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Estimates of edge detection filters in human vision

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ABSTRACT

Edge detection is widely believed to be an important early stage in human visual processing. However, there have been relatively few attempts to map human edge detection filters. In this study, observers had to locate a randomly placed step edge in brown noise (the integral of white noise) with a $1/f^2$ power spectrum. Their responses were modelled by assuming the probability the observer chose an edge location depended on the response of their own edge detection filter to that location. The observer's edge detection filter was then estimated by maximum likelihood methods. The filters obtained were odd-symmetric and similar to a derivative of Gaussian, with a peak-to-trough width of 0.1–0.15 degrees. These filters are compared with previous estimates of edge detectors in humans, and with neurophysiological receptive fields and theoretical edge detectors.

1. Introduction

Edges are an important feature of the retinal image because they indicate the position of object boundaries and shadows. For that reason, edge detection has long been considered a vital first step in visual processing. Neurons sensitive to edges are common in the visual cortex (Hubel & Wiesel, 1962, 1968) and their receptive fields have been mapped in detail. However, less has been done to map the "receptive fields" or templates that underlie the detection of edges in humans. Previous psychophysical investigations of edge detectors have used indirect methods, such as subthreshold summation (Kulikowski & King-Smith, 1973; Shapley & Tolhurst, 1973); or have concentrated on demonstrating the existence of odd-symmetric detectors without characterizing their spatial properties (Burr, Morrone, & Spinelli, 1989; Stromeyer & Klein, 1974). Here I use a method based on classification images (Murray, 2011) to map the templates used in edge detection and localization.

Classification images were introduced by Beard and Ahumada (1998). The idea is that when noise is added to a stimulus, that noise sometimes takes on the aspect of what the observer is looking for when they perform a psychophysical task. By correlating observer responses with the noise, it is possible to determine what observers are really looking for when they perform a visual task. Typically, the averaged noise over one response type (yes, or correct) and the averaged noise of the other response type (no, or incorrect) are subtracted to form an image of the points in the stimulus the observer uses to perform the task (Murray, Bennett, & Sekuler, 2002). This is equivalent to the Fisher discriminant, hence the name "classification" image (because the Fisher discriminant is a tool for statistical classification). Here, however, we use a more general maximum likelihood technique. Nonetheless, we will still refer to the estimated observer templates as classification images.

In the experiment, observers had to detect and locate a horizontal step edge by clicking a mouse at its perceived location. The step edge was embedded in brown noise with frequency spectrum proportional to $1/f^2$. Brown noise was used because it is ecologically relevant (natural images have a $1/f^2$ power spectrum (Burton & Moorhead, 1987; Field, 1987)), and because, unlike white noise, it is the kind of noise that yields *localized* optimal edge detectors (McIlhagga, 2011). The probability that the observer clicked at a particular location was assumed to be a function of the edge detector output at that location. Using maximum likelihood estimation, the filter that best fitted the observer responses was estimated. The filters that were found are like derivative of Gaussian filters, with a peak-to-trough width of 0.1–0.15 degrees. These filters are similar to those found by Shapley and Tolhurst (1973).

2. Methods

2.1. Experimental procedure

On each trial, observers were shown a 10 degree tall and 4.5 degree wide stimulus consisting of a horizontal step edge embedded in horizontal brown noise. The step edge was dark above and light below, and could appear anywhere in the central vertical 5 degrees of the stimulus. The brown noise was generated by a cumulative sum of white noise samples with a standard deviation of 0.002 in contrast units, where the contrast of a point with luminance L is given by $L/L_{mean}-1$. That is, the brown noise at scan line y is given by $\sum_{j<y} w_j$,

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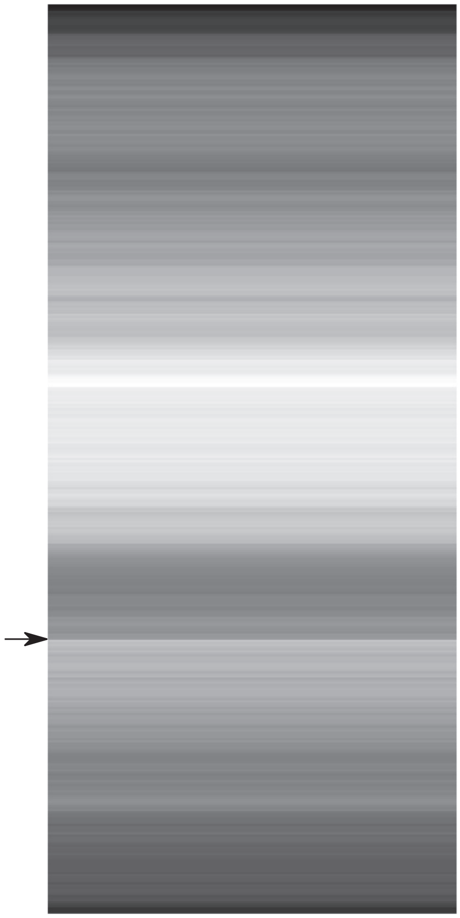

Fig. 1. Example stimulus. The stimulus was 10 degrees tall and 4.5 degrees wide. A step edge (marked here by the arrow) could appear anywhere in the central vertical 5 degrees.

where w_j is a sample of white Gaussian noise for scanline j. The brown noise was then shifted so that the mean was zero. An example stimulus is shown in Fig. 1.

The stimulus stayed on screen until the observer moved a mouse pointer to click where they believed the edge to be. If the observer clicked within 0.25 degrees of the true edge location, they were deemed correct. The edge contrast was controlled by a staircase. If the observer was deemed correct twice in a row, the edge contrast was reduced by 20%; if deemed incorrect once it was increased by 25%. This staircase was used to control the contrast of the edge to a point where the task was moderately difficult, and not for the purpose of threshold calculation. Following the observer's response, there was a 1 s delay before the next stimulus was presented.

Five observers A, C, H, T, and W participated in the experiment (W is the author). All were aware of the purpose of the experiment. Observers C, H, and W also collected data using white noise instead of brown noise (observers A and T were unavailable for the white noise experiment). A full set of data was collected over a few days, in 12 experimental blocks consisting of 150 trials. At the beginning of each block, observers were shown a high contrast step edge without noise, so they knew what they were looking for. The first 10 trials in each block were discarded prior to analysis. The experiment complied with University of Bradford Ethics Procedures and was conducted in accordance with the Code of Ethics of the World Medical Association (Declaration of Helsinki).

2.2. Calibration & apparatus

Stimuli were displayed on a Sony Multiscan E450 CRT monitor driven by a Bits + + device in Colour + + mode (Cambridge Research Systems Ltd. Kent, UK). In Colour + + mode, adjacent 8-bit pixels in the frame buffer are paired to yield 16 bits per pixel for each electron gun, and the 14 most significant bits are passed to a D/A converter. Stimuli were calculated and displayed by Matlab (MATLAB Release 2007b, The MathWorks, Inc., Natick, Massachusetts, United States), using the Psychophysics Toolbox (Brainard, 1997; Kleiner, Brainard, & Pelli, 2007; Pelli, 1997). The gamma of the monitor was measured using a ColorCal meter (Cambridge Research Systems, Kent, UK) and linearized with a lookup table. Display resolution was 1024 by 768 pixels, and the monitor was viewed at a distance of 1 m. Angular resolution was 50.86 pixels per degree.

2.3. Data analysis

Observer responses were analysed by assuming that they first convolved the stimulus with an edge detection filter f_x to yield a response

$$r_x^{(i)} = s_x^{(i)} * f_x$$

Here $r_x^{(i)}$ is the filter response at position x on trial i, $*$ indicates convolution, and $s_x^{(i)}$ is the stimulus contrast at position x in that trial. This is diagrammed in Fig. 2 (a) and (b).

The most likely location for the edge is the point where the response $r_x^{(i)}$ is maximized. However, the filter response in Fig. 2(b) has several local maxima, and it is possible that the observer might instead choose a local maximum instead of the global one. Thus, rather than being

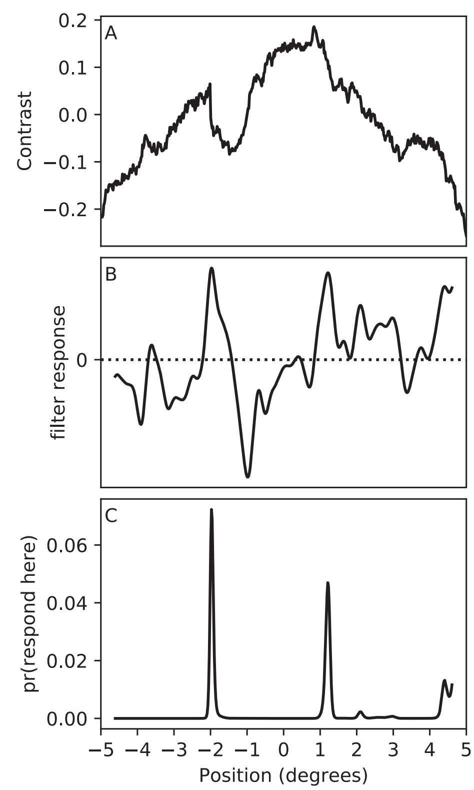

Fig. 2. The edge detection model. Panel A (top) shows the contrast of a step edge embedded in brown noise as a function of position. This is the contrast profile of the stimulus in Fig. 1. This contrast profile is convolved with an edge detection filter to yield a filter response shown in Panel B (middle). The filter response is transformed into a probability that the observer locates the edge by applying a softmax function (panel C, bottom). The true edge location is at −2 degrees, and this is the most likely response for this filter, but a response at about 1.2 degrees is also possible.