General motivation

The purpose of the experiments reported in this thesis is to explore how our perception of the spatial structure of a pattern changes as it is shifted from our central visual field into the periphery. The experiments presented follow up on an interesting finding that appeared in a 1987 *Nature* article by Bennett and Banks (Bennett & Banks, 1987). What these authors found was that, unlike central vision, an observer's ability to discriminate between a particular set of patterns could be substantially reduced in the periphery by changing the local spatial configuration of the pattern (i.e., by changing the *relative spatial phase* information). Yet, despite a number of follow-up experiments (Bennett & Banks, 1991), it remained unclear how these changes in phase information were limiting the observer's performance. In terms of the signal-to-noise ratio associated with the observer, limitations can either be due to greater uncertainty about the signal (i.e., noise) or to a lower ability to make use the signal information. Since their experiments, several new techniques have been developed to disambiguate between these two types of limitations. The experiments in this thesis will employ three of these techniques. One technique will be used to measure the amount of internal noise associated with the observer. A second technique will determine if this noise level is affected by the contrast level of the stimulus, and a third will provide an estimate of how efficiently the observer samples information from the stimulus. Together, these techniques will provide a clearer picture of what additional limitations are imposed on the observer when the presentation of a pattern is shifted into the periphery.

The main focus of this thesis is to examine how the perception of a pattern changes as the pattern appears farther from the center of the visual field. Studies of visual perception typically consider the centermost region where visual acuity is the highest. As patterns are shifted beyond this foveal region, visual acuity decreases and patterns become more difficult to distinguish. Visual regions outside of the fovea such as the parafovea and periphery extend our visual field beyond the narrow scope of the fovea and provide cues as to where to direct attention. However, as the visual scope widens, our ability to locate and identify precise visual characteristics diminishes. A number of studies have been carried out to relate perceptual ability across the visual field. Results from these studies have typically been interpreted in two ways. According to one view, the performance of an observer detecting a signal in the fovea can be matched by scaling the stimulus presented in the periphery by a cortical magnification factor. Others have suggested that only low frequency information is preserved as the stimulus is shifted to the periphery resulting under-sampling of the higher frequency information (Thibos, Still & Bradley, 1996). Hence we might expect, based on either of these models, that patterns comprised of the same amplitude spectra would be equally discriminable in the periphery. However, Bennett and Banks (1987) found a considerable disparity in the discriminability of two patterns that differed only in their relative phase information. This result suggests that both the amplitude and phase spectra influence the relation between central and peripheral pattern discrimination. The experiments performed in this thesis were designed to determine what additional limitations were placed on the observer due to changing the relative phase information. Two potential limitations were considered to account for the decline in the observer's performance. One possibility was that observers had greater internal variability associated with their responses. A second possibility was that observers sampled from the signal less efficiently.

To provide some intuition about what is meant by relative phase information and why it is important in the study of pattern perception, some background on the Fourier transform might be instructive. The patterns used in these experiments were composed of a combination of sine and cosine waves. By definition sine and cosine waves are periodic patterns that continuously repeat themselves. The periodicity found in these grating patterns, which can be seen simply by looking at how the patterns vary across space, can be transformed onto a set of basis functions that represent the pattern in the frequency domain. In the frequency domain, a pattern is broken up into different amounts of sine and cosine waves arranged in such a way that they can be recombined to form the original pattern. This forward and reverse mapping of a pattern onto a set of sines and cosines is what the Fourier transform accomplishes. The amounts and the arrangement of the sines and cosines are more formally defined as the amplitude and phase spectra produced by the Fourier transform. The frequencies necessary to provide a complete representation of the original pattern are integer multiples or harmonics of the fundamental frequency. Bracewell (1989) uses the metaphor of a prism to describe the Fourier transform. That is, similar to the way a prism splits light into colors, the Fourier transform splits a pattern into its harmonics.

Changing the phase of one harmonic relative the other changes how the two waves line up with one another. Since the patterns used in this thesis contained just two harmonics, there was only one phase relation that changed the relative spatial position between them. Changes in this phase relation have been described in terms of two types of visual features—bars and edges (Field & Nachmias, 1984). When the two waves were aligned so that the peaks added together, the large peak resulted in a bar-like pattern; and when the two waves were shifted so that the peak of one wave aligned with a zero-crossing of the other, an edge-like pattern was formed. Together these bar and edge-like features form a basis for even more complicated visual patterns. In Figure 1.1 below, the effect of adding together multiple sine waves (the odd harmonics) aligned with one another can be seen. In this alignment, all of the harmonics have the same phase and the result is a square wave. In terms of visual features, this might be considered a “pure bar” stimulus because the edges make up such a small portion of the stimulus.

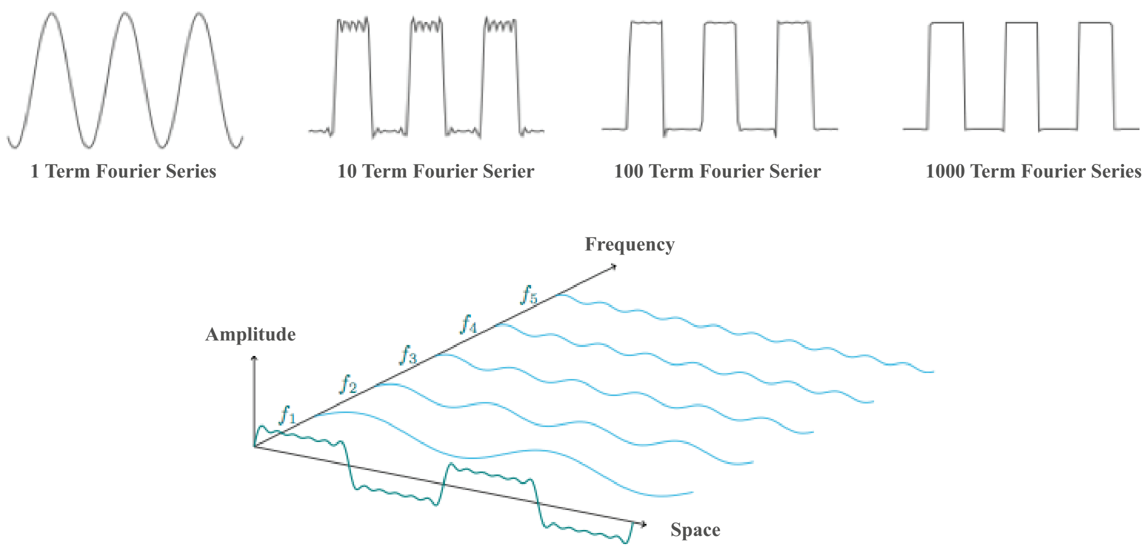

Figure 1.1: Fourier representation of a sine and square wave. The top row shows how increasing the number of Fourier components influences the shape of a square wave. In the 3-D plot below, a square wave with 5 components is broken out into its component frequencies. When all of the components are aligned (in phase), they add together to form the bars that make up a square wave.

The contribution relative contribution of different frequencies along the amplitude spectrum can provide some useful insight into the overall appearance of a pattern or image. The amplitude spectrum indicates how much of each wave is needed to represent the pattern, and the phase determines the placement of the waves relative to one another. For more complicated patterns, such as a natural image, low frequencies correspond to slow changes in the pixel intensities across the image and high frequencies to faster differences across the image. Natural images tend to contain a disproportionate amount of low frequencies. High frequencies within an image correspond to features like an edge or horizon. Systematically removing or redistributing portions of the amplitude spectrum typically does not to alter the overall percept of the image. On the other hand, the phase spectrum of an image is more difficult to disambiguate. The starting position of waves of nearby frequency often provides little to no intuition about the appearance of the image. However, altering the phase spectrum can completely change the appearance of an image as demonstrated by Oppenheim and Lim (1981). The effect of substituting the amplitude or phase spectrum of an image or pattern with the amplitude or phase spectrum from a white noise sample is shown in Figure 1.2 below.

This suggests that there is useful information about the structure on an image contained in the phase spectrum, particularly for images with similar amplitude spectra. Yet, despite its potential to provide useful characteristics about the structure of an image, the phase spectrum has received relatively little attention in the study of visual pattern perception. Some examples of more complex visual patterns are provided below in Figure 1.2 along with their corresponding amplitude and phase spectra.

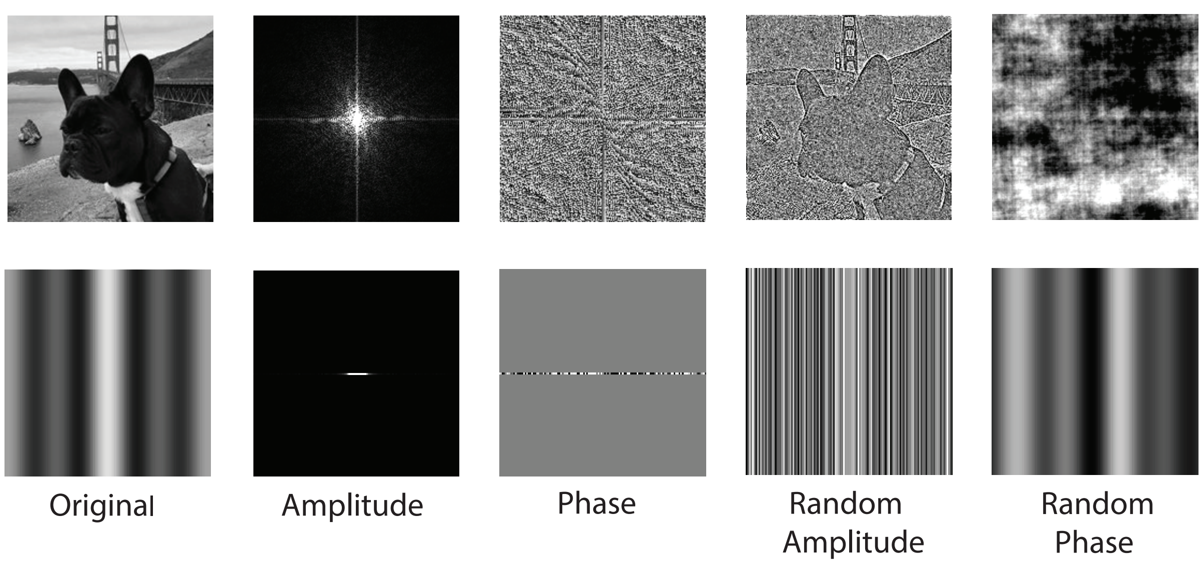

Figure 1.2: Fourier Transform. This figure provides two examples of the amplitude and phase spectra of a natural image (top row) and one of the stimuli used in these tasks (bottom row). In the amplitude spectra the frequency increases away from the center of the spectrum. The concentration of brightness around the center of the amplitude spectrum in the top row indicates a disproportionate amount of low frequency information. Along with some high frequency components that extend out from the center along the horizontal and vertical axis. When the amplitude spectrum is replaced with the amplitude spectrum of a sample of white noise (shown in the 'random amplitude' column), the amplitudes are distributed evenly along the spectrum and the edges outlining the dog become more apparent. When the phase spectrum of the original is replaced with the phase spectrum from a sample of white noise ('random phase' column), the scene from the top row is no longer discernable and the presence of low frequencies (gradual changes) becomes (more) apparent. In the bottom row, the example pattern varies in only one dimension. Hence, the Fourier transform can be represented along a single dimension. As expected, the amplitudes are restricted to 2 and 4 cycles/image with some smearing due to the Gaussian envelope. Phase covers the entire spectrum; however, there is no energy associated with higher frequencies. Replacing the amplitude spectrum (column 4) results in a pattern that is very similar to the actual stimulus with noise used in the experiments except that the amplitudes of the first and second harmonic are random. Swapping the phase spectrum (column 5) simply changes the phase relations of the harmonics that contribute energy in the original pattern. Hence, the pattern retains the edge and bar-like features.

Background: role of phase in detection and discrimination

The use of the Fourier transform in the study of pattern perception was established by a classic experiment in which the additional contrast necessary for an observer to distinguish a square wave from its fundamental corresponded to the amplitude of the third harmonic (Campbell & Robson, 1968). This result prompted a number of subsequent studies that explored the extent to which human observers mimicked the behavior of a Fourier analyzer (e.g., Pantle & Sekuler, 1968; Blakemore & Campbell, 1969; Graham & Nachmias, 1971). In other words, these experiments were testing a model in which multiple independent channels tuned to different frequencies could account for the performance of human observers. Evidence from more sophisticated experiments suggested that interaction among the channels was necessary to account for results across a wider range of frequencies—casting doubt on the simple Fourier analyzer model (Tolhurst, 1972; DeValois, 1977; Tolhurst & Barfield, 1978). Yet even as more advanced Fourier analyzers models, these models still relied entirely on the frequency information. This exclusion of phase information was supported by a number of empirical results. For example, detection of simple and compound grating patterns did not depend on phase. Using a discrimination-at-detection procedure in which observers were asked to detect a two-component grating pattern and to choose between two alternatives when the pattern was detected, observers were unable to determine whether a higher harmonic had been added in 0° or 180° phase (Graham & Nachmias, 1971; Nachmias & Weber, 1975). In a more recent study Huang et al. (2006) found that, for stimuli that varied along two-dimensions, observers were not able to discriminate between a pair of phase reversed Gabor or multi-component stimuli at detection threshold. Only under one extreme circumstance were these authors able to find a difference related to phase at detection threshold and that was when observers were asked to distinguish between a dark and light Gaussian blob.

While phase appears to play a minimal role in an observer's ability to discriminate between a pair of stimuli at detection threshold, observers have little difficulty discriminating between the two possible alternatives whose contrasts are sufficiently above threshold. For a two-component grating pattern, elevating the contrast of either component was sufficient for discrimination to occur (Nachmias and Weber, 1975). The ability of human observers to discriminate between grating patterns that differ only in terms of phase led others to investigate how much the phase angle needed to be shifted in order for the two patterns to appear as different. Burr (1980) found that the minimum phase angle required to discriminate a pair of two-component gratings (f+3f) combined in a square-wave ratio (3:1) was about 30° from 0° (sine phase) and as small as 20° at the highest contrast value. An even smaller angle was observed by Badcock (1984). In his experiments, a highly trained observer was able to distinguish between pairs of stimuli that differed by as little as 10°, although the other two observers required 20-30° in the same condition. Regardless of the minimum angle, these results suggest that small shifts in the phase of the grating pattern are imperceptible to human observers.

Background: phase and performance

Another potential reason why the phase spectrum has been largely ignored is that measures of performance such as contrast energy do not depend on the phase. That is, the amount of energy necessary to match the human observer's performance is the same regardless of the phase spectrum. This follows from Parseval's theorem, which shows that the spatial distribution of energy is determined by the amplitude spectrum only. According to the theorem, the squared length of the data vector v is equal to the normalized squared length of the Fourier coefficients f,

$$|v|^2 = \frac{D}{2}|f|^2.$$

While changes in phase do not alter the overall contrast energy, they do alter contrast within sub-regions of the stimulus—i.e., local contrast. Differences in local contrast can influence the mean, minimum, and maximum of the luminance profile. For two-component grating patterns there are two phase relations that can affect the luminance profile of a grating pattern. One is the base angle between the fundamental (f) and the origin. The shift in the higher harmonic $(2f, 3f)$ relative to the fundamental is typically referred to as the phase angle. In order to minimize the differences between the luminance profiles of the stimulus pair and to ensure that the phase differences are discriminable, a stimulus pair can be formed by adding 180° to the phase angle. Since a 180° shift in the phase angle corresponds to an inversion of the higher harmonic, these types of experiments are called phase reversal discriminations.

Background: phase reversal discrimination tasks

Field and Nachmias (1984) applied this technique by fixing the phase angles at 0° and 180° and varying the base phases from 0-180° to measure contrast sensitivity across a range of for two-component gratings $(f + 2f, f - 2f)$. Their results, obtained by varying the contrast of the second harmonic relative to a fundamental in cosine phase, showed an interesting pattern: thresholds increased as the phase angle between the first and second harmonic increased between 0° and 90°. When the thresholds were placed on a polar plot, where the angle was the phase angle between the first and second harmonic and the radius was the magnitude of the threshold, the changes in threshold followed straight lines resulting in a rectangular pattern.

This trend, which was reproduced by Bennett & Banks (1987) and pictured in Figure 1.5 below, is consistent with a model that was sensitive to two types of visual features---bars and edges. According to their model, features were defined relative to the center of the visual field. A bar appeared at the peaks and troughs of the contrast profile, and an edge occurred where the contrast profile crossed zero. Based on their stimuli, a pure bar occurred only at a base phase of 0° and a pure edge at a base phase of 90°. An observer's performance at any other base phase could be predicted by assuming that observer used only the portion of visual information provided by the more salient feature; i.e., the portion of contrast that falls into either the sine (edge) or cosine (bar) detector or “channel”, depending on which is more sensitive.

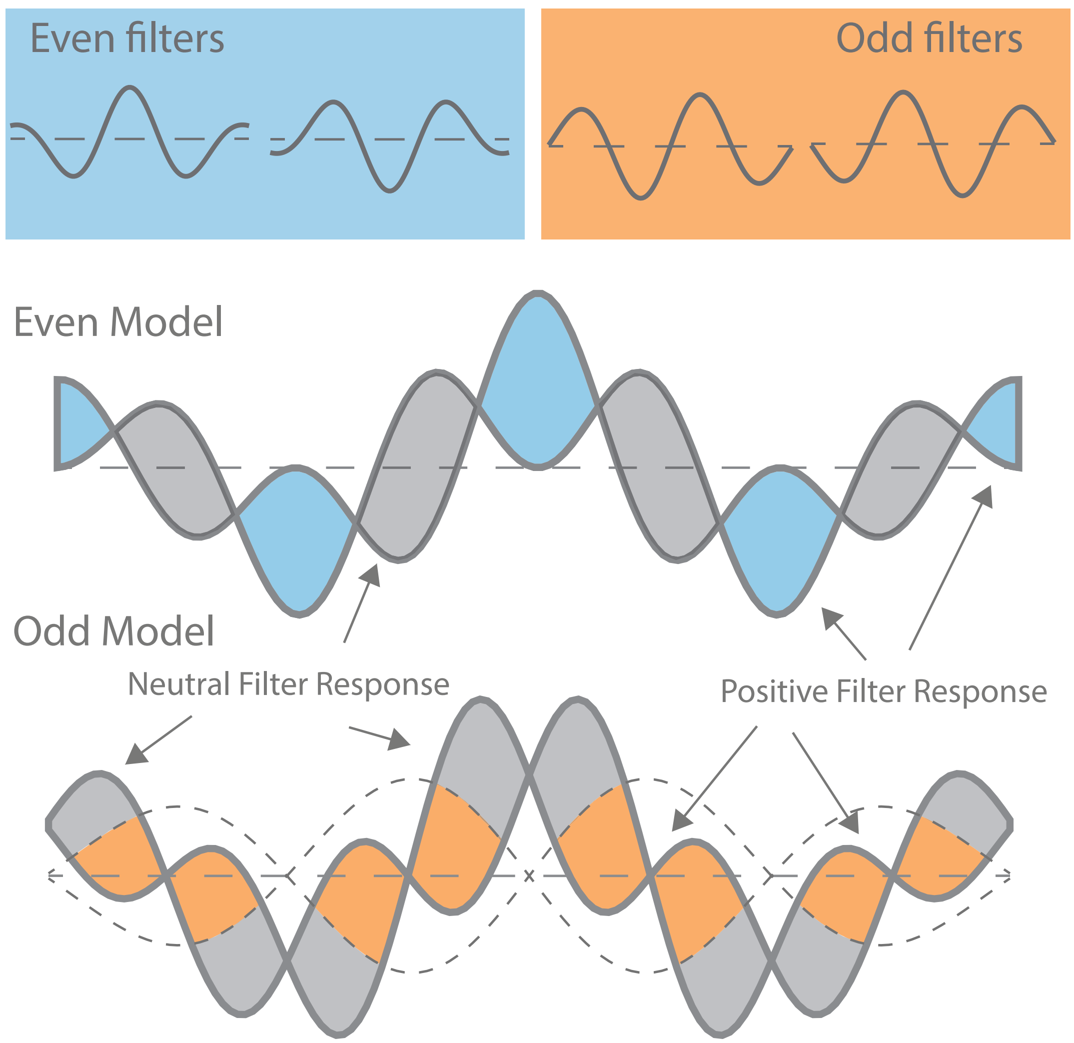

Figure 1.5: Two-channel model. According to the two-channel model proposed by Field and Nachmias (1984) there is a set of filters tuned to respond to bars and edges. The bar or even filters are sensitive to regions of the pattern that remain above or below background contrast. The dark gray lines represent the contrast profiles of the stimuli used in these tasks. The blue highlighted regions correspond to the even features or bars that the filters detect in the cosine condition. In this condition, the most discriminative regions of the patterns correspond to the peaks and troughs of the contrast profiles. The amount of information in these regions falls off evenly in either direction. Since the luminance profiles in the cosine condition are mirror symmetric, the task could not be performed using the response of the odd filters. In the sine condition, the two alternatives cannot be discriminated using the contrasts at the peaks and troughs of the waveform. Instead, odd filters are sensitive to changes in the contrast of the pattern. A sharp change in contrast indicates the presence of an edge. Odd filters respond to differences in the slopes of the contrast profiles. The responses of the odd filter are highlighted in orange. In contrast to the even filters, these regions are centered on the zero-crossings of the waveform and grow evenly away from the center. Also note that, while the areas of the orange regions that represent the model response are consistent with the model described in Bennett and Banks (1987), the shape of these regions represents a best guess given their description of the model. The use of the Gaussian filter also introduces

some anomaly in that the troughs of the contrasts profile can also be used by both filters to detect a difference.

These results suggested that human sensitivity across base phase angles tended to improve as discriminative information fell disproportionately into one channel or the other, with some observers showing a small improvement in cosine phase over sine phase.

Background: peripheral vision

Some clarification is necessary on the terms used to specify where in the visual field the stimuli in these experiments appear. As noted by Swanson & Fish (1995) there is a set boundaries, defined in degrees of visual angle, to establish separations between regions of the visual field. According to these authors, the fovea spans the innermost 5-degree diameter, the parafovea extends to 8 degrees and perifovea end at 18 degrees—presumably where the periphery begins. These regions are indicated on the figure below. The shape of the regions in figure below matches the textbook description provided by Purves et al. (2001). The asymmetry at the bottom of the in the binocular regions reflects some obstruction from the nose. Due to physiological constraints of the eye, the width of the visual field is also greater than the height. Another technical term that is used throughout this thesis is eccentricity. Eccentricity is the degree of horizontal shift away from the center of the visual field.

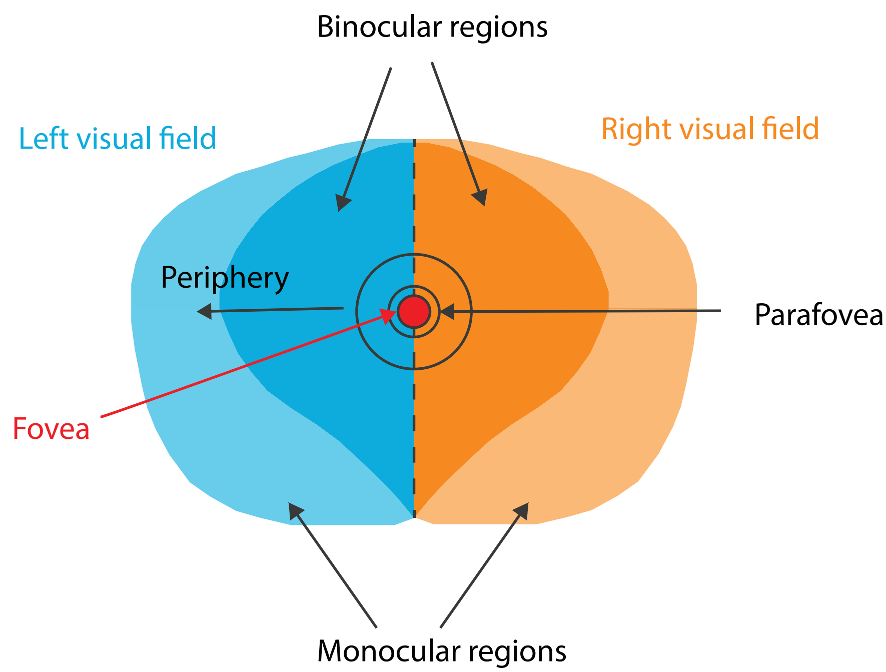

Figure 1.6: Visual field. Modeled after a textbook figure that appears in Purves et al. (2001), this figure shows the visual field that results from the overlap between the visual fields of the left and right eyes. An estimate of the boundaries that separate the Fovea, Parafovea, and Periphery are indicated.

Some instances occur in this thesis where the term periphery is used to refer to regions of the visual field that fall within the parafovea or even the fovea. This is partly due to the emphasis of the Bennett & Banks (1987) result on the distinction between central and peripheral vision. In these experiments there are no presentations that occur in the periphery. Hence, periphery is being used more loosely to refer to the marked loss in sensitivity that is associated with the periphery. Another quality that distinguishes central and peripheral vision is the amount of spatial uncertainty. As the absorption of light shifts from a high density of cones in the fovea to rods, which grow increasingly sparse as eccentricity increases, sensitivity to high frequencies diminishes. This is reflected in Nyquist frequency, which is a measure of the highest frequency that can accurately be represented, decreasing from roughly 50-60 cycles/degree in the fovea down to about 3-4 cycles/degree in the periphery (Thibos, 1991). Frequencies above the Nyquist limit are assumed to be aliased, which results in a blurred or undersampled perception (Thibos, 1996).

Background: phase and the periphery

The role of phase information has also been investigated under peripheral viewing conditions. Harvey, Rentschler, and Weiss (1985) found that while contrast thresholds were roughly double for detecting a checker board pattern presented at 2° eccentricity relative to thresholds obtained for presentations in the fovea. Also at 2° eccentricity, the minimum phase angle necessary to discriminate a pair of patterns increased by about 3.8 times—from 35° to 140° on average. Discriminations of two-component grating patterns $(f + 3f)$ also followed a similar trend when presented 2° in the right periphery (Rentschler & Treutwein, 1985). These authors found that peripheral deficiencies with patterns differing in the maximum and minimum contrast could be accounted for by a scaling the signal by a cortical magnification factor across eccentricities; however, differences with mirror (odd) symmetric patterns were not consistent with a scaling account.

Bennett and Banks (1987) investigated phase reversal discriminability of two-component grating patterns $(f + 2f, f - 2f)$ in the fovea and at 5°, 10°, 20°, and 40° eccentricity using a procedure similar to Field and Nachmias (1984). The two-channel model used by Field and Nachmias to account for their results was also consistent with the findings of Bennett and Banks, provided that the feature detectors were able to locate the places in the waveform where the features occurred. As pattern presentation was shifted further into the periphery, the two points necessary to compute the model prediction, the contrasts necessary for pure edge and pure bar discriminations, grew disproportionally to one another. For presentations shifted 10° into the periphery the contrast necessary to discriminate an odd-symmetric pair was about 2.5 times greater than for an even-symmetric pair, and by 20° odd pairs required nearly 9 times more contrast than even pairs.

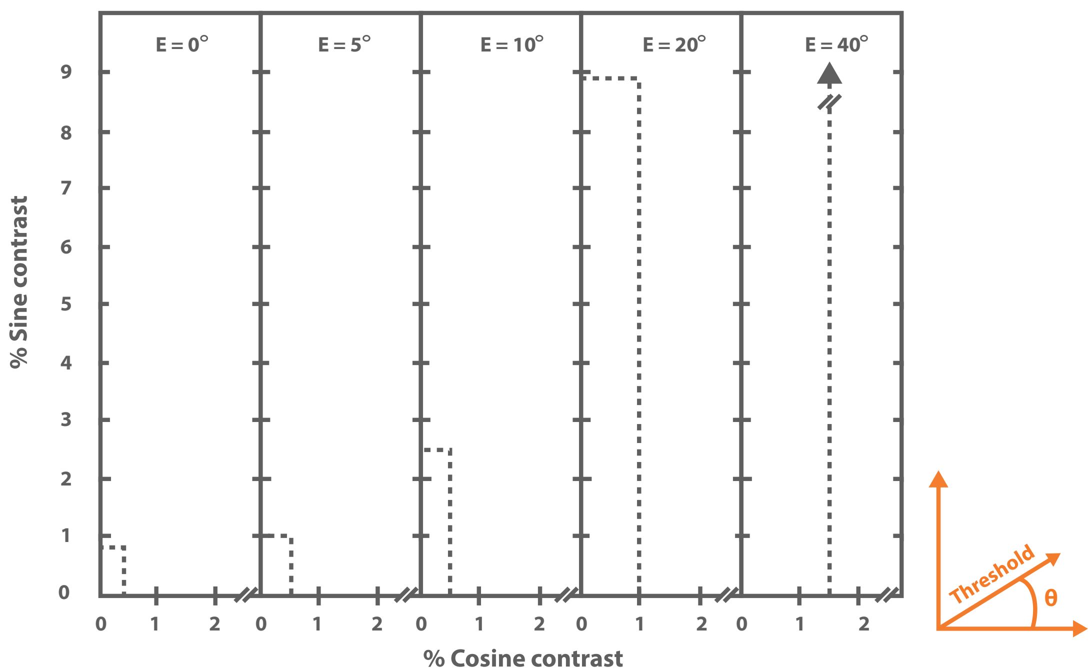

Figure 1.7: Reproduced results from Bennett & Banks (1987). Following the orange diagram on the right, thresholds were plotted in polar coordinates according the magnitude and phase angle (θ) between the first and second harmonics. Moving from left to right eccentricity increased from 0-40°. Data from their experiments tended to fall along the dotted lines, which represents the predictions of a model that uses the proportion of information available to the more sensitive channel. Straight lines indicate that this proportion remained constant regardless of the phase angle. The scale of the plots helps to visually reduce the effect of noise at smaller eccentricities.

Bennett and Banks (1991) discuss some possibilities to account for this disparity between peripheral discrimination of odd and even symmetric patterns. One possibility is that stimuli presented peripherally and centrally differ by a cortical magnification factor (Hubel & Wiesel, 1974; Virsu & Rovamo, 1979) and that sine and cosine features are scaled according to different factors. The increase in the odd-even ratio, however, was greater than this linear prediction, suggesting that the change in performance across the two channels as stimulus presentations were shifted into the periphery could not be related by a common factor. Another possibility to account for a non-linear even-odd ratio was a compression of the waveform introduced during the early stages of visual processing. Since an odd-symmetric waveform is mirror symmetric, this compression would not affect the relative contrast of the sine only pair and would lead to a monotonic change in the odd-even ratio as the fundamental contrast increased. However, adjusting the fundamental contrast did not appear to systematically change the odd-even ratio. Despite these possibilities, Bennett and Banks (1991) were not able to provide an adequate account of the increasing change in the odd-even ratio.

Since their efforts several new techniques have been developed to parse out what may have led to the decline in performance with sine information. These techniques, which are based on signal detection theory, involve introducing noise to the stimulus to determine the source of the observer's inefficiency. In signal detection theory (Green & Swets, 1966) human observers are assumed to respond probabilistically to a given stimulus. Accordingly, human observer responses can be represented as a combination of signal extracted from the stimulus and internal noise introduced by the observer. The ratio of these two variables is defined as the observer's sensitivity or d'. Changes in sensitivity can arise from differences in the signal or noise portion of this ratio (Pelli & Farell, 1999).

Hence, the goal of these experiments[1] is to investigate whether the deficiency with sine information is due to an increase in the amount of internal noise associated with the observer or a decrease in the observer's ability to extract information from the stimulus.

Measuring human performance in terms of the signal energy plus internal noise has several advantages over other measures such as percent correct. For one, it leads to an unbiased estimate of the observer's performance. That is, measuring performance in terms of the signal to noise ratio required by the ideal observer to match the performance of the human observer does not depend on whether the observer is more likely to choose one response over the other (Birdsall & Tanner, 1958; Green & Swets, 1966). This measure, d', is depicted in the figure below. In a typical signal detection task, such as the one below, the observer is asked to detect the presence or absence of a signal added to noise. The observer's response to noise alone is assumed to produce a distribution of responses centered on μ_n. Adding a signal to the noise produces a shifted distribution of responses centered on μ_s. For simplicity, the distributions are assumed to have the same standard deviation (σ) or width at half height. d' is a measure of how far the signal shifts the distribution in units of σ. Whether the observer answers "yes" or "no" to having detected the signal depends on whether the observer's response exceeded the threshold, shown in green. In theory, shifting the threshold does not affect the value of d'.

[1] The purpose of the following sections is to provide an overview of the methods used in this thesis. The next chapter is dedicated to providing a more detailed account of these techniques (noise masking, response consistency, and response classification) and includes formal definitions of a number of the concepts.

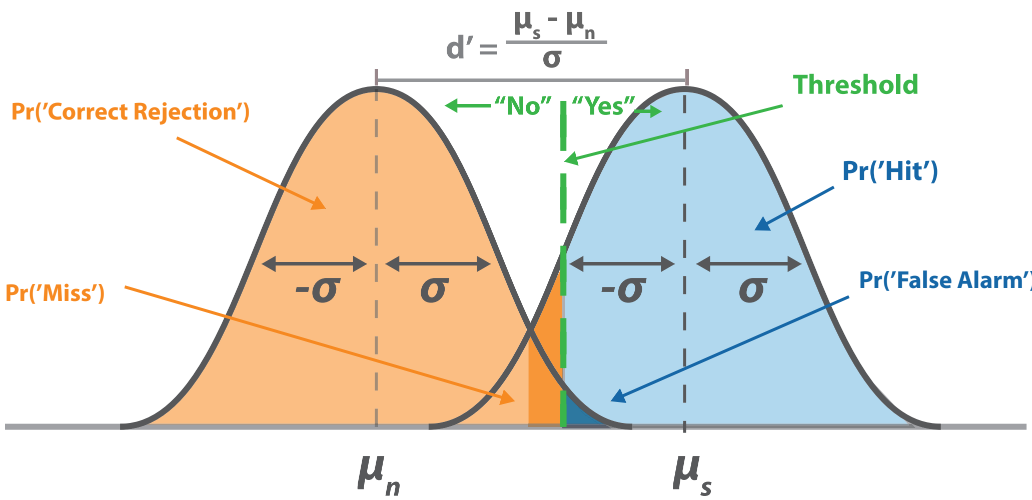

Figure 1.2: Signal detection task. The four possible outcomes that result from a yes-no detection task are depicted. A Hit occurs when the signal is correctly detected; likewise, a correct response to the absence of the signal is a Correct Rejection. When the signal is present but not detected, a Miss (or type II error) occurs, and when the observer responds signal when only noise was present a False Alarm (or type I error) occurs. d' can also be calculated as $d' = Pr(\text{'}Hit\text{'}) - Pr(\text{'}FA\text{'})$, i.e., as the difference between the light and dark blue regions.

Another advantage of using d' is that, taking the ratio of human to ideal performance provides a measure of how efficiently human observers make use of stimulus information. This efficiency measure provides a control for the intrinsic task difficulty, and can therefore be used to compare the performance of human observers across tasks that differ in the amount of information contained by the stimulus. Without this control, the possibility that any perceptual differences are simply due to differences in stimulus information cannot be ruled out as a potential confound.

In order to specify how this ratio changes for changes for sine and cosine information, some assumptions about the observer are necessary. According to Pelli (1981, 1990), observers are limited by an irreducible source of internal variability that is contrast-invariant and adds to the observer's internal representation of the stimulus. A decision is reached by performing a contrast-invariant calculation on the observer's representation of stimulus plus internal noise.

This calculation determines how efficiently the observer samples information from the stimulus. In this early noise black-box model, changes in the observer's sensitivity are determined by differences in sampling efficiency and/or contrast-invariant internal noise.

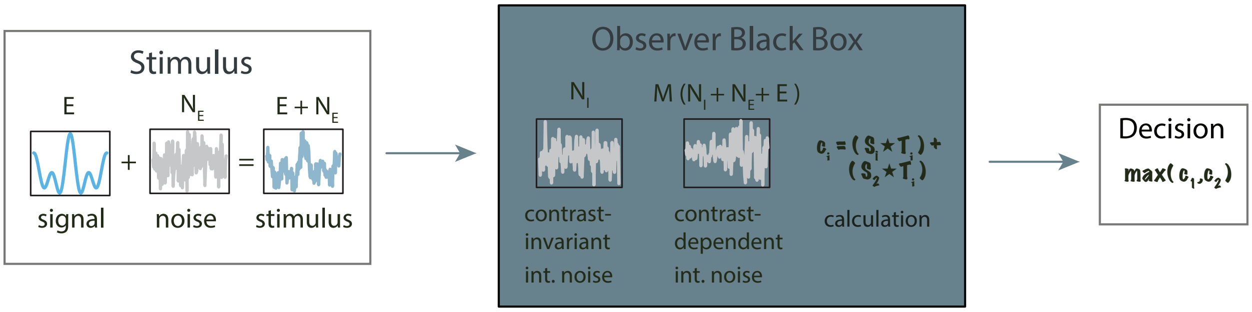

Figure 1.8: Black box model. According to the black box model, the stimulus is transformed into a response by a contrast-invariant calculation. Noise is introduced prior to the calculation. A more detailed description of the calculation is provided in the methods section.

To estimate of the to how the contrast-invariant portions of this ratio change, the stimulus is embedded in a sample of external noise. An estimate of the observer's internal noise can be made by varying the noise spectral density (NSD) of this external noise sample to reveal at point at which the internal and external noise levels are equivalent (Pelli, 1990). Since the two noise sources are assumed to be independent, changes in the observer's ability to perform the task will be gradual in regions where there is a large disparity between internal and external noise and more pronounced as the two levels reach parity. That is, at low levels of external noise contrast the observer's internal noise limits performance, and as the noise level increases, the contribution of each noise quantity to the total amount of noise evens out until eventually the external noise outweighs the internal noise. A plot of the observer's contrast energy threshold against noise spectral density, or a *noise-masking function*, reveals a point at which the internal and external noise levels are assumed to be equivalent. This equivalent noise is also the level of external noise necessary to double the observer's threshold. The shape of the noise masking function is also diagnostic of whether changes in performance are due to the contrast-invariant signal or noise portion of the observer's sensitivity. A shift in the equivalence point indicates a change in internal noise. Whereas for a change in the sampling efficiency, the equivalence point remains fixed and the intercept of the function is shifted. A second possibility also exists to account for the change in the sampling efficiency.

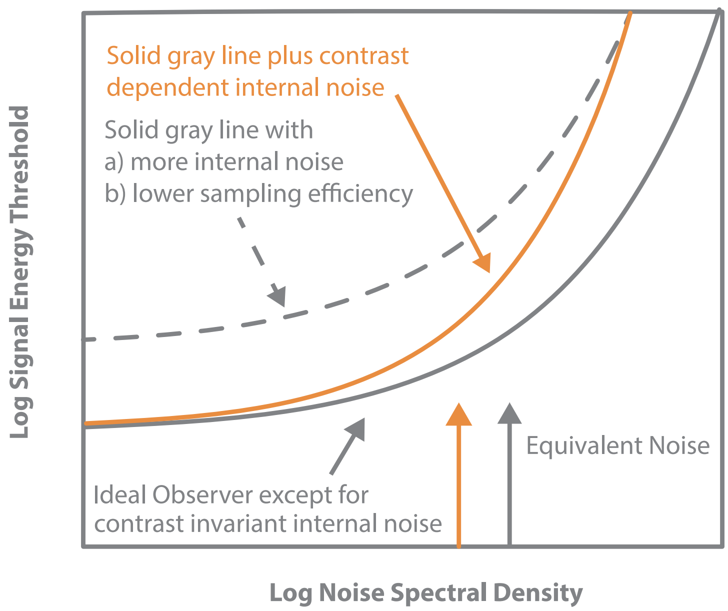

Figure 1.9: Noise masking function. Plotting the noise spectral density against the threshold energy in log-log coordinates reveals the observer's equivalent noise. Relative to the ideal observer, the noise masking function of an observer that is limited by an additional source of contrast invariant noise will be shifted downward. A change in the shape of the noise masking function suggests that the level of internal noise depends on the external noise level. The orange line above shows an observer whose

Burgess and Colborne (1988) found evidence that the internal noise level grows in proportion to the external noise level. This suggests that internal noise has a fixed contrast-invariant component (as in the Pelli model) and a second component that is proportional to the external noise level.   Assuming the second component is non-negligible, adding these two components produces a change in the slope of the noise masking function.   An estimate of the contrast dependent component of internal noise can be obtained by using a response consistency procedure (Burgess and Colborne, 1988; Green and Swets, 1966). This technique works by repeating the same sequence of noise through a second pass of trials. The responses of an observer without internal noise would be the same for both presentations of identical noise. However, since human observers are also limited by internal noise, their responses to the same stimulus will be different on some portion of the trials. These response inconsistencies along with the proportion of correct responses can be used to provide an estimate of the observer's internal to external noise ratio. At high levels of internal noise, the contrast-invariant component of internal noise will be small relative to the contrast-dependent component. Therefore, measurements of response consistency can be used to determine the contribution of contrast dependent noise to the total internal noise limiting human observers.

Once an estimate of the internal noise has been provided, any changes in sensitivity that are not due to a combination of contrast-invariant and contrast-dependent internal noise are due to a change in the sampling efficiency. While increased noise suggests that performance is degraded evenly (on average) across all parts of the image, differences in sampling efficiency suggest systematic changes in observer's use of stimulus information and may be associated with a change in strategy. For example, the observer may shift their attention to less informative regions of the stimulus or even introduce new features into uninformative regions of the stimulus (Gold, Sekuler, & Bennett, 2004). These changes in sampling efficiency can be mapped directly onto the stimulus by using a reverse correlation technique to provide an estimate of the observer's underlying template. Reverse correlation works by averaging the noise fields for each of the possible responses and combining them to form a map of the individual pixel weights (Ahumada, 2002). This estimate of the observer's underlying template can then be used to identify regions of the stimulus that are more highly correlated with a particular response. The spatial distribution of weights can also be thought of as a behavioral estimate of the observer's receptive field used to perform the task. This technique can also be applied in the frequency domain to provide an estimate of the amplitude and phase spectrum associated with an observer's underlying template (See Murray, 2011 for a complete review). Levi and Klein (2002) used this technique to compare detection and discrimination of sine wave patterns in the fovea and parafovea. Their results showed that observers tended to over weight high frequency components in the fovea and low frequency components in the periphery. These weightings suggest differences in the receptive field shape between the fovea and periphery.

Overall this research aims to provide a more complete account of the factors affecting discrimination of a pair of spatially modulated sinusoidal grating patterns and the deficit that arises for peripherally viewed odd-symmetric patterns. While detection of these types of patterns is typically assumed to be limited only by contrast, phase has also been shown to be an important predictor of the discriminability between two equal contrast gratings. For some grating pairs, the role of phase becomes more pronounced as gratings are shifted into the periphery where spatial sensitivity is reduced. By using a combination of techniques that rely on the use of external noise, an estimate of the observer's underlying template and internal noise can be provided. These two characteristics of the observer can be used to test the predictions of the two-channel model and to determine how the shape of the observer's receptive field changes with eccentricity. Changes in the receptive field shape also imply differences in the peripheral contrast sensitivity function. These differences between foveal and peripheral vision suggest that the basic mechanisms that encode contrast and position in the periphery may be qualitatively different from those in the fovea.

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