



Texture sparseness, but not local phase structure, impairs second-order segmentation



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ABSTRACT

Texture boundary segmentation is typically thought to reflect a comparison of differences in Fourier energy (i.e. low-order texture statistics) on either side of a boundary. However in a previous study (Arsenault, Yoonessi, & Baker, 2011) we showed that the *distribution* of energy within a natural texture (i.e. its higher-order statistical structure) also influences segmentation of contrast boundaries. Here we examine the influence of specific higher-order texture statistics on segmentation of contrast- and orientation-defined boundaries. Using naturalistic synthetic textures to manipulate the sparseness, global phase structure, and local phase alignments of carrier textures, we measure segmentation thresholds based on forced-choice judgments of boundary orientation. We find a similar pattern of results for both contrast and orientation boundaries: (1) randomizing all structure by globally phase scrambling the texture reduces segmentation thresholds substantially, (2) decreasing sparseness also reduces thresholds, and (3) removing local phase alignments has little or no effect on segmentation thresholds. We show that a two-stage filter model with an intermediate compressive nonlinearity and expansive output nonlinearity can account for these data using synthetic textures. Furthermore, the model parameter fits obtained using synthetic textures also predict the segmentation thresholds presented in Arsenault, Yoonessi, and Baker (2011) for natural and phase-scrambled natural texture carriers.

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1. Introduction

The segmentation of boundaries is an important problem that the visual system must solve before any more complex object processing can occur. Boundaries between objects result in discontinuities in a variety of image properties, among which changes in texture are a particularly interesting example because the means by which they are segmented is not yet well understood. Texture can be represented in terms of spatial statistics, but it is unclear what subset of these statistics is actually employed by segmentation mechanisms. Much previous research has aimed to determine the precise statistical differences that *enable* segmentation when they differ on either side of a boundary (Julesz, 1962; Julesz, Gilbert, & Victor, 1978; Beck, 1983), such as contrast or orientation. Although textures contain, and their neuronal representation may encode, many other statistics that are constant on either side of a boundary, the potential *influence* of these statistics has been largely unexamined. For example in Fig. 1 the texture statistics of the bark (A) and leaves (B) do not vary across the boundary, so they cannot *enable* segmentation, but the modulation defined over the

leaves is easier to segment – thus the nature of the texture *influences* segmentation. Although this demonstration makes the influence of the texture structure apparent, it is unclear which specific aspects of the structure exert this influence.

An early study demonstrating the influence of texture properties was that of Caelli (1980) who examined the influence of a box-shaped feature common throughout the stimulus on segmentation of a boundary defined by a difference in the orientation of line segments within the boxes. He found that segmentation was more difficult when the boxes were present than when the line segments were presented alone. Arsenault, Yoonessi, and Baker (2011) used contrast modulations applied to natural textures to show that higher-order texture statistics can impair contrast boundary segmentation, even though those statistics are not relevant to the segmentation task. We noticed that textures with a greater difference in threshold between the intact and phase-scrambled conditions appeared to be more sparse. We applied a number of image statistical measures that have been used in the literature to quantify the density of textures or natural scenes, and found that edge density (Bex, 2010) correlated strongly with the difference between thresholds. From this, we suggested local edge structure and sparseness as two candidates for texture properties that might influence segmentation, resulting in such a performance difference.

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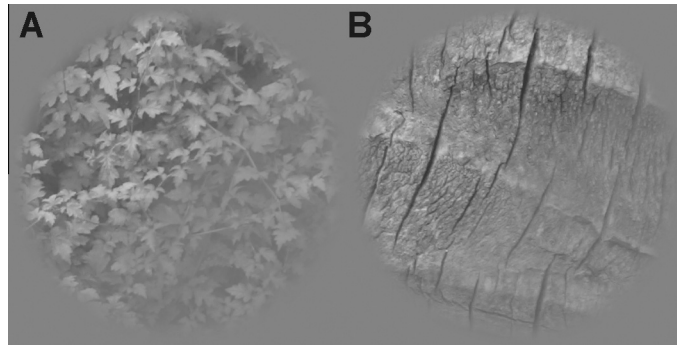


Fig. 1. In both of these textures, a contrast difference enables the percept of a right oblique boundary. The properties of the materials (leaves and bark) forming the carrier textures are different in structure, which results in a difference in the strength of the boundary percept (the modulation of the leaves (A) is easier to see than the modulation of the bark (B)), even though the difference in contrast across the boundary is identical in both stimuli. In this example, the characteristics of the textures can be said to influence segmentation.

It is difficult to assess the roles of specific statistics using natural textures because most individual properties cannot be varied independently or manipulated parametrically. While we have reason to suspect that sparseness or local edge structure might be important influencing statistics, our previous results are only correlational. In the following experiments, we address these challenges by creating synthetic textures consistent with observations of the statistical properties of natural textures using broadband “edgelet” micropatterns. These textures allow us to not only manipulate global structure through phase scrambling as in our previous study (Arsenault, Yoonessi, & Baker, 2011), but also to control the presence of local structure (by phase-scrambling individual micropatterns) and sparseness (by changing the number of micropatterns).

In this paper, we explore not only which higher-order texture properties may be at the root of the observed threshold reduction following phase scrambling, but also why these properties might have the impact they do on segmentation. It could be the case that the overall contrast-defined boundary was masked by local contrast modulations caused by variegated regions of high-contrast features that form the structure of sparse textures (Allard & Faubert, 2007). Alternatively, it could be that the presence of broadband contours in the texture distracts observers from the less-salient contrast boundary, or some combination of these two effects.

A widely accepted model for contrast boundary segmentation, the filter–rectify–filter (FRF) model, is a helpful starting point when thinking about how texture properties can affect segmentation. The most general form of the model consists of a stage of relatively high spatial frequency linear filtering, followed by a pointwise rectification (typically implemented with a square law), and a second stage of linear filtering, on the scale of the boundary to be segmented. Depending on the shape of the rectification (expansive, compressive), images with the same global contrast but different local structure could produce different responses. For example, a texture with its contrast energy concentrated in locally high-contrast regions will produce a greater response for expansive nonlinearities than a texture with an even distribution of contrast energy over space. Given this possibility, sparseness and local broadband edges are particularly logical statistical properties of interest, because both result in localized concentrations of image energy.

Here we first aim to verify that these synthetic textures contain the relevant properties of natural textures by demonstrating again the effect of phase-scrambling on contrast boundary segmentation thresholds as in Arsenault, Yoonessi, and Baker (2011). By varying texture density and phase structure, we are also able to differentiate the influence of local phase alignments, global phase relationships, and sparseness in segmentation of both contrast and orientation boundaries. We chose to study contrast boundaries

because they are the simplest kind of texture boundary, and orientation boundaries because we have observed that natural textures are frequently narrowband for orientation and this type of boundary has been widely studied (e.g. Landy & Oruç, 2002; Meso & Hess, 2011). We implement a filter–rectify–filter model and fit the shape of the rectification to account for the pattern of both our contrast and orientation boundary segmentation results. Having fit the results using synthetic textures, we assess how well this model can also predict the thresholds obtained using contrast modulations of natural textures in Arsenault, Yoonessi, and Baker (2011).

2. General methods

2.1. Stimuli

Each stimulus consisted of a single texture pattern that was contrast-modulated with a half-disc envelope, or two texture patterns ‘quilted’ together to form a disc with distinct halves (a procedure illustrated in Fig. 2A). The textures we used were designed to mimic the image statistics of natural textures, while allowing for control of specific texture properties, by randomly scattering a large number of *edgelet* micropatterns.

2.1.1. Micropatterns

To emulate the local edge structure of natural textures, we used *edgelet* micropatterns each of which contained a spatially localized edge composed of phase-aligned Fourier components. The edge of a micropattern of size s was created by adding together the Fourier components of a half-cycle of a square wave ($f, 3f, 5f, \dots, nf$ where $n = s/4$), with decreasing amplitudes (scaled by $1/f$), of a given orientation (θ) and aligned in sine-phase ($\phi = 0$). One cycle of the lowest spatial frequency pattern was combined with like-oriented in-phase harmonics of gratings (\mathbf{G}) to form a square wave “edge” (\mathbf{D}):

$$\mathbf{D}_{x,y}(\theta, s) = \sum_{k=0}^{\frac{s}{4}} \frac{1}{f} \mathbf{G}_{x,y}(\theta, \phi, f, s), \quad f = 2k \quad (1)$$

These edges were tapered by a Gaussian window, whose sigma was $1/8$ of the size of the micropattern ($\sigma = s/8$), for the final *edgelet* (\mathbf{D}') (Fig. 2B – top):

$$\mathbf{D}' = \mathbf{D}_{x,y} e^{-\left(\frac{(x-\frac{s}{2})^2}{2\sigma^2} + \frac{(y-\frac{s}{2})^2}{2\sigma^2}\right)} \quad (2)$$

To generate novel textures rapidly, we created a library of 48 such ‘intact’ micropatterns at four sizes (16, 32, 64, 128 pixels, or 0.22, 0.44, 0.87, and 1.74 degrees of visual angle), each at twelve orientations evenly spaced in 30° increments.

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