then retaining the hypothesized task-relevant frequencies should lead to a smaller drop in performance in the DE model than retaining the frequencies that are not task-relevant. This is not the case.

As stated in Okubo and Michimata (2002), the LH categorical advantage is tenuous. As shown in Slotnick et al. (2001) and replicated in this work, the RH coordinate advantage does not always present either. We also have shown that the proposed mechanism driving lateralization in categorical and coordinate processes does not fit with the DE model. Consequently, we argue that a re-examination of categorical and coordinate processing is warranted.

Chapter 3, in part, has been submitted for publication of the material as it may appear in Proceedings of Cognitive Science Society, 2017, Prasad, Vishaal; Cipollini, Ben; Cottrell, Garrison W., London, UK, 2017. The thesis author was the primary investigator and author of this paper.

Chapter 4

Conclusion and Future Steps

We show in this paper that the DE model replicates human data on the categorical and coordinate dichotomy, and we call into question the analysis of Slotnick et al. (2001) in explaining their coordinate blob/dot results. Our results follow theirs, which suggests the anomalous result is not merely a methodological flaw as the authors presupposed. Their analysis that difficulty mediates lateralization on coordinate/categorical is flawed. As such, we suggest instead that the RH advantage on coordinate processing is simply absent on this stimulus. This simpler explanation dovetails with the observation that the LH advantage on categorical processing is tenuous (Okubo & Michimata, 2002). This calls for a reexamination into or reinterpretation of the dichotomy of coordinate and categorical processing.

We also show that, despite replicating experiments on spatial frequencies well, the DE model doesn't behave strictly in accordance with them on the stimuli from Slotnick et al. (2001). If indeed there exists a fundamental difference between coordinate and categorical spatial relations, our results also call into question Kosslyn's hypothesis about coordinate and categorical processing reducing to frequency processing. Spatial frequencies certainly play a large role in lateralized frequency processing, but they are not necessarily the only factor at play. If that is the case, then the DFF theory will not sufficiently account for

visual lateralization. In contrast, the DE model has the flexibility to account for frequency processing results while simultaneously not being beholden to them.

Okubo & Michmata (2002) provide some support to Kosslyn's hypothesis about frequency processing differences driving the categorical and coordinate split by contrast-balancing their stimuli. In light of the DE model's spatial frequency-agnostic results on the Slotnick et al. (2001) stimuli, we look to test the model on the same contrast-balanced stimuli and investigate if the model accounts for that data.

In addition, we have shown that DE models of a larger sigma encode more information at higher spatial frequencies, and vice-versa for smaller sigmas. Furthermore, this relationship is mediated by stimulus size; as image size increases, so too does the spatial frequency at which the LH networks (with a larger sigma) outperform the RH networks. This provides us with the neurologically plausible explanation that the relative frequency effect results from lateralization in different cortical areas. Accordingly, we plan to investigate whether or not image size can convincingly account for the relative frequency effects in our model.

If we can account for the relative frequency effect and contrast balancing, we have superseded the DFF theory with a model that is biologically grounded and is informative about experiments to run in the biology and psychology.

Chapter 4, in part, has been submitted for publication of the material as it may appear in Proceedings of Cognitive Science Society, 2017, Prasad, Vishaal; Cipollini, Ben; Cottrell, Garrison W., London, UK, 2017. The thesis author was the primary investigator and author of this paper.

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