73 Visual Perception of Texture

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WHAT IS VISUAL TEXTURE, and how might a study of the visual perception of texture help us to better understand human vision? In this chapter we will attempt to give the reader a feel for how the study of texture perception is useful in understanding the impact of texture, as well as in providing a better understanding of basic visual mechanisms that respond not only to texture but to all visual stimuli. This review will be relatively brief and, of necessity, incomplete. We hope to give an overview of the different research areas concerned with texture perception and of the current issues. For a longer early review, we refer the reader to Bergen (1991).

Consider the scene in Figure 73.1. The border between the sky and the trees/grass involves a difference in luminance, one that would easily be signaled by a linear mechanism such as a simple cell in primary visual cortex. The boundary between the zebras and the background also involves a change in chromaticity (although not visible in the black-and-white image in Fig. 73.1), which might be signaled by color-opponent mechanisms. But the borders between pairs of zebras involve neither a difference in color nor a difference in average luminance. These borders include stretches of boundary that are black on one side and white on the other, stretches where the colors are reversed, and stretches where there is no local visual information to signal the boundary (where black abuts black or white abuts white). Nevertheless, we perceive a smooth, continuous occlusion boundary at the edge of each animal. It is as if the visual system possesses the capability of segmenting regions of the image based on a local textural property, such as separating "vertical stuff" from "horizontal stuff."

Thus, texture is a property that is statistically defined. A uniformly textured region might be described as "predominantly vertically oriented," "predominantly small in scale," "wavy," "stubbly," "like wood grain," or "like water." As Adelson and Bergen (1991) put it, texture is a property of *stuff* in the image, in contrast to visual features such as lines and edges, the *things* in the image (analogous to the linguistic difference between mass nouns like *water* and count nouns like *mouse*).

Another way of characterizing visual texture is by the uses to which it might be put. Texture is a property of an image region. Regions in the visual field can be characterized by differences in texture, brightness, color, or other attributes. Relatively early processes in the visual system can use texture information to perform a tentative segmentation of the visual image into regions to ease the processing load on subsequent computational stages. The analysis of a single textured image region can lead to the perception of categorical labels for that region ("This looks like wood" or "This surface looks slippery"). The appearance of texture allows the observer to determine whether two textured regions appear to be made of the same or different stuff. If two abutting image regions have different surface texture, this may lead to the detection of the intervening texture border (like the border between adjacent zebras in Fig. 73.1). Such texture-defined boundaries may then be used to segment figure from ground and for two-dimensional shape identification. Finally, continuous changes in texture properties may result in the percept of three-dimensional shape (Gibson, 1950). A purpose of much research in this area is to define the mechanisms and representational schemes used to characterize texture, and thus to determine whether the same underlying mechanisms are responsible for each of the above perceptual capabilities.

Texture segregation

TEXTURE FEATURES Much of the work on perception concerns the ability of observers to discriminate certain texture pairs effortlessly. For example, Figure 73.2 shows rectangular regions of Xs and Ts on a background of Ls. Observers can perceive effortlessly that there is a region of Xs different from the background, that this region has smooth, continuous borders, and that these borders form a rectangular shape. This is referred to as the *segregation of figure from ground* or *segmentation of the image into multiple homogeneous regions*. At the same time, none of these observations may be made about the region of Ts without the use of effortful scrutiny of the individual texture elements one by one.

This sort of observation led a number of investigators to consider what aspects of image structure led to preattentive segregation of textures. Beck and Attneave and their colleagues (Beck, 1972, 1973; Olson and Attneave, 1970) hypothesized that textural segmentation is based on the distribution of simple properties of *texture elements*, where the simple properties are things like the brightness, color, size, the slopes of contours, and other elemental descriptors of a texture. Marr (1976) added contour terminations as an important feature.

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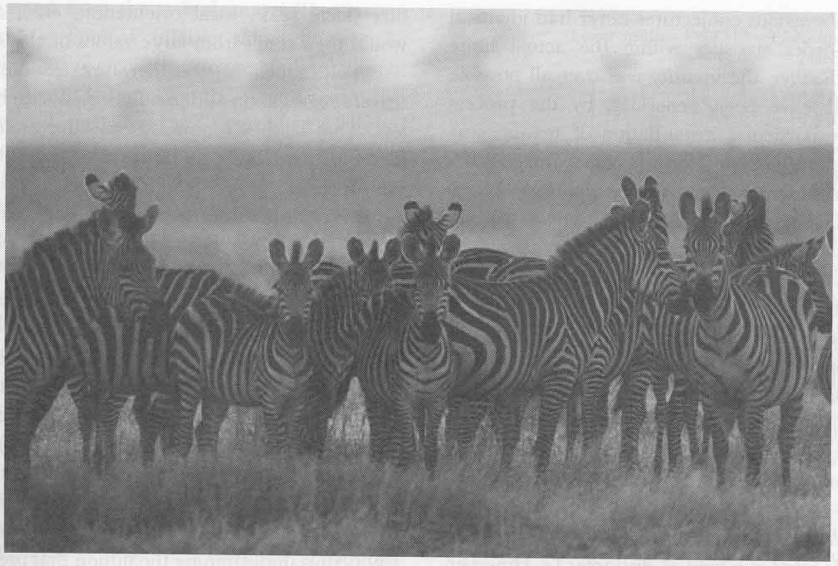

FIGURE 73.1. Types of image borders. A natural image containing borders signaled by differences in luminance, color, and/or textural content.

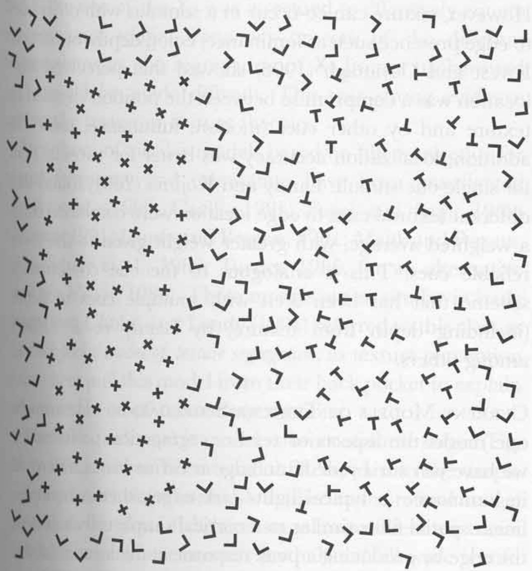

FIGURE 73.2. Texture segregation. Note that the region of Xs on the left is easily segregated from the background of Ls. One immediately perceives the borders between the two regions and the shape of the region containing the Xs. By contrast, the border between the Ts and Ls is difficult to see, and the shape of the region of Ts can only be discerned slowly, effortfully, and with item-by-item scrutiny.

Julesz's early efforts centered on image statistics. He first suggested (Julesz et al., 1973) that differences in dipole statistics were most important for texture pairs to segregate. (These are the joint image statistics of the gray levels found at the opposite ends of a line segment of a particular length and orientation, as it is placed at all possible image locations, gathered for all possible pairs of gray levels, dipole lengths, and orientations.) But counterexamples to this were found (e.g., Caelli and Julesz, 1978). It was then suggested that textures with identical third-order statistics would prove indiscriminable. (Analogous to dipole statistics, these are joint image statistics of the gray levels found at the three corners of a triangle with a particular size, shape, and orientation as it is placed at all possible image locations, gathered for all possible triplets of gray levels, triangle shapes, sizes, and orientations.) Again, counterexamples to this hypothesis were found (Julesz et al., 1978).

Julesz noted that the counterexamples were suggestive of an alternative explanation for texture segregation similar to those of Beck and Marr. Julesz found that texture pairs that segregated easily but had identical third-order statistics also differed in the amount of an easily discernible image feature (e.g., Caelli et al., 1978). The task then became one of identifying the list of image features, which Julesz (1981) dubbed *textons*, that were sufficient to explain segregation performance. The initial list of textons included such features as size, orientation, line terminations, and line crossings.

It has been noted that the third-order statistics used by Julesz were population statistics. That is, the counterexamples to Julesz's various conjectures never had identical second- or third-order statistics within the actual finite images observed. Rather, the identity was over all possible images that could have been generated by the process that generated the particular instantiation of texture currently in view. In fact, for continuous images, image pairs with identical third-order statistics must be identical images, rendering that version of the conjecture trivial (Yellott, 1993), and finite, discrete images are determined by their dipole statistics (Chubb and Yellott, 2000). On the other hand, Victor (1994) makes the case for the appropriateness of the use of population statistics for theorizing about texture segregation.

The feature-based theories were echoed in research in the visual search field (Treisman, 1985). A target pattern in a field of distracter patterns was easily found whenever the target and distracters differed in a feature (e.g., size, orientation) similar to the texton features that led to effortless texture segregation. For example, a target X was effortlessly and immediately located in a field of distracter Ls. However, when the target was a T, the task became effortful and required serial scrutiny of the texture elements, requiring more time with every additional distracter added to the stimulus (Bergen and Julesz, 1983). When the choice of target and distracters requires the observer to attend to a specific combination of two features, the search becomes difficult and observers often perceive *illusory conjunctions* between features of neighboring objects (Treisman and Schmidt, 1982). Somewhat analogous effects using texture elements having combinations of two features have been noted in texture segregation as well (Papathomas et al., 1999). However, Wolfe (1992) suggests that texture segregation and parallel visual search do not always follow the same rules.

A number of other observations have been made concerning when texture element stimuli do or do not segregate. Beck (1982) has pointed out that textures segregate based not only on the particular texture elements used but also on their arrangement, reminiscent of the Gestalt laws of figural goodness. As in the search literature (Treisman and Gormican, 1988), texture segregation may show asymmetries (Beck, 1973; Gurnsey and Browse, 1989). For example, a patch of incomplete circles will easily segregate from a background of circles, whereas the reverse pattern results in poor segregation. It has been suggested that this is due to a difference in the variability of responses of underlying visual mechanisms to the two possible texture elements (Rubenstein and Sagi, 1990).

Nothdurft (1985) suggested that finding an edge between two textures is analogous to finding a luminance-defined edge. To determine a luminance boundary involves locating large values of the derivative of luminance (the luminance gradient) across an image. Finding texture boundaries might involve the determination of other aspects of image structure (local scale, local orientation, etc.), and segregation would then result from large values of the *structure gradient*.

Finally, much of the literature assumes that effortless texture segregation and parallel visual search are truly effortless. That is, they require no selective attention to operate (demonstrated by, e.g., Braun and Sagi, 1990). However, Joseph et al. (1997) had observers perform an effortful secondary task and noted a large decrement in search performance in a search task that typically yields performance independent of the number of distracters. Thus, it is possible that even parallel search and, by extension, effortless texture segregation still require selective visual attention. Alternatively, texture segregation may not require focal visual attention, but attention may be used to alter the characteristics of visual mechanisms responsible for texture segregation (e.g., Yeshurun and Carrasco, 2000). Early literature also assumed that texture segregation was effortless in the sense of being immediate. However, at least some textures take substantial time to process (e.g., Sutter and Graham, 1995), thus undermining the notion that preattentive texture segregation is always immediate and effortless.

We have treated texture as if it is somehow an isolated cue that can signal the presence, location, and shape of an edge. However, texture can co-occur in a stimulus with other cues to edge presence such as luminance, color, depth, or motion. Rivest and Cavanagh (1996) showed that perceived edge location was a compromise between the position signaled by texture and by other cues (motion, luminance, color). In addition, localization accuracy was better for two-cue than for single-cue stimuli. Landy and Kojima (2001) found that different textural cues to edge location were combined using a weighted average, with greater weight given to the more reliable cues. This is analogous to the cue combination scheme that has been seen with multiple cues to depth (including depth from texture) by Landy et al. (1995), among others.

CURRENT MODELS OF TEXTURE SEGREGATION How might one model the aspects of texture segregation performance we have just surveyed? If an edge is defined by a difference in luminance (a typical light/dark edge), then a bandpass linear spatial filter similar to a cortical simple cell can detect the edge by producing a peak response at the location of the edge. But, a typical texture-defined edge (e.g., Figs. 73.2 and 73.4*A*) has the same average luminance on either side of the edge and thus will not be detected by any purely linear mechanism.

Several early investigators (e.g., Beck, 1972; Julesz, 1981) suggested that observers calculate the local density of various image features, and that differences in these texton or feature statistics on either side of a texture-defined edge result in effortless texture segregation. However, it was never clearly described exactly what an image feature was and how it would be computed from the retinal image. The image features discussed (e.g., lines of different slopes, line terminations and crossings) were clearly tied to the kinds of stimuli employed in most texture studies of the period (basically, pen-and-ink drawings) and would not be applied easily to natural gray-scale images.

An alternative line of modeling suggests that we need look no further than the orientation- and spatial frequency–tuned channels already discovered in the spatial vision literature through summation, identification, adaptation, and masking experiments using sine wave grating stimuli (De Valois and De Valois, 1988; Graham, 1989, 1992). For example, Knutsson and Granlund (1983) suggested that the distribution of power in different spatial frequency bands might be used to segregate natural textures, and ran such a computational model on patchworks of textures drawn from the Brodatz (1966) collection (a standard collection of texture images often used in the computational literature).

Bergen and Adelson (1988) pointed out that even the example of Xs, Ls, and Ts (Fig. 73.2) could be accounted for by the distribution of power in isotropic channels similar in form to cells found in the lateral geniculate nucleus (LGN) and layer 4 of primary visual cortex. Further, they showed that if the size of the Xs was increased to effectively equate the dominant spatial frequency or *scale* of the different texture elements, the segregation of Xs from a background of Ls could be made difficult. This was strong evidence against the texton or feature theories.

A plethora of similar models based on filters selective for spatial frequency and orientation have been investigated (Bovik et al., 1990; Caelli, 1985; Fogel and Sagi, 1989; Graham, 1991; Landy and Bergen, 1991; Malik and Perona, 1990; Sutter et al., 1989; Turner, 1986; for an alternative view, see Victor, 1988). These models are so similar in basic design that Chubb and Landy (1991) referred to this class as the *back pocket model of texture segregation*, as texture perception researchers pull this model from their back pocket to explain new phenomena of texture segregation.

The basic back pocket model consists of three stages (Fig. 73.3). First, a set of linear spatial filters, akin to the simple cells of primary visual cortex, is applied to the retinal image. Second, the outputs of the first-stage linear filters are transformed in a nonlinear manner (by half- or full-wave rectification, squaring, and/or gain control). Finally, another stage of linear filtering is used to enhance texture-defined contours. If this third stage consisted only of spatial pooling, the resulting outputs would resemble those of cortical complex cells. But often this linear filter is modeled as bandpass and orientation-tuned, so that it enhances texture-defined edges much as an orientation-tuned linear spatial filter enhances luminance-defined edges.

This process is illustrated in Figure 73.4. Figure 73.4*A* shows an orientation-defined texture border (Wolfson and Landy, 1995). In Figure 73.4*B* a vertically oriented spatial filter has been applied. The responses are larger to the vertically oriented portion of the image, but these responses are both strongly positive (when the filter is centered on a texture element) and negative (when the filter is positioned off to the side of a texture element). As a result, the average value of the output is identical on either side of the texture border, but on the left the response variability is greater. In Figure 73.4*C* the responses of Figure 73.4*B* have been rectified, resulting in larger responses in the area of vertically oriented texture. Finally, in Figure 73.4*D*, a second-order, larger-scale, vertically oriented spatial filter has been applied, resulting in a peak response at the location of the texture-defined edge. For a detection experiment ("Was there a texture-defined edge in this briefly-flashed stimulus?" or "Were there two different texture regions or only one?"), a model would try to predict human performance by the strength of the peak response in Figure 73.4*D* as compared to peaks in responses to background noise in stimuli *not* containing texture-defined edges. For further examples, see Bergen (1991) and Bergen and Landy (1991).

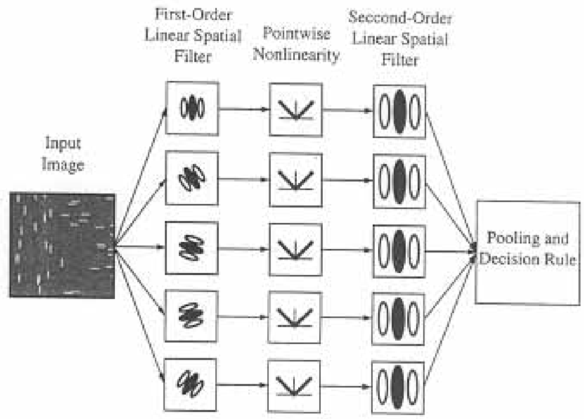

FIGURE 73.3. The back pocket model of texture segregation. The retinal image is first processed by a bank of linear spatial filters. Then some form of nonlinearity is applied. Here, a pointwise full-wave rectification is indicated. Next, a second stage of linear spatial filtering is applied to enhance the texture-defined edge. Subsequent decision processes are dependent on the particular psychophysical task under study.

A wide variety of terminology has been used to describe the basic model outlined in Figure 73.3, making the literature difficult for the neophyte. The basic sequence of a spatial filter, a nonlinearity, and a second spatial filter has been called the *back pocket* model (Chubb and Landy, 1991), an *LNL* (linear, nonlinear, linear) model, an *FRF* (filter, rectify, filter) model (e.g., Dakin et al., 1999), *second-order processing* (e.g., Chubb et al., 2001), or a *simple* or *linear channel* (the first L in LNL) followed by a *comparison-and-decision stage* (e.g., Graham et al., 1992).

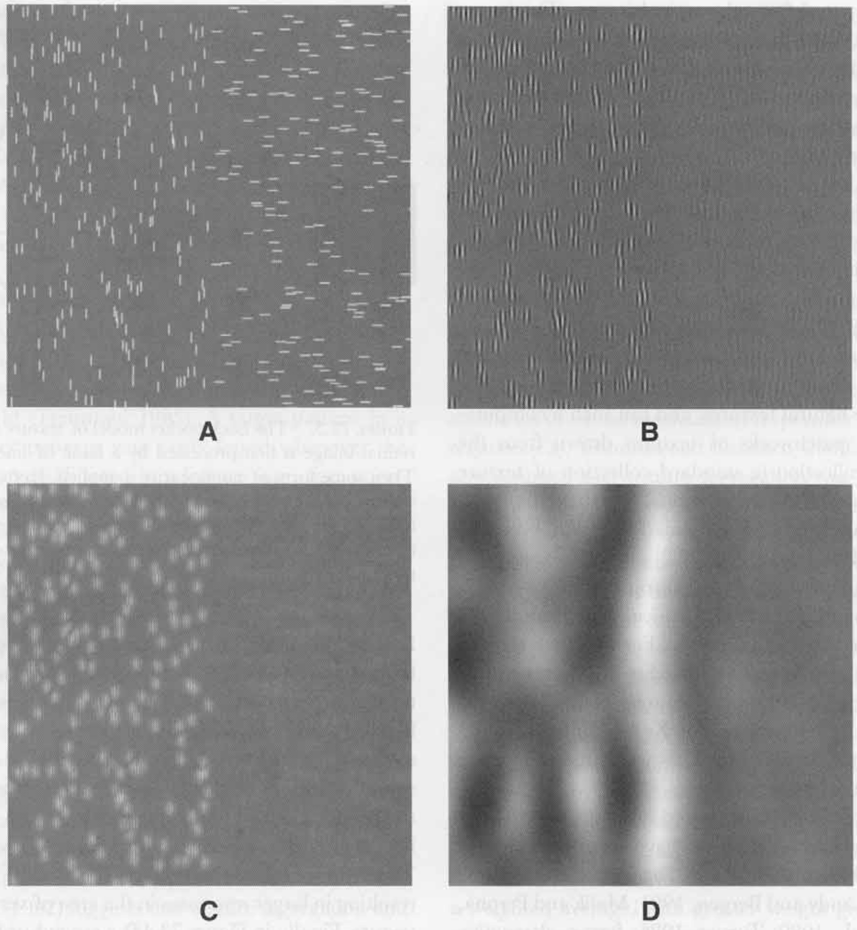

FIGURE 73.4. Back pocket model. *A*, An orientation-defined edge. *B*, The result of the application of a linear, vertically oriented spatial filter. *C*, The result of a pointwise nonlinearity (squaring). *D*, A second, large-scale, vertically oriented spatial filter yields a peak response at the location of the texture-defined border in *A*.

About the term "second-order" The term *second-order* can be particularly troublesome. In some hands, and as we will use it here, it merely refers to the second stage of linear filtering following the nonlinearity in a model like that of Figure 73.3. As such, it has been applied to models in a wide variety of visual tasks (Chubb et al., 2001). But *second-order* has another technical definition that has also been used in similar contexts. If the nonlinearity in Figure 73.3 is a squaring operation, then the pixels in the output image (after the second stage of linear filtering) are all computed as second-order (i.e., quadratic) polynomials of the pixels in the model input.

In this chapter, we will refer to the model of Figure 73.3 as a second-order model, meaning that it contains a second-order linear spatial filter. Of necessity, this second-order linear filter must follow an intervening nonlinearity. Otherwise, there would simply be two sequential linear filters, which are indistinguishable from a single, lumped linear spatial filter. We will use this term regardless of the polynomial order of the intervening nonlinearity.

There is also a more general use of *second-order*. In this usage, a second-order entity (e.g., a neuron) pools, after some intervening nonlinearity, the responses from a number of other entities (called *first-order*) but, in this more general usage, the first-order entities do not form a linear filter characterized by a single spatial weighting function, as they do in Figure 73.3. Rather, the first-order entities can be an assortment of neurons sensitive to various things (e.g, different orientations or different spatial frequencies). See the introduction to Graham and Sutter (1998) for a brief review of such general suggestions.

Third-order models Second-order models are not the end of the story. For example, Graham et al. (1993) used an element-arrangement texture stimulus consisting of two types of elements, arranged in stripes in one region and in a checkerboard in another region. Consider the case where each texture element is a high-frequency Gabor pattern (a windowed sine wave grating) and the two types of elements differ only in spatial frequency. Consider a second-order model like that just described, with the first linear filter tuned to one of the two types of Gabor patches and the second linear filter tuned to the width and orientation of stripes of elements. This second-order model would yield a response to these element-arrangement textures that is of the same average level, although of high contrast in the striped region and low contrast in the checked region. To reveal the texture-defined edge between the checkerboard and striped regions, therefore, requires another stage of processing, which could be a pointwise nonlinearity followed by an even larger-scale linear spatial filter (another NL), thus producing a sequence LNLNL. For an illustration of such a model's responses, see Graham et al. (1993), Figure 4.

Here we will call this LNLNL sequence a third-order model. But, to avoid confusion, let us note that Graham and her colleagues refer to the first LNL as a complex channel or second-order channel and the final NL is an instance of what they call the comparison-and-decision stage.

About the terms "Fourier" and "non-Fourier" There is also possible confusion about the terms *Fourier* and *non-Fourier*. A stimulus like that in Figure 73.4*A*, in which the edge can be found by the model in Figure 73.3, has been referred to as *non-Fourier* (first applied to motion stimuli by Chubb and Sperling, 1988). The term was used because the Fourier spectrum of this stimulus does not contain components that correspond directly to the texture-defined edge. But some others (e.g., Graham and Sutter, 2000) have used the term *Fourier channels* for the first linear filters (the simple channels) in Figure 73.3 and reserved the term *non-Fourier* for the complex channels (the initial LNL) in what we called third-order models above (LNLNL).

This confusing terminology is the result of a difference in emphasis. In this chapter, we concentrate on models that localize (i.e., produce a peak response at) edges between two abutting textures. But, others (e.g., Graham and Sutter, 2000; Lin and Wilson, 1996) have emphasized response measures that can be used to discriminate between pairs of textures (whether simultaneously present and abutting or not) by any later, nonlinear decision process. Thus, finding the edge in an orientation-defined texture like that of Figure 73.3 is, in Graham and Sutter's terms, *Fourier-based*, as the power spectra of the two constituent textures differ, whereas finding the edge in a Gabor-patch element-arrangement texture like that of Graham et al. (1993) is *non-Fourier-based*, as the power spectra of the two constituent textures do not differ.

Model Specification The models of texture segregation just described are complicated, with many details that require elucidation. Are the initial linear filters of a second-order pathway the same spatial filters as the spatial frequency channels that have been described using grating experiments? What is the nature of the following nonlinearity? Are there fixed, second-order linear filters, and what is their form? This is an area of current active research, and most of these issues have not been convincingly decided.

Graham et al. (1993) and Dakin and Mareschal (2000) provide evidence that the initial spatial filters in a second-order pathway used to detect contrast modulations of texture are themselves tuned for spatial frequency and orientation. In the same article, Graham and colleagues also demonstrated that the initial spatial filters in a third-order pathway (their complex channels) were orientation- and spatial-frequency-tuned as well.

The back pocket model includes a nonlinearity between the two stages of linear spatial filtering that is required to demodulate the input stimuli. For small first-order spatial filters, Chubb et al. (1994) provided a technique called *histogram contrast analysis* that allowed them to measure aspects of the static nonlinearity, showing that it included components of higher order than merely squaring the input luminances. Graham and Sutter (1998) found that this nonlinearity must be expansive. They also (Graham and Sutter, 2000) suggested that a gain control mechanism acts as an inhibitory influence among multiple pathways of the types called second-order and third-order here.

First-order spatial frequency channels were first measured using sine wave grating stimuli and various experimental paradigms including adaptation, masking, and summation experiments (reviewed in Graham, 1989). Recently, researchers used analogous experiments to examine the second-order linear filters. To do so, researchers hope to deliver to the second-order filter something like the sine wave grating stimuli of classical spatial frequency channel studies. The usual ploy is to use a stimulus that has a sine wave (or Gabor) pattern to modulate some aspect of textural content across the stimulus. The assumed first-order filter and the subsequent nonlinearity demodulate this stimulus, providing as input to the second-order linear filter a noisy version of the intended grating or Gabor pattern.

Studies of texture modulation detection have revealed a very broadband second-order texture contrast sensitivity function (CSF) using a variety of texture modulations including contrast (Schofield and Georgeson, 1999, 2000; Sutter et al., 1995), local orientation content (Kingdom et al., 1995), and modulation between vertically and horizontally oriented, filtered noise (Landy and Oruç, 2002). This

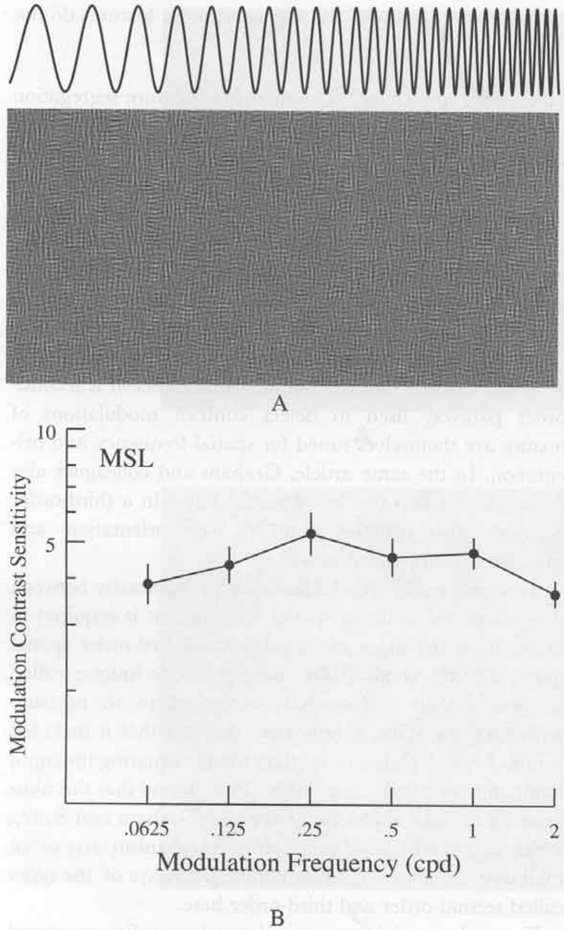

FIGURE 73.5. The second-order contrast sensitivity function. *A*, This figure is constructed using a modulator image to additively combine vertical and horizontal noise images (Landy and Oruç, 2002). The modulator, shown as a function above the texture, has a spatial frequency that increases from left to right, and its contrast increases from bottom to top. Large modulator values result in a local texture dominated by vertically oriented noise and small values by horizontally oriented noise. Note that threshold modulation contrast is nearly independent of spatial frequency. *B*, Example data from a forced-choice modulation contrast detection experiment using sine wave modulators of noise patterns.

function is far more broadband than the corresponding luminance CSF. A demonstration of this effect is shown in Figure 73.5*A*. A modulator pattern is used to combine additively a vertical and a horizontal noise texture. The modulator increases in spatial frequency from left to right and in contrast from bottom to top. As you can see, the texture modulation becomes impossible to discern at approximately the same level for all spatial frequencies. The sample data in Figure 73.5*B* confirm this observation.

Evidence for multiple second-order filters underlying this broad second-order CSF has been equivocal, with evidence both pro (Arsenault et al., 1999; Landy and Oruç, 2002; Schofield and Georgeson, 1999) and con (Kingdom and Keeble, 1996). Many studies have found texture discrimination to be scale-invariant, suggesting the existence of a link between the scale of the corresponding first- and second-order spatial filters (Kingdom and Keeble, 1999; Landy and Bergen, 1991; Sutter et al., 1995). It has also been suggested that the orientation preferences of the first- and second-order filters tend to be aligned (Dakin and Mareschal, 2000; Wolfson and Landy, 1995). This alignment of first- and second-order filters has also been supported for element-arrangement stimuli that require a third-order model to detect the texture-defined edges (Graham and Wolfson, 2001).

If there is an obligatory link between the scales of the first- and second-order filters, this suggests that the preferred second-order scale should depend on eccentricity. This was first demonstrated by Kehrer (1989), who noted that performance on an orientation-defined texture-segregation task at first improves as the target texture moves into the periphery and then worsens as the eccentricity increases further. The poor foveal performance was dubbed the *central performance drop* (CPD). This argument that the CPD is due to the relation between the scale of the second-order pattern and the local scale of the second-order filter was made by Yeshurun and Carrasco (2000), who, in addition, suggested that the second-order spatial filters are narrowed as a consequence of the allocation of selective attention.

The temporal properties of the first- and second-order filters are not well understood, although some information is available (Lin and Wilson, 1996; Motoyoshi and Nishida, 2001; Schofield and Georgeson, 2000; Sutter and Graham, 1995, Sutter and Hwang, 1999).

The possibility that the wiring between first- and second-order filters is more complicated than that shown in Figure 73.3 remains open as well (see, e.g., the appendix in Graham and Sutter, 1998; Mussap, 2001), with particular interest in possible lateral excitatory and inhibitory interactions among different positions within the same filter (Motoyoshi, 1999; Wolfson and Landy, 1999).

Early filters are not the only visual processes that play an important role in determining the conscious perception of textured stimuli. Consider He and Nakayama (1994), who constructed a series of binocular demonstration stimuli involving both texture and disparity. The foreground surface consisted of a set of textured squares. The background stimuli consisted of a region of I shapes surrounded by L shapes that, monocularly, segregated quite easily. However, when seen in depth with the squares (that abutted the Ls and Is) in front, both the Ls and Is were perceived as occluded by the squares. They underwent surface completion; that is, they were both perceived as larger rectangles occluded by the squares, and texture segregation became effortful. This suggests that higher-level, surface-based representations are involved in judgments about the objects perceived on the basis of textured regions in the stimulus.

Texture appearance

The previous section concentrated on research concerning observers' ability to detect borders between differing textures. Here we consider research more directly measuring the appearance of textures. If two images both appear to be a grassy field, then at some level of analysis, the representations of the two images must be similar. To understand the appearance of texture might involve developing such a representation, as well as a metric within that representation space so that textures are perceived as similar if their representations are close and dissimilar if far. Indeed, there is even evidence that texture appearance (or, at least, region-based) mechanisms can be responsible for texture segregation in some cases (Wolfson and Landy, 1998), as certain texture pairs can be discriminated just as well when they are separated as when they abut (forming an edge). Using region-based as well as edge-based mechanisms may be optimal for segregation processes (Lee, 1995).

One approach to this problem of measuring texture appearance is a classical one: elicit similarity judgments from observers and try to build a representation. Having done so, one can then ask whether the underlying dimensions have any semantic basis or whether dimensions satisfy any of the properties of other perceptual dimensions (such as the additivity and metamerism of color space). Three dimensions appeared to suffice for sets of natural textures (Rao and Lohse, 1996) as well as artificial ones (Gurnsey and Fleet, 2001; Harvey and Gervais, 1978). A texture analogy to color matching experiments with artificial one-dimensional textures provides satisfactory appearance matches with four texture primaries (Richards and Polit, 1974). As with color matching, this technique shows that one can account for texture matches with the four primaries, but it does not explain texture appearance. Color appearance depends on the particular metameric match, as well as on color context. Similarly, texture appearance can depend on context. For example, Durgin (2001) shows that the perceived texture density of a texture patch depends on the density of the surrounding texture.

An alternative approach is to analyze an instance of texture to estimate its representation and then use that representation to generate new instances of texture. The proposed representational scheme is considered successful if the newly generated textures are classified as "made of the same stuff as the original" by observers. The first such model, by Heeger and Bergen (1995), represented the input texture image as the histograms of values in each level of an

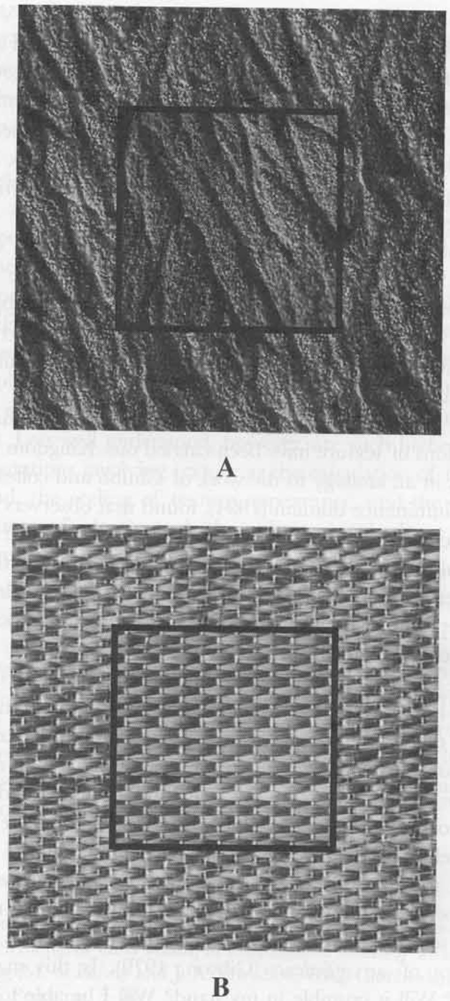

FIGURE 73.6. Texture appearance, representation, and extrapolation. In the technique of Portilla and Simoncelli (2000), a texture is first analyzed using a bank of linear spatial filters varying in preferred spatial frequency and orientation. A set of statistics, both first-order and correlational, on that set of filter responses becomes the representation of the given texture. This representation may be used to generate new instances of the texture. In each panel, the inset square is the original texture, and the rest of the image is new texture generated using the technique.

oriented pyramid representation of the image, that is, as the statistics of the responses from a collection of orientation- and spatial frequency–tuned spatial filters. The resulting newly generated texture images were occasionally striking in their similarity to the original. But, in other instances, especially those involving correlations between different image areas at long distances, the results were quite poor. More recent models incorporate higher-order statistics including correlations between pairs of filter responses across space, spatial frequency, and orientation (De Bonet and Viola, 1998; Portilla and Simoncelli, 2000; Zhu et al., 1998). Figure 73.6 shows two sample textures (inset squares) that were extrapolated using the technique of Portilla and Simoncelli (2000). Clearly, the technique has captured a good deal of that which defines the appearance of these textures. The technique is somewhat less successful with purely periodic textures (tiles), binary or pen-and-ink textures, or with pseudotextures that are, for example, collections of small objects (e.g., a pile of jellybeans). It remains to be seen whether a metric (Euclidean, Minkowski, or other) applied to one of these texture representation spaces will correlate well with observers' judgments of the perceptual similarity of textures.

Few psychophysical tests of these new statistical characterizations of texture have been carried out. Kingdom et al. (2001), in an analogy to the work of Chubb and colleagues in the luminance domain (1994), found that observers were most sensitive to kurtosis in the histograms of wavelet (that is, multiscale, orientation-tuned) coefficients in artificial textures. Durgin (2001) has suggested that texture density is a separate dimension from either mean (luminance) or variance (root-mean-squared contrast).

The texture representation schemes just discussed are image-based. That is, all content of the representation is based on simple statistics based on responses of filters to the texture. A complete theory of texture perception might involve recognition that natural textures are associated with real-world materials, and the appearance of texture may well relate to perception of the particular material from which the image derived (wood, plastic, water, grassland, etc.) or properties of the real-world material that might relate to actions the observer might wish to take. This is the concept of an *affordance* (Gibson, 1979). Is this material sticky? Will it crumble in my hand? Will I be able to walk on it in bare feet? A great deal of work has been done, notably in the computer graphics world, to understand image properties of natural materials in order to simulate these materials in virtual displays. By contrast, very little research has been done on the perception of real-world textural properties. Recently, some effort has been made to understand the variety of images one can find of natural textures as viewpoint and lighting conditions are varied (Dana et al., 1999).

Shape from texture

Gibson (1950) pointed out that the perspective distortion of surface texture is a cue to surface layout. For example, consider a ground plane that is painted with randomly placed circles. As the surface recedes into the distance, three different *texture gradients* may be distinguished: size (farther-away texture elements are smaller in the retinal image), density (farther-away texture elements are closer together in the retinal image), and compression (farther-away elements are more slanted relative to the line of sight and hence form more eccentric ellipses in the retinal image).

The computational literature is replete with suggested algorithms for the computation of shape from texture. These algorithms vary in how restrictive an assumption is made about the surface texture. The earliest algorithms (e.g., that of Witkin, 1981) assumed an isotropic texture (all orientations were equally represented on the surface, which is true of the above example). More recent algorithms (e.g., that of Aloimonos, 1988) only assume texture homogeneity (i.e., the texture is statistically the same at all positions on the surface). A particularly interesting algorithm is that of Malik and Rosenholtz (1997). This algorithm makes weak assumptions about the underlying surface texture. It looks for affine distortions in image statistics from one location to another, as seen in the responses of a bank of spatial filters varying in orientation and spatial frequency preference, much like the first stage in the current models of texture segregation.

Psychophysical research on the perception of shape from texture has followed a similar history. Cutting and Millard (1984) discussed the three possible texture gradients and manipulated them independently in their stimuli. They found that perception of slant for planar stimuli depended mainly on the size gradient, whereas perception of curved stimuli was almost completely determined by the compression gradient. Rosenholtz and Malik (1997) found texture isotropy to be unnecessary for human observers to estimate surface orientation, consistent with their computational theory. Li and Zaidi (2000) examined the types of surface texture that would give a veridical percept of shape when mapped onto a corrugated surface in perspective, and found that several aspects of the Fourier power spectrum were predictive of observer accuracy, corresponding to the availability of oriented energy along lines of maximum and minimum curvature in the surface.

A second line of psychophysical research has been to derive ideal (maximum a posteriori) observers and to compare the reliability of human observers' estimates of surface layout with those of the ideal observer. Blake et al. (1993) derived such a model with the assumption of isotropic, homogeneous surface texture and demonstrated that observers' estimates of surface curvature must use the compression gradient. Buckley et al. (1996) applied the same strategy to the estimation of surface slant, and found that texture compression dominates observer judgments even for fields of view large enough that, for the ideal, texture density should dominate. Finally, in a series of three papers, Knill (1998a, 1998b, 1998c) derived ideal observers for slant from texture that use the three texture gradient cues and derived the reliability of each cue as a function of slant and field of view. He found that human observers became more reliable with increasing slant and field of view, just as did the ideal observers. Again, performance was so good that observers must have used texture compression and, at least in part, an assumption of isotropy.

Neurophysiology

The physiological substrate for the first-stage linear filters in texture segregation models is likely to be the spatial frequency and orientation-selective cells in cortical area V1. Further, V1 is sufficiently complicated that other attributes of the current models, such as the normalization or other nonlinearities and subsequent spatial pooling, could certainly also occur in V1. There are also lateral interactions between neurons in V1 (both excitatory and inhibitory) that go beyond the classical receptive field. There has been some controversy over the function of these lateral interactions in V1. Some have suggested that lateral interactions enhance responses to popout stimuli (Kastner et al., 1997, 1999; Nothdurft et al., 1999), to texture elements near texture borders (Nothdurft et al., 2000), to orientation contrast (Knierim and Van Essen, 1992; Sillito et al., 1995), and to figure rather than ground (Lamme, 1995; Zipser et al., 1996). Li (2000) even described a neural network model of segmentation that includes such processes.

However, the responses to orientation contrast stimuli are a complex function of the contrasts of the figure and ground (Levitt and Lund, 1997), suggesting that these V1 responses are primarily the result of a gain control mechanism that is only an initial stage of the computation of texture borders and figure-ground. Consistent with this view, several groups have found that input from outside the classical receptive field is mainly suppressive and suggest that it is not involved with figure-ground analysis (Freeman et al., 2001; Rossi et al., 2001; Sceniak et al., 2001; Walker et al., 2000). An in-depth review of a large range of results from areas V1 up through MT, and V4 (Lennie, 1998) concludes that it may be too much to attribute such functions as popout and figure-ground segregation to area V1, and that these functions probably occur in V2 through V4 or even at higher levels. Lennie suggests that "Spatial interactions in V1 probably have a less exotic role; they provide lateral inhibition in the domain of local structure so that, by analogy with lateral inhibition in the luminance domain, signals from regions of common structure are suppressed and contrasts in structure are made salient." In this view, it is not until area V4 that the system has even grouped regions of similar structure to find contours, regions, and surfaces and, perhaps, computed surface slant. And thus, in this view, many of the processes called into play by texture stimuli (e.g., the conscious perception of a surface as having a particular texture) would be determined predominantly by still higher-level cortical areas. A recent functional magnetic resonance imaging study of static texture segregation (Kastner et al., 2000) concurs, finding little response to texture borders in V1 or V2/VP and increasing responses as one proceeds downstream from V3 to V4 and TEO.

Conclusions

The perception of texture is a rich and varied area of study. In the early coding of texture borders, there is some common ground between current psychophysical data and models and the physiology of primary visual cortex, such as the suggestion that texture border coding involves a succession of linear spatial filters and nonlinearities that include static nonlinearities as well as contrast gain control mechanisms. Less well understood, however, are such higher-level computations involving texture as the calculation of figure-ground, the coding of texture appearance, and the determination of depth and three-dimensional shape from texture cues.

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REFERENCES

Adelson, E. H., and J. R. Bergen, 1991. The plenoptic function and the elements of early vision, in *Computational Models of Visual Processing* (M. S. Landy and J. A. Movshon, eds.), Cambridge, MA: MIT Press, pp. 3–20.

Aloimonos, J., 1988. Shape from texture, *Artificial Intelligence*, 38:345–360.

Arsenault, A. S., F. Wilkinson, and F. A. A. Kingdom, 1999. Modulation frequency and orientation tuning of second-order texture mechanisms, *J. Opt. Soc. Am. A*, 16:427–435.

Beck, J., 1972. Similarity grouping and peripheral discriminability under uncertainty, *Am. J. Psychol.*, 85:1–19.

Beck, J., 1973. Similarity grouping of curves, *Percept. Motor Skills*, 36:1331–1341.

Beck, J., 1982. Textural segmentation, in *Organization and Representation in Perception* (J. Beck ed.), Hillsdale, NJ: Erlbaum, pp. 285–317.

Bergen, J. R., 1991. Theories of visual texture perception, in *Vision and Visual Dysfunction*, vol. 10B (D. Regan ed.), New York: Macmillan, pp. 114–134.

Bergen, J. R., and E. H. Adelson, 1988. Early vision and texture perception, *Nature*, 333:363–364.

Bergen, J. R., and B. Julesz, 1983. Parallel versus serial processing in rapid pattern discrimination, *Nature*, 303:696–698.

Bergen, J. R., and M. S. Landy, 1991. Computational modeling of visual texture segregation, in *Computational Models of Visual*

Processing (M. S. Landy and J. A. Movshon, eds.), Cambridge, MA: MIT Press, pp. 253–271.

Blake, A., H. H. Buelthoff, and D. Sheinberg, 1993. Shape from texture: ideal observers and human psychophysics, *Vis. Res.*, 33:1723–1737.

Bovik, A. C., M. Clark, and W. S. Geisler, 1990. Multichannel texture analysis using localized spatial filters, *IEEE Trans. Pattern Anal. Machine Intelligence*, 12:55–73.

Braun, J., and D. Sagi, 1990. Vision outside the focus of attention, *Percept. Psychophys.*, 48:45–58.

Brodatz, P., 1966. *Textures*, New York: Dover.

Buckley, D., J. P. Frisby, and A. Blake, 1996. Does the human visual system implement an ideal observer theory of slant from texture? *Vis. Res.*, 36:1163–1176.

Caelli, T., 1985. Three processing characteristics of visual texture segmentation, *Spatial Vis.*, 1:19–30.

Caelli, T., and B. Julesz, 1978. On perceptual analyzers underlying visual texture discrimination: Part I, *Biol. Cybern.*, 28:167–175.

Caelli, T., B. Julesz, and E. N. Gilbert, 1978. On perceptual analyzers underlying visual texture discrimination: Part II, *Biol. Cybern.*, 29:201–214.

Chubb, C., J. Econopouly, and M. S. Landy, 1994. Histogram contrast analysis and the visual segregation of IID textures, *J. Opt. Soc. Am. A*, 11:2350–2374.

Chubb, C., and M. S. Landy, 1991. Orthogonal distribution analysis: a new approach to the study of texture perception, in *Computational Models of Visual Processing* (M. S. Landy and J. A. Movshon, eds.), Cambridge, MA: MIT Press, pp. 291–301.

Chubb, C., L. Olzak, and A. Derrington, 2001. Second-order processes in vision: introduction, *J. Opt. Soc. Am. A*, 18:2175–2178.

Chubb, C., and G. Sperling, 1988. Drift-balanced random stimuli: a general basis for studying non-Fourier motion perception, *J. Opt. Soc. Am. A*, 5:1986–2007.

Chubb, C., and J. I. Yellott, Jr., 2000. Every discrete, finite image is uniquely determined by its dipole histogram, *Vis. Res.*, 40:485–492.

Cutting, J. E., and R. T. Millard, 1984. Three gradients and the perception of flat and curved surfaces, *J. Exp. Psychol. Gen.*, 113:198–216.

Dakin, S. C., and I. Mareschal, 2000. Sensitivity to contrast modulation depends on carrier spatial frequency and orientation, *Vis. Res.*, 40:311–329.

Dakin, S. C., C. B. Williams, and R. F. Hess, 1999. The interaction of first- and second-order cues to orientation, *Vis. Res.*, 39:2867–2884.

Dana, K. J., B. van Ginneken, S. K. Nayar, and J. J. Koenderink, 1999. Reflectance and texture of real-world surfaces, *ACM Trans. Graphics*, 18:1–34.

De Bonet, J. S., and P. Viola, 1998. A non-parametric multi-scale statistical model for natural images, in *Advances in Neural Information Processing Systems 9* (M. I. Jordan, M. J. Kearns, and S. A. Solla, eds.), Cambridge, MA: MIT Press, pp. 773–779.

De Valois, R. L., and K. K. De Valois, 1988. *Spatial Vision*, New York: Oxford University Press.

Durgin, F. H., 2001. Texture contrast aftereffects are monocular; texture density aftereffects are binocular, *Vis. Res.*, 41:2619–2630.

Freeman, R. D., I. Ohzawa, and G. Walker, 2001. Beyond the classical receptive field in the visual cortex, *Prog. Brain Res.*, 134:157–170.

Fogel, I., and D. Sagi, 1989. Gabor filters as texture discriminator, *Biol. Cybern.*, 61:103–113.

Gibson, J. J., 1950. *The Perception of the Visual World*, Boston: Houghton Mifflin.

Gibson, J. J., 1979. *The Ecological Approach to Visual Perception*, Boston: Houghton Mifflin.

Graham, N., 1989. *Visual Pattern Analyzers*, New York: Oxford University Press.

Graham, N., 1991. Complex channels, early local nonlinearities, and normalization in perceived texture segregation, in *Computational Models of Visual Processing* (M. S. Landy and J. A. Movshon, eds.), Cambridge, MA: MIT Press, pp. 273–290.

Graham, N., 1992. Breaking the visual stimulus into parts, *Curr. Dir. Psychol. Sci.*, 1:55–61.

Graham, N., J. Beck, and A. Sutter, 1992. Nonlinear processes in spatial-frequency channel models of perceived texture segregation: effects of sign and amount of contrast, *Vis. Res.*, 32:719–743.

Graham, N., and A. Sutter, 1998. Spatial summation in simple (Fourier) and complex (non-Fourier) texture channels, *Vis. Res.*, 38:231–257.

Graham, N., and A. Sutter, 2000. Normalization: contrast-gain control in simple (Fourier) and complex (non-Fourier) pathways of pattern vision, *Vis. Res.*, 40:2737–2761.

Graham, N., A. Sutter, and C. Venkatesan, 1993. Spatial-frequency- and orientation-selectivity of simple and complex channels in region segmentation, *Vis. Res.*, 33:1893–1911.

Graham, N., and S. S. Wolfson, 2001. A note about preferred orientations at the first and second stages of complex (second-order) texture channels, *J. Opt. Soc. Am. A*, 18:2273–2281.

Gurnsey, R., and R. A. Browse, 1989. Asymmetries in visual texture discrimination, *Spatial Vis.*, 4:31–44.

Gurnsey, R., and D. J. Fleet, 2001. Texture space, *Vis. Res.*, 41:745–757.

Harvey, L. O. Jr., and M. J. Gervais, 1978. Visual texture perception and Fourier analysis, *Percept. Psychophys.*, 24:534–542.

He, Z. J., and K. Nakayama, 1994. Perceiving textures: beyond filtering, *Vis. Res.*, 34:151–162.

Heeger, D., and J. R. Bergen, 1995. Pyramid-based texture analysis/synthesis, in *Proceedings of ACM SIGGRAPH 1995*. New York: Association for Computing Machinery, pp. 229–238.

Joseph, J. S., M. M. Chun, and K. Nakayama, 1997. Attentional requirements in a "preattentive" feature search task, *Nature*, 387:805–807.

Julesz, B., 1981. Textons, the elements of texture perception, and their interactions, *Nature*, 290:91–97.

Julesz, B., E. N. Gilbert, L. A. Shepp, and H. L. Frisch, 1973. Inability of humans to discriminate between visual textures that agree in second-order statistics—revisited, *Perception*, 2:391–405.

Julesz, B., E. N. Gilbert, and J. D. Victor, 1978. Visual discrimination of textures with identical third-order statistics, *Biol. Cybern.*, 31:137–140.

Kastner, S., P. de Weerd, and L. G. Ungerleider, 2000. Texture segregation in the human visual cortex: a functional MRI study, *J. Neurophysiol.*, 83:2453–2457.

Kastner, S., H. C. Nothdurft, and I. N. Pigarev, 1997. Neuronal correlates of pop-out in cat striate cortex, *Vis. Res.*, 37:371–376.

Kastner, S., H. C. Nothdurft, and I. N. Pigarev, 1999. Neuronal responses to orientation and motion contrast in cat striate cortex, *Vis. Neurosci.*, 16:587–600.

Kehrer, L., 1989. Central performance drop on perceptual segregation tasks, *Spatial Vis.*, 4:45–62.

Kingdom, F. A. A., A. Hayes, and D. J. Field, 2001. Sensitivity to contrast histogram differences in synthetic wavelet-textures, *Vis. Res.*, 41:585–598.

Kingdom, F. A. A., and D. R. T. Keeble, 1996. A linear systems approach to the detection of both abrupt and smooth spatial variations in orientation-defined textures, *Vis. Res.*, 36:409–420.
Kingdom, F. A. A., and D. R. T. Keeble, 1999. On the mechanism for scale invariance in orientation-defined textures, *Vis. Res.*, 39:1477–1489.
Kingdom, F. A. A., D. R. T. Keeble, and B. Moulden, 1995. Sensitivity to orientation modulation in micropattern-based textures, *Vis. Res.*, 35:79–91.
Knierim, J. J., and D. C. Van Essen, 1992. Neuronal responses to static texture patterns in area V1 of the alert macaque monkey, *J. Neurophysiol.*, 67:961–980.
Knill, D. C., 1998a. Surface orientation from texture: ideal observers, generic observers and the information content of texture cues, *Vis. Res.*, 38:1655–1682.
Knill, D. C., 1998b. Discrimination of planar surface slant from texture: human and ideal observers compared, *Vis. Res.*, 38:1683–1711.
Knill, D. C., 1998c. Ideal observer perturbation analysis reveals human strategies for inferring surface orientation from texture, *Vis. Res.*, 38:2635–2656.
Knutsson, H., and G. H. Granlund, 1983. Texture analysis using two-dimensional quadrature filters, in *Proceedings of the IEEE Computer Society Workshop on Computer Architecture for Pattern Analysis and Image Database Management*, Silver Spring, MD: IEEE Computer Society, pp. 206–213.
Lamme, V. A. F., 1995. The neurophysiology of figure-ground segregation in primary visual cortex, *J. Neurosci.*, 15:1605–1615.
Landy, M. S., and J. R. Bergen, 1991. Texture segregation and orientation gradient, *Vis. Res.*, 31:679–691.
Landy, M. S., and H. Kojima, 2001. Ideal cue combination for localizing texture-defined edges, *J. Opt. Soc. Am. A*, 18: 2307–2320.
Landy, M. S., L. T. Maloney, E. B. Johnston, and M. J. Young, 1995. Measurement and modeling of depth cue combination: in defense of weak fusion, *Vis. Res.*, 35:389–412.
Landy, M. S., and İ. Oruç, 2002. Properties of 2nd-order spatial frequency channels, *Vis. Res.*, 42:2311–2329.
Lee, T. S., 1995. A Bayesian framework for understanding texture segmentation in the primary visual cortex, *Vis. Res.*, 35:2643–2657.
Lennie, P., 1998. Single units and cortical organization, *Perception*, 27:889–935.
Levitt, J. B., and J. S. Lund, 1997. Contrast dependence of contextual effects in primate visual cortex, *Nature*, 387:73–76.
Li, A., and Q. Zaidi, 2000. Perception of three-dimensional shape from texture is based on patterns of oriented energy, *Vis. Res.*, 40:217–242.
Li, Z., 2000. Pre-attentive segmentation in the primary visual cortex, *Spatial Vis.*, 13:25–50.
Lin, L. M., and H. R. Wilson, 1996. Fourier and non-Fourier pattern discrimination compared, *Vis. Res.*, 36:1907–1918.
Malik, J., and P. Perona, 1990. Preattentive texture discrimination with early vision mechanisms, *J. Opt. Soc. Am. A*, 7:923–932.
Malik, J., and R. Rosenholtz, 1997. Computing local surface orientation and shape from texture for curved surfaces, *Int. J. Comput. Vis.*, 23:149–168.
Marr, D., 1976. Early processing of visual information, *Philos. Trans. R. Soc. Lond. B*, 275:483–519.
Motoyoshi, I., 1999. Texture filling-in and texture segregation revealed by transient masking, *Vis. Res.*, 39:1285–1291.
Motoyoshi, I., and S. Nishida, 2001. Temporal resolution of orientation-based texture segregation, *Vis. Res.*, 41:2089–2105.
Mussap, A. J., 2001. Orientation integration in detection and discrimination of contrast-modulated patterns, *Vis. Res.*, 41:295–311.
Nothdurft, H. C., 1985. Sensitivity for structure gradient in texture discrimination tasks, *Vis. Res.*, 25:1957–1968.
Nothdurft, H. C., J. L. Gallant, and D. C. Van Essen, 1999. Response modulation by texture surround in primate area V1: correlates of "popout" under anesthesia, *Vis. Neurosci.*, 16:15–34.
Nothdurft, H. C., J. L. Gallant, and D. C. Van Essen, 2000. Response profiles to texture border patterns in area V1, *Vis. Neurosci.*, 17:421–436.
Olson, R. K., and F. Attneave, 1970. What variables produce similarity grouping? *Am. J. Psychol.*, 83:1–21.
Papathomas, T. V., A. Gorea, A. Feher, and T. E. Conway, 1999. Attention-based texture segregation, *Percept. Psychophys.*, 61:1399–1410.
Portilla, J., and E. P. Simoncelli, 2000. A parametric texture model based on joint statistics of complex wavelet coefficients, *Int. J. Comput. Vis.*, 40:49–71.
Rao, A. R., and G. L. Lohse, 1996. Towards a texture naming system: identifying relevant dimensions of texture, *Vis. Res.*, 36:1649–1669.
Richards, W., and A. Polit, 1974. Texture matching, *Kybernetik*, 16:155–162.
Rivest, J., and P. Cavanagh, 1996. Localizing contours defined by more than one attribute, *Vis. Res.*, 36:53–66.
Rosenholtz, R., and J. Malik, 1997. Surface orientation from texture: isotropy or homogeneity (or both)? *Vis. Res.*, 16:2283–2293.
Rossi, A. F., R. Desimone, and L. G. Ungerleider, 2001. Contextual modulation in primary visual cortex of macaques, *J. Neurosci.*, 21:1698–1709.
Rubenstein, B. S., and D. Sagi, 1990. Spatial variability as a limiting factor in texture-discrimination tasks: implications for performance asymmetries, *J. Opt. Soc. Am. A*, 7:1623–1643.
Sceniak, M. P., M. J. Hawken, and R. Shapley, 2001. Visual spatial characterization of macaque V1 neurons, *J. Neurophysiol.*, 85:1873–1887.
Schofield, A. J., and M. A. Georgeson, 1999. Sensitivity to modulations of luminance and contrast in visual white noise: separate mechanisms with similar behavior, *Vis. Res.*, 39:2697–2716.
Schofield, A. J., and M. A. Georgeson, 2000. The temporal properties of first- and second-order vision, *Vis. Res.*, 40:2475–2487.
Sillito, A. M., K. L. Grieve, H. E. Jones, J. Cudeiro, and J. Davis, 1995. Visual cortical mechanisms detecting focal orientation discontinuities, *Nature*, 378:492–496.
Sutter, A., J. Beck, and N. Graham, 1989. Contrast and spatial variables in texture segregation: testing a simple spatial-frequency channels model, *Percept. Psychophys.*, 46:312–332.
Sutter, A., and N. Graham, 1995. Investigating simple and complex mechanisms in texture segregation using the speed-accuracy tradeoff method, *Vis. Res.*, 35:2825–2843.
Sutter, A., and D. Hwang, 1999. A comparison of the dynamics of simple (Fourier) and complex (non-Fourier) mechanisms in texture segregation, *Vis. Res.*, 39:1943–1962.
Sutter, A., G. Sperling, and C. Chubb, 1995. Measuring the spatial frequency selectivity of second-order texture mechanisms, *Vis. Res.*, 35:915–924.

Treisman, A. M., 1985. Preattentive processes in vision, *Comput. Vis., Graphics Image Processing*, 31:156–177.

Treisman, A. M., and S. Gormican, 1988. Feature analysis in early vision: evidence from search asymmetries, *Psychol. Rev.*, 95:15–48.

Treisman, A. M., and H. Schmidt, 1982. Illusory conjunctions in the perception of objects, *Cogn. Psychol.*, 14:107–141.

Turner, M. R., 1986. Texture discrimination by Gabor functions, *Biol. Cybern.*, 55:71–82.

Victor, J. D., 1988. Models for preattentive texture discrimination: Fourier analysis and local feature processing in a unified framework, *Spatial Vis.*, 3:263–280.

Victor, J. D., 1994. Images, statistics, and textures: implications of triple correlation uniqueness for texture statistics and the Julesz conjecture: comment, *J. Opt. Soc. Am. A*, 11:1680–1684.

Walker, G. A., I. Ohzawa, and R. D. Freeman, 2000. Suppression outside the classical cortical receptive field, *Visual Neurosci.*, 17:369–379.

Witkin, A. P., 1981. Recovering surface shape and orientation from texture, *Artificial Intelligence*, 17:17–45.

Wolfe, J. M., 1992. "Effortless" texture segmentation and "parallel" visual search are *not* the same thing, *Vis. Res.*, 32: 757–763.

Wolfson, S. S., and M. S. Landy, 1995. Discrimination of orientation-defined texture edges, *Vis. Res.*, 35:2863–2877.

Wolfson, S. S., and M. S. Landy, 1998. Examining edge- and region-based texture mechanisms, *Vis. Res.*, 38:439–446.

Wolfson, S. S., and M. S. Landy, 1999. Long range interactions between oriented texture elements, *Vis. Res.*, 39:933–945.

Yellott, J. I., Jr., 1993. Implications of triple correlation uniqueness for texture statistics and the Julesz conjecture, *J. Opt. Soc. Am. A*, 10:777–793.

Yeshurun, Y., and M. Carrasco, 2000. The locus of attentional effects in texture segmentation, *Nat. Neurosci.*, 3:622–627.

Zhu, S. C., Y. Wu, and D. Mumford, 1998. Filters, random fields and maximum entropy (FRAME)—towards a unified theory for texture modeling, *Int. J. Comput. Vis.*, 27:107–126.

Zipser, K., V. A. F. Lamme, and P. H. Schiller, 1996. Contextual modulation in primary visual cortex, *J. Neurosci.*, 16:7376–7389.