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Discrimination of spatial phase: The roles of luminance distribution and attention

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ABSTRACT

We can easily discriminate certain phase relations in spatial patterns but not others. Phase perception has been found different in the fovea vs. periphery, and for single patterns vs. textures. Different numbers of mechanisms have been proposed to account for the regularities of phase perception.

In this study, I attempt to better understand the mechanisms behind discrimination of spatial phase. In order to reveal the role of luminance cues, I use histogram matching of patterns with different phases. Possible effects of attention were studied using visual search experiments with varied stimulus set size. Simple and compound Gabor patches, broadband lines and edges, and textures composed of those patterns were used as stimuli.

The experiments indicate that phase discrimination is mediated by two mechanisms. The first uses luminance differences and operates pre-attentively, in parallel across the visual field. The second compares relative positions of dark and bright segments within an image, and is strictly limited by capacity of attention.

1. Introduction

According to Fourier theory, every visual image can be represented as a sum of sinusoidal waveforms with different orientations and spatial frequencies (e.g., Campbell & Robson, 1968; Piotrowski & Campbell, 1982). Each waveform has its amplitude (contrast) and phase (position). Supposedly, our visual system uses some elements of Fourier transform when analyzing input images. For example, neurons in V1 are frequently modeled as Gabor filters sensitive to local sinusoidal luminance pattern with a particular spatial frequency, orientation, and phase (e.g., Jones & Palmer, 1987).

After the Fourier theory was introduced to vision research, and periodic patterns became usual stimuli, researchers started to measure human sensitivity to spatial phase (e.g., Nachmias & Weber, 1975).

Phase sensitivity of human observers does not look very impressive. We can perceive relative phase difference between first and third harmonic of about 30 degrees (Burr, 1980), and absolute phase difference of Gabor patterns of about 50 degrees (Huang, Kingdom, & Hess, 2006) only.

Field and Nachmias (1984) found that discrimination of phase between fundamental and second harmonic could be explained by four channels, sensitive to following phase relations: +cosine (bright line), −cosine (dark line), +sine (left edge), and −sine (right edge). These authors also reported that cosine channels must be more sensitive than sine channels.

Rentschler and Treutwein (1985) discovered a heavy drop in phase discrimination when a grating stimulus was presented in the visual periphery and the task required telling apart the patterns that were mirror images of each other. This may indicate that sine channels are either absent or have very low sensitivity in the periphery (Bennett & Banks, 1987). Rentschler et al. (1988) showed that similar loss of phase sensitivity occurs even in the fovea when an observer has to segregate textures composed of compound Gabors and their mirror images. Malik and Perona (1990) also demonstrated a similar effect and included only ± cosine mechanisms in their texture model.

Burr, Morrone, and Spinelli (1989) introduced broad-band stimuli composed of 256 harmonics that could have different phases. Their experiments confirmed the existence of four phase sensitive mechanisms (detectors of bars and edges of different polarity). Interestingly, Morrone, Burr, and Spinelli (1989) found that, with their stimuli, there was no any special loss of phase sensitivity in the periphery and the results were qualitatively similar in the fovea and periphery.

Portilla & Simoncelli (2000) texture model uses two types of phase statistics based on relative phases of sub-bands of adjacent scales. Qualitatively, these statistics measure dominant polarity of “lines” (bright vs dark), and direction of edges (left bright, right dark, or vice versa).

Two recent studies (Huang et al., 2006; Hansen & Hess, 2006) were able to reveal only two phase mechanisms, ± cosine, in human vision. They proposed that usual perception of phase relations is based on

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encoding of relative positions and contrasts of local bright and dark parts within the image.

There has been a longstanding controversy about the nature of mechanisms behind phase discrimination. Are there explicit units in the visual system that are sensitive to waveforms with particular absolute or relative phase angles (Lawden, 1983; Field & Nachmias, 1984; Portilla & Simoncelli, 2000), or are the results better consistent with a set of simple feature detectors sensitive to local luminance maxima, minima, gradients etc. (Badcock, 1984a,b; Hess & Pointer, 1987)? In part, the problem may be ill-posed, because both spatial and spatial-frequency views should describe the same reality, and the visual system can use both types of features. Still, it is important to reveal the exact cues that allow us to see phase relationships in images.

In some studies, random variation of contrast has been used to eliminate luminance cues (e.g. Bennett & Banks, 1991). Although this method makes absolute luminance uninformative, relative luminance of different parts or features still may carry the same information. Here I propose using histogram-matching to control luminance cues. Histogram matching is a traditional method of digital image processing that has been used to enhance or normalize images of natural objects or scenes (e.g. Gonzalez & Woods, 2008). However, it appears to be also a good tool for creating stimulus patterns with interesting psychophysical properties. The method equalizes the luminance distributions of two images while leaving positions of local features unchanged.

Studies of phase discrimination have rarely manipulated attention. Sometimes, foveal presentation has been equated with attentional perception (Klein & Tyler, 1986), or brief presentation of textures — with pre-attentive processing (Malik & Perona, 1990). In theory, phase can be loosely related with relative position, and perception of relative position of visual features is definitely dependent on attention (Cheal, Lyon, & Hubbard, 1991; Põder, 1999). This is a good reason to look at the role of attention in phase discrimination more closely.

In this study, I attempt to clarify the mechanisms behind the discrimination of spatial phase, specifically the roles of local luminance cues, and attention. I use histogram matching in order to reveal the role of luminance cues, and I vary number of objects (or texture patches) in visual search task to study the role of attention. I use both Gabor patches and broadband stimuli (bars, edges), as separate objects, and as components of textures.

2. Methods

2.1. Stimuli

Stimuli were displayed on CRT monitor with 1024×768 resolution. The luminance function of the monitor was measured by Hagner EC1 photometer and approximated by a power function. The inverse of this function was used for the gamma correction. Background luminance was approximately 50 cd/m^2, and stimuli had Weber contrast 1.0.

Gabor patterns were vertically oriented, fundamental wavelength was 15 pixels (about 0.5 deg.), and standard deviation of Gaussian window 7.5 pixels. The Gabors were either in sine or cosine phases. Compound Gabors were composed of the fundamental and second harmonic, both in the same (either sine or cosine) phase. Amplitude of the second harmonic was ⅓ of the fundamental. The broadband stimuli were edges and lines composed of 256 harmonics (Burr et al., 1989).

Histogram-matched patterns were produced using Matlab functions *hist* and *histeq* (Image Processing Toolbox). At first, luminance histograms for both (e.g., sine and cosine) patterns were calculated (function *hist*). These were summed to calculate the total/average histogram. Finally, the pixel values of the original patterns were adjusted to fit the average histogram (function *histeq*). All elementary patterns used in this study are presented in Table 1.

In Experiment 1, texture patches were used as stimuli. These consisted of 12–15 identical Gabor elements placed in random positions within a circular aperture with the radius of 80 pixels. Minimum inter-element distance was imposed to avoid any considerable overlap of Gabors. A texture patch had a pixel-wide black border. Some elements along the border could be only partially visible. In Experiments 2–4, single objects (Gabors, compound Gabors, lines, edges) rather than texture patches were used as stimuli.

Search display consisted of 1–5 items placed around the fixation point. Eccentricity was 160 pixels for texture patches (approximately 6 deg., measured from the center of a texture patch), and 80 pixels (3 deg.) for single objects. The items were distributed evenly along an imaginary ring centered at fixation; the first angular position was selected randomly. Examples of stimulus displays are given in Fig. 1.

2.2. Procedure

Two types of visual search experiment were used. In oddity search (Experiments 1, and 2a), from 2 to 5 items (texture patches, or single objects) were exposed for a short duration (180 ms). The items could be either all with the same phase, or there was one with alternative phase (with probability 0.5). Observer's task was to determine whether there was an odd (different phase) item present or not. The pair of patterns and number of displayed items was fixed within a block of trials. Both patterns from a pair had equal chances of playing the role of the target (odd item, if present) or distractors (all other items).

In fixed target search (Experiments 2b, 3, and 4), observers searched for a fixed object, shown before a block of trials. Target was present with probability 0.5. In target-absent trials, homogeneous set of distractors was displayed. Set size was varied from 1 to 4 but fixed within a block of trials. Exposure duration was 60 ms in Experiments 2b and 3, and 12 ms in Experiment 4.

2.3. Observers

Twenty observers (7 male, 13 female), including the author, took part in this study. Four to seven observers participated in each experiment. The work was carried out in accordance with the Code of Ethics of the World Medical Association, and informed consent was obtained for experimentation with human subjects.

2.4. Analysis of set-size effects

I follow a usual assumption (Neisser, 1967; Treisman & Gelade, 1980) that pre-attentive processing is equally efficient regardless of the number of relevant items while attentional processing has certain capacity limitations, and its efficiency drops with increasing number of items (set size). It is important that, even without any capacity limitation, proportion correct should decrease with increasing set size, because of integration of information from multiple items (if we assume that internal representations are noisy; Shaw, 1980; Palmer, Ames, & Lindsey, 1993).

I used a simple model of search (McLean, 1999; Mazyar, Van den Berg, & Ma, 2012; Põder, 2017) to tell apart small set-size effects attributable to ideal information integration, and large ones consistent with limited capacity attentional processing. I assume that discriminability of a single item depends on the number of items in a display (set-size) according to a power function

$$d'_{1n} = \frac{d'_1}{n^{\frac{b}{2}}}$$

where d'_1 is discriminability for set-size one, n is set-size, b is a measure of set-size effect: $b = 0$ for unlimited capacity (independent processing of items), and $b = 1$ for fixed capacity (sample size) model. For some limited capacity (e.g., serial) models, b can be larger than 1.

I used simulated ideal decision model (assuming Gaussian noise) to find search performance (d-prime) as a function of local SNR (d'_{1n}) and