Integration of first- and second-order orientation

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The problem of how visual information such as orientation is combined across space bears on key visual abilities, such as texture perception. Orientation signals can be derived from both luminance and contrast, but it is not well understood how such information is pooled or how these different orientation signals interact in the integration process. We measured orientation discrimination thresholds for arrays of equivisible first-order and second-order Gabors. Thresholds were measured as the orientation variability in the arrays increased, and we estimated the number of samples (or efficiency) and internal noise of the mechanism being used. Observers were able to judge the mean orientation of arrays of either first- or second-order Gabors. For arrays of first-order and arrays of second-order Gabors, estimates of the number of samples used increased as the number of Gabors increased. When judging the orientation of arrays of either order, observers were able to ignore randomly oriented Gabors of the opposite order. If observers did not know which Gabor type carried the more useful orientation information, they tended to use the information from first-order Gabors (even when this was poorer information). Observers were unable to combine information from first- and second-order Gabors, though this would have improved their performance. The visual system appears to have separate integrators for combining local orientation across space for luminance- and contrast-defined features.

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1. INTRODUCTION

Many patterns in the visual world are primarily defined by modulations in luminance or contrast. The response of cells to luminance-defined patterns is typically described by a model employing linear filters.[1] The response of the visual system to contrast-defined patterns is typically described by a model in which there is a nonlinearity such as rectification sandwiched between two stages of linear filtering.[2–5] Several models of this type have been proposed to account for the ability of observers to see contrast-modulated spatial structure be it static or in motion (e.g., see Refs. 6–8). A model that estimates the spatiotemporal gradients present in an image has been useful in accounting for the perception of moving second-order stimuli (e.g., see Ref. 9). A similar model is capable of resolving static second-order structure; however, it has not been extensively applied to orientation discrimination performance.[10]

If contrast-defined structure is to provide useful information, then the visual system must be able to resolve the precise orientation of contrast modulations. When observers are asked to discriminate the minimum orientation difference from the vertical, thresholds for contrast-modulated patterns are higher than those for luminance modulations.[11] However, these thresholds depend on the spatial frequency of the contrast modulation and the duration of presentation. When the contrast modulation is presented at the optimum spatial frequency and for long durations (~500 ms), thresholds for luminance and contrast modulations are much closer, or even the same. The orientation of contrast-defined structure is therefore processed accurately by the visual system in many circumstances. However, in the natural world, to segment texture patterns the visual system must be able to estimate both average orientations and orientation changes. This places conflicting demands on the visual system: It must be able to factor out differences in orientation or features, by combining them, while keeping these differences available, e.g., to compute boundaries.

There is conflicting evidence as to whether this is possible. Second-order patterns will induce an illusionary tilt in an adjacent pattern to a similar degree as first-order patterns.[12,13] Similarly, Smith *et al.*[14] found that there are limited interactions between second-order textures over space. They measured the ability of observers to judge the orientation of either luminance or contrast modulations of binary noise and found that the perceived orientation of a contrast modulation can be influenced by the presence of a surrounding contrast modulation. They also found that the perceived orientation of a central contrast modulation can be influenced by a surrounding luminance modulation. The illusion induced by the second-order component of a pattern is, however, robust to many of the stimulus manipulations that destroy the first-order illusion, suggesting that it might reflect a different process. Similarly, adapting to the position of a second-order pattern will induce positional adaptation effects, as will adapting to a first-order pattern.[15] Unlike the effect of adapting to first-order patterns, the effects of adapting to second-order patterns will occur if the pattern is presented interocularly and decays slowly, consistent with a later or higher process than first-order adaptation effects.

This evidence is consistent with the idea that second-

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order orientation is resolved by a later process than first-order structure. Both first-order and second-order patterns show simple interactions over space. However, such studies have tested only local interactions, i.e., between two abutting stimuli. These types of interaction are insufficient to estimate the dominant orientation in a texture or the direction of a contour. In a test of far-reaching interactions, observers were unable to link the orientation of multiple second-order elements into a path or contour.[16] This suggested that second-order orientation information cannot be used to understand larger, more complex image features such as partially obscured contours or possibly texture boundaries. Observers are also poor at comparing multiple estimates of second-order motion[17–19] and stereo[20] when they are presented in different spatial locations.

Here we used observers' ability to judge the mean orientation of an array of Gabors to investigate whether information from multiple second-order elements can ever be combined. For first-order, luminance-defined patterns, observers' performance for discriminating the mean orientation of arrays of Gabors has been found to be almost as good as their performance judging the orientation of sine-wave gratings.[21] Performance is good when the task is to judge the orientation of a set of Gabors with similar orientation. Performance deteriorates as the orientations of Gabors are drawn from wider distributions of orientations. The rate that sensitivity decreases allows one to estimate the efficiency with which the observer is able to combine such information.

We use an equivalent noise[22] technique to describe the performance of observers when they judge the orientation of arrays of first- and second-order Gabors. This is a well-established technique for investigating both detection and orientation of one-dimensional and two-dimensional signals of varying complexity (e.g., see Refs. 23–26). Dakin[27] has shown that such a model describes observers' data well when they are performing this task. The equivalent noise model assumes that when observers' performance with noiseless stimuli is not ideal, internal noise is the reason. This internal noise is a combination of all the sources of uncertainty in making the response: errors encoding the stimulus, errors in the retinal signals, errors initiating a finger press, etc. When external noise is added to the stimulus, performance will deteriorate when the external noise exceeds the internal noise. In the case of our mean orientation task, in which observers are forced to average across many elements, a logical choice for the external noise source is the variability of the individual orientations themselves. At low levels of external noise (i.e., narrow orientation distributions), one need consider the orientation of only a very few elements to successfully perform a judgment of mean orientation. Thus performance is limited by, and therefore may be used to quantify, internal noise (the observers' uncertainty as to the orientation of each element). As the width of the orientation distribution increases, the orientation of elements becomes more variable, and this external noise swamps the effect of any uncertainty the observer has about the orientation of any one element. Observers are now forced to combine many orientations to estimate the mean, and the degree to which this strategy overcomes the orientation variability in the stimulus allows one to quantify sampling efficiency, or how many samples the observers are using. Thus we consider a judgment of mean orientation to be limited by two sources of variance, that of the internal noise and that of the external noise moderated by sampling efficiency. The relationship among internal noise, external noise, and efficiency (effective number of samples) can be expressed as

$$\sigma_{\mathrm{obs}} = (\sigma_{\mathrm{int}}^2 + \sigma_{\mathrm{ext}}^2/n)^{1/2}, \tag{1}$$

where σ_{obs} is the observer's threshold (standard deviation, see Section 2), σ_{int}^2 is the variance of the internal noise, σ_{ext}^2 is the variance of the external noise, and n is the number of samples. The equivalent noise model can be used to estimate the internal noise in and the number of samples taken by the visual system when observers are judging mean orientation.

For first-order orientation, observers are able to efficiently combine orientation information over the Gabor array[27] and, specifically, use a sample size that scales with the number of Gabors presented (suggesting an informational limit on the integration process). In this study we investigated whether this is also true for second-order, contrast-defined orientation information.

If similar performance is found with first- and second-order Gabor arrays, then it is possible that both types of orientation are combined over space by a common integrator. To investigate if combination occurs between these two types of signal, we also measured performance with arrays made of mixtures of first- and second-order elements.

2. METHODS

A. Observers

There were five observers. Three of these were the authors; the others were naïve as to the purposes of the experiment. All had normal or corrected-to-normal vision.

B. Equipment

The stimuli were presented on a Sony Trinitron 520GS monitor, driven by an ATI Rage 128 graphics card. The screen had a mean luminance of 33 cd/m^2. The programs for running the experiments were written on an Apple Macintosh G3 computer by use of the Matlab environment (MathWorks Ltd) and code from the Psychophysics Toolbox[28] and the VideoToolbox[29] packages. The monitor had a resolution of 1152 × 870 pixels and had a frame refresh rate of 75 Hz. One pixel on the screen was 0.32 mm^2. The screen was viewed binocularly at 52 cm. Pseudo-12-bit contrast accuracy was achieved by combining the RGB outputs of the graphics card by use of a video attenuator.[30] The nonlinear relationship between the voltage sent to the display and the luminance output to the screen was characterized with a Graseby S370 photometer and calibration routines from the VideoToolbox. The output luminance of the screen was corrected to linear by use of a look-up table. After calibration and correction, the linearity of the screen's output luminance was rechecked. An equal input voltage increment sent to the screen led to an equal luminance increment at the screen.

C. Stimuli

The stimuli were arrays of Gabor micropatterns. The modulation of each Gabor micropattern could be either first or second order. For both types of micropattern, the peak spatial frequency of the modulator (either luminance or contrast) was 0.7 cycles/deg, and the standard deviation of the Gaussian envelope was 0.4°.

The second-order Gabor micropattern was a contrast modulation (modulation depth 1) of a two-dimensional binary noise pattern. This noise pattern was windowed by the Gaussian envelope and had a peak contrast of 75%. The noise elements were 1 pixel in size. The second-order Gabors can be described by the equation:

$$L_{(x,y)} = L_{(\mathrm{mean})} + [1 + \cos(\alpha\theta + \phi)]RC_{(x,y)}\mathrm{env}, \quad (2)$$

where θ is the spatial frequency of the oriented modulation, α is the orientation, ϕ is the phase (randomized), $L_{(\mathrm{mean})}$ is the mean luminance of the screen, RC is a random distribution of $\pm L_{(\Delta\ \mathrm{max})}/2$, and env is the Gaussian envelope (0–1). Luminance profiles of the stimuli can be seen in Fig. 1 below. With narrowband carriers, an oriented contrast modulation can cause a change in the first-order orientation content,[31] however; this is the case only when the ratio of the spatial frequencies of the carrier and modulation are within approximately an octave. Although the carriers used here are binary and therefore spatially broadband, they have a white power spectrum and as such are perceptually dominated by their high-spatial-frequency structure. Because any first-order artifacts (also known as sidebands) must be affecting the low-spatial-frequency aspects of the carrier, they will be very low contrast and are likely to be invisible to observers. Dakin and Mareschal[31] proposed that the simplest way to confirm that no useful (i.e., oriented) first-order artifacts are introduced is to generate a phase-randomized version of the second-order stimulus. This has an identical power spectrum, and therefore sideband structure, but no useful contrast structure. We phase scrambled typical stimuli from the experiment and confirmed that no useful orientation information was present. This confirms that it is only second-order structure that carries useful orientation information in our stimulus. Finally, some authors have proposed that contrast modulations should be presented only with dynamic carriers; however, for orientation judgments, performance is the same for static and dynamic carriers.[32]

The first-order Gabor micropatterns were presented in the presence of a 75% contrast mask, to match the contrast of the carrier component of the second-order patterns. The first-order Gabors can be described by the equation:

$$L_{(x,y)} = L_{(\mathrm{mean})} + [R_{(x,y)} + C\cos(\alpha\theta + \phi)]\mathrm{env}, \quad (3)$$

where θ, α, ϕ, $L_{(\mathrm{mean})}$, and env have the same meanings as above, R is a random distribution of increases and decreases (with equal probability) in the noise contrast, and C is the contrast of the luminance modulation.

In each trial, typically, 16 micropatterns were randomly positioned in a circular array within the stimulus area. The contrast values of overlapping patches were summed. Gray levels falling outside the permissible range of the screen were clipped at the maximum or minimum gray level appropriately. Since patterns contained a high-contrast carrier, high-density textures would have a large number of clipped regions. For this reason, we limited the density with which the Gabor patches could be placed. The center of the distribution was the center of the screen, and the stimulus area was between 6° and 24° wide.

The orientation of the modulation in each Gabor micropattern was selected from a Gaussian distribution with a mean equal to the cued orientated (i.e., 90°± the cue generated by the adaptive probit estimation procedure, see below) and a variable bandwidth. The bandwidth standard deviation, σ, was varied from 0 (all elements aligned) to 32° (high orientation variability or noise). Figure 1 shows examples of first- and second-order stimuli with bandwidths σ=0°, 8°, and 24°.

D. Procedure

The experiments measured the ability of observers to discriminate whether the mean orientation of an array of

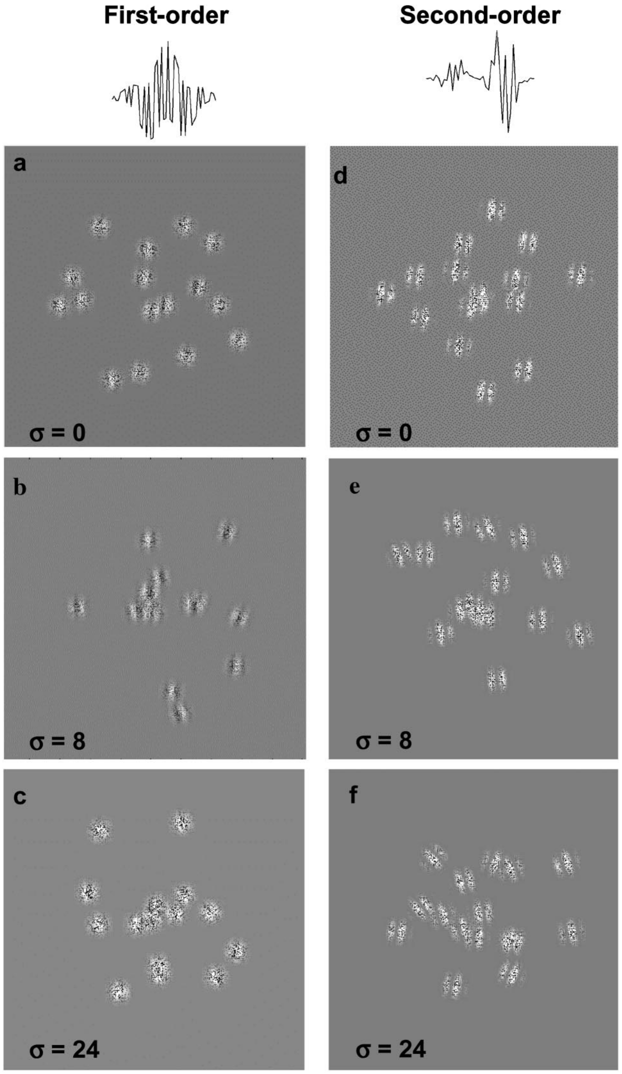

Fig. 1. Examples of stimuli: (a)–(c) Typical arrays of first-order and (d)–(f) second-order Gabors are shown. The orientation of each Gabor is drawn from a Gaussian distribution with standard deviation as shown in the leftmost column. Observers judged whether the mean orientation of all the Gabors in the array was tilted left or right of vertical.

Gabors was clockwise or counterclockwise of vertical. Prior to commencing the experiment, all observers were trained on the task until their performance reached a stable level (two or three runs).

The observers' task was a single-interval binary-forced choice. An array of Gabors was presented in the center of the display for 500 ms, and the observers were asked to judge whether the overall orientation of the texture was tilted right or left compared with their internal standard for vertical. Observers signaled their response with a key press. No feedback was given.

Performance was measured as the mean orientation of the generating orientation distribution of the micropattern array was varied around vertical. Adaptive probit estimation, an adaptive method of constant stimuli, was used to sample a range of mean orientations appropriate to each observer's performance.[33] A session consisted of up to 9 interleaved runs of 64 trials, one run for each of the orientation bandwidths tested. At least three runs were undertaken for each data point plotted. Data were pooled across all runs with each stimulus configuration and orientation bandwidth, and a bootstrapping procedure was used to fit a cumulative Gaussian function to the data. This procedure yielded estimates of the standard deviation (reciprocal of slope) and bias parameters of the fitting function. The term orientation threshold is used throughout to refer to the standard deviation of the best-fitting psychometric function. Estimates of the associated 95% confidence intervals were derived by using a bootstrapping procedure that pooled data across separate runs for a given observer.[34]

Observers showed little systematic bias on the task, and the data reported are based on the orientation thresholds with their 95% confidence intervals. The thresholds for each observer with each stimulus were fitted with an equivalent noise model to estimate the observers' internal noise and the number of information samples that they used for each task. Separate estimates of both internal noise and number of samples were made for each condition (radius, density, and combination of Gabor type). 95% confidence intervals for the model parameters were estimated from 1000 bootstrap replications. The reported 95% confidence intervals are the range containing 95% of the distribution of the replicated parameters (i.e., we did not assume a Gaussian distribution). Where parameters are described as significantly or not significantly different reflects a comparison of the appropriate confidence intervals.

E. Equating the Visibility of First- and Second-Order Gabors

Since we were interested in comparing the integration of local first-order signals with that of local second-order signals, we first ensured that performance levels were equivalent for isolated first- and second-order elements. We reduced the contrast of the first-order elements until orientation discrimination performance was equal to that found for isolated second-order elements. In so doing, we assumed that any loss of orientation resolution sensitivity that might occur with our isolated Gabors would not disadvantage our main task that exclusively involves integration of orientation. To achieve this, before the main experiment, we measured each observer's threshold for discriminating the orientation of an individual Gabor. The first- and second-order Gabors were as described above. One Gabor was presented in a random position within the stimulus area. The orientation of the Gabor was rotated clockwise or anticlockwise of vertical and was under control of adaptive probit estimation, as in the main experiment. The observers indicated with a key press whether the Gabor was oriented to the left or right of vertical, and an orientation threshold was estimated from the best-fitting psychometric function from their data.

The orientation discrimination threshold for second-order Gabors was measured at the maximum modulation depth. Orientation discrimination thresholds were measured for a range of luminance-modulation contrasts of first-order Gabors. As expected, for first-order Gabors, orientation discrimination thresholds increased with decreasing contrast. Figure 2 shows example data from one observer, with 95% confidence intervals (vertical bars). In the main experiment, second-order Gabors were always presented at their maximum modulation depth. The contrast of the first-order Gabors was adjusted to match orientation discrimination performance for second-order Gabors (25% or lower contrast).

3. RESULTS

Observers were always required to judge the mean orientation of arrays of first-order or second-order Gabor patches. In experiment 1, we varied the density and radius of the arrays of Gabors. In experiment 2, we investigated whether observers could ignore randomly oriented Gabors presented at the same time as the Gabors to be judged. Experiment 3 investigated what information the visual system uses by examining the effect of mixing first-order and second-order Gabors. The results of each experiment are now described in turn.

A. Experiment 1: Varying Density and Radius

For first-order Gabors, it has previously been found that increasing the density of Gabors within a fixed stimulus

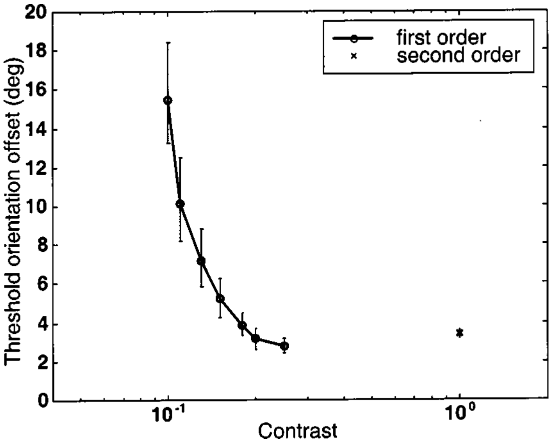

Fig. 2. Orientation discrimination thresholds for one Gabor. Data are shown for one observer, HAA. The discrimination thresholds for a range of contrasts of first-order Gabors are shown compared with the discrimination threshold for a second-order Gabor at maximum modulation depth.

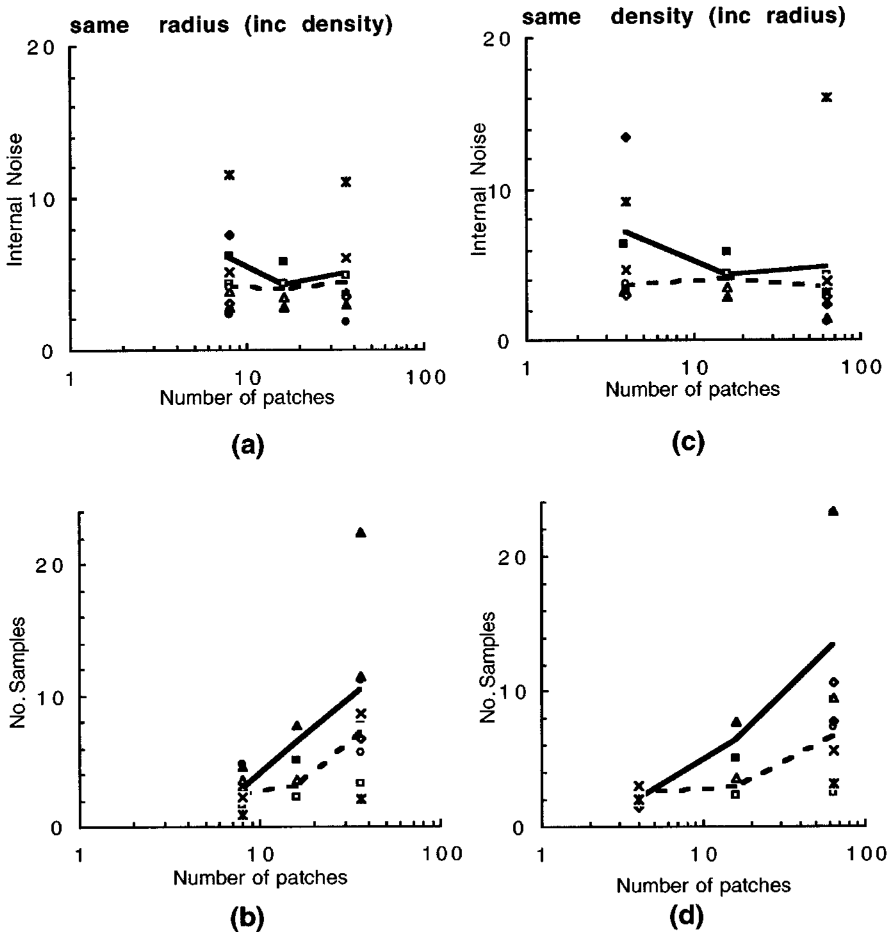

Fig. 3. Summary of parameters derived from fits of the equivalent noise model. (a),(b) Results of conditions in which the radius remained constant, so that as more Gabor patches are presented there is a corresponding increase in density. (c),(d) Results of conditions in which the density remained constant, so that as more Gabor patches are presented the stimulus area increased. (a),(c) show the estimated internal noise for the observers, and (b),(d) show the estimated number of samples used by the observers. In all four plots the parameter is plotted against the number of Gabor patches. Curves represent the mean estimate (solid, first order; dashed, second order). Points represent the estimated parameters from each observer. Each shape represents a different observer. Solid shapes and stars are data from first-order conditions; open symbols and ×'s are data from second-order conditions.

radius leads to increasing estimates of internal noise and of the number of samples taken by the observer.[27] Dakin[27] also found that when the density of first-order Gabors was fixed and the radius of the array was increased (thus increasing the number of samples present), observers performed as if they were using more samples. The aim of this first experiment was to investigate whether observers could combine orientation information from multiple second-order Gabors. To provide a comparison, we compared performance for multiple arrays of either first-order or second-order Gabors, equated for orientation discrimination performance at the single-element level.

Figure 3 summarizes the estimated parameters from the equivalent noise model. Each plot represents averaged and individual data from five observers. Each subplot plots the model parameter against the number of Gabor patches presented. Figures 3(a) and 3(b) summarize data from the conditions under which the radius of the array was constant; so as more Gabors were presented, the density increased. For both first-order (solid symbols and curves) and second-order (open symbols, dashed curves) Gabors, the estimate of internal noise [Fig. 3(a)] remains approximately constant. The estimated number of samples used by the observers increases with the number of patches presented [Fig. 3(b)]. Although the number of samples used is higher for first order than for second order and, as with previous studies, there are some interobserver differences, the difference between estimates for the two types of pattern is not significant.

Figures 3(c) and 3(d) summarize the results from the conditions under which the density was fixed; as more Gabor patches were presented, the radius of the array was also increased. The estimated internal noise [Fig. 3(c)] remained approximately constant for first-order Gabors (solid symbols). For second-order Gabors the internal noise was also approximately constant. For both first-order and second-order Gabors, the estimated number of samples [Fig. 3(d)] increases with increasing number of Gabor patches presented. The estimated number of samples is lower for second-order Gabors than for first-order Gabors, but, again, this difference is not significant.

For first-order Gabors, our results replicate those of previous research except that we find that, when the array radius is fixed, only the estimated number of samples increased. This discrepancy could be due to the fact that we used an added noise mask, and, as a consequence (to avoid clipping), we were restricted to lower densities than previously investigated. Observers are able to combine information from multiple second-order Gabor patches; furthermore, observers' ability to discriminate the mean orientation of arrays of second-order Gabors is similar to their ability to discriminate the mean orientation of arrays of first-order Gabors.

B. Experiment 2: Ignoring Randomly Oriented Gabors

Observers can judge the mean orientation of arrays of exclusively first-order or exclusively second-order Gabors. It is possible that the same, common integrator acts on both first-order and second-order patterns. It may be beneficial to combine estimates from the two types of pattern to achieve a more robust estimate of image properties. The next experiment was conducted to investigate whether this is the case. We compared performance in three different conditions:

1. Signal alone. Arrays (diameter 12.5°) of 32 signal Gabors. The orientation of signal Gabors was drawn from a Gaussian distribution centered on the mean orientation, exactly as described in Section 2 and used in experiment 1.
2. Signal plus random, different orders. Thirty-two signal Gabors were presented, as in condition 1, plus 32 random Gabors. The orientation of every random Gabor was reselected on each trial. When the signal Gabors were first order, the random Gabors were second order and vice versa.
3. Signal plus random, same order. Thirty-two signal Gabors plus 32 random Gabors, as in condition 2 except that the signal and random Gabors were either both first order or both second order.

Conditions were not interleaved so observers always knew whether the signal was carried by first- or second-order Gabors. If the visual system combines the information from signal and random Gabors, the estimated number of samples will fall. If some elements are randomly oriented and are combined to estimate mean orientation, there will be a decrease in the estimated number of samples, since only half (on average) the samples used actually contain orientation information. If the visual system is able to segment the pattern on the basis of Gabor type, then the estimated number of samples is expected to be the same with, or without, randomly oriented Gabors of a different order.

The results for these conditions are shown in Figs. 4 and 5. Figures 4 and 5 show the results when the signal was first order or second order, respectively. Each subplot shows orientation discrimination thresholds plotted for each width, σ, of the distribution of orientations in the signal distribution. The error bars are 95% confidence intervals. Also shown on each subplot are the estimated parameters for the equivalent noise model for each case.

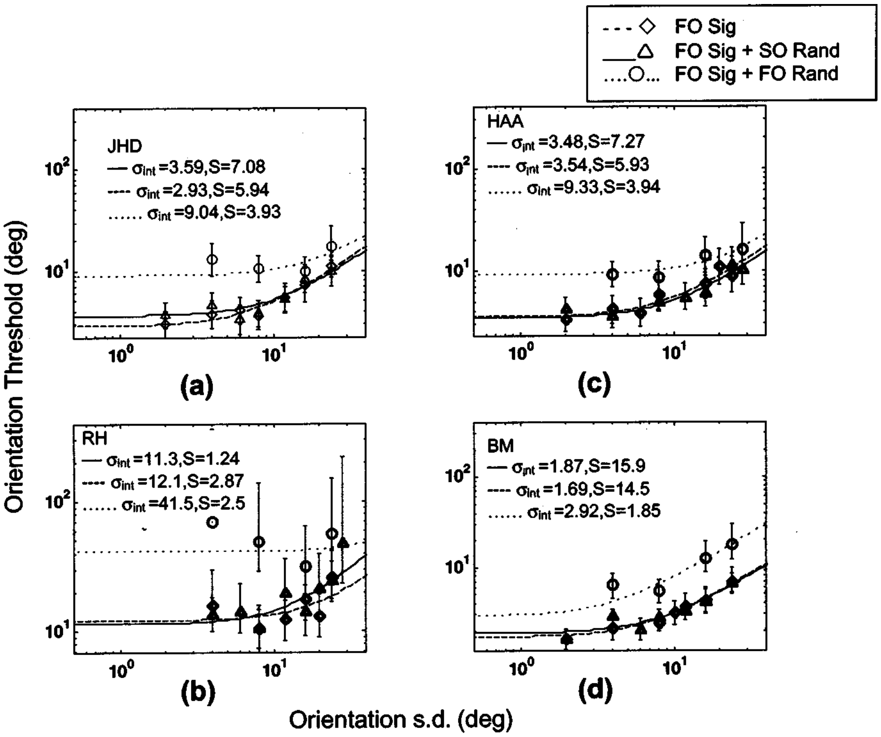

Fig. 4. Graphs comparing observers' performance judging the mean orientation of arrays of first-order Gabors with, or without, intermixed randomly oriented Gabors. Orientation thresholds were measured as the standard deviation of the distribution of orientations in the signal population increased. Each plot shows thresholds and the fitted equivalent noise model for performance when there were 32 first-order signal Gabors (dashed curves, diamonds) and 32 first-order signal Gabors and 32 second-order random Gabors (solid curves, triangles). The data from the case with 32 first-order signal plus 32 random first-order Gabors are summarized by the fitted function (dotted curves, circles). JHD: naïve observer. RH, HAA, and BM: authors. FO, first order; SO, second order; s.d., standard deviation.

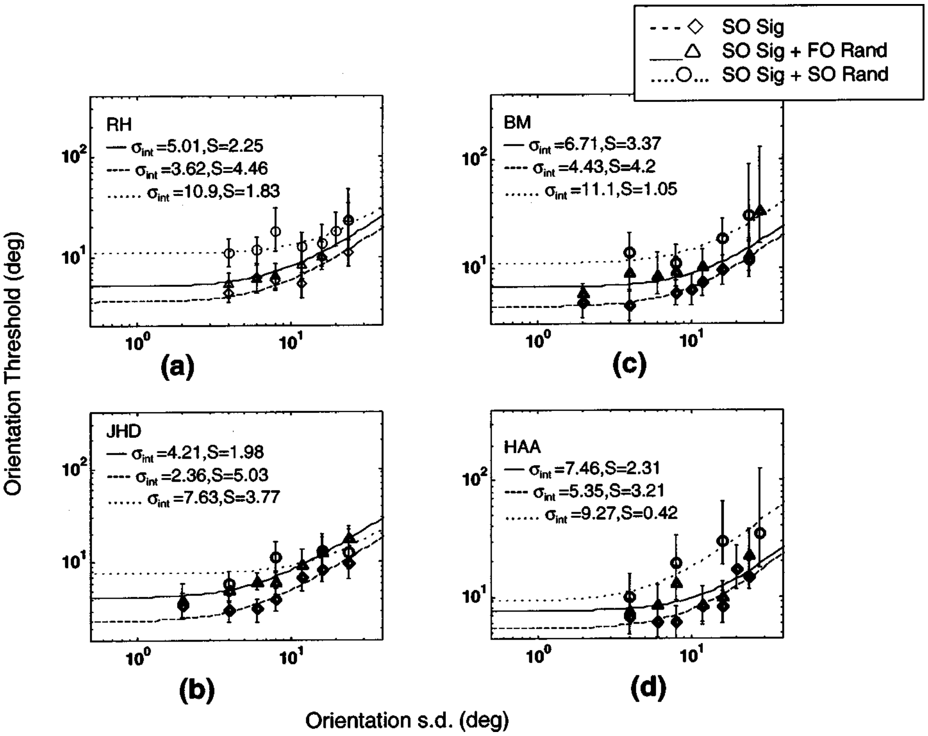

Fig. 5. Graphs comparing observers' performance judging the mean orientation of arrays of second-order Gabors either with or without intermixed randomly oriented Gabors. Orientation thresholds were measured as the standard deviation of the distribution of orientations in the signal population increased. Each plot shows thresholds and the fitted model for performance when there were 32 second-order signal Gabors (dashed curves, diamonds) and 32 second-order signal Gabors and 32 first-order random Gabors (solid curves, triangles). The data from the case with 32 second-order signal plus 32 random second-order Gabors are summarized by the fitted function (dotted curves, circles).

Adding randomly oriented second-order Gabors to first-order signal Gabors does not affect observers' ability to discriminate the mean orientation of the first-order Gabors (see Fig. 4). Performance with first-order signal plus random second-order Gabors (solid curve, triangles) is the same as performance with first-order signal Gabors alone (dashed curve, diamonds). If the visual system were unable to segment the image on the basis of type of Gabor or if there were some effect of the additional (nonoriented) first-order information in the random second-order Gabors, then we would predict that performance with first-order signal and random second-order Gabors would be similar to performance with both signal and random Gabors being first order (dotted curves, circles), since these also contain the nonoriented first-order noise. This is not the case.

When the signal Gabors were second order, the results are not so clear (see Fig. 5). Observers have the lowest estimated internal noise and highest number of samples when they judge the mean orientation of second-order signal Gabors alone (dashed curve, diamonds). When randomly oriented first-order Gabors are also presented (solid curve, triangles), the estimated number of samples decreases but is still greater than when both the signal and random Gabors are second order (dotted curves, circles).

The visual system seems able to judge the mean orientation of first-order Gabors in the presence of second-order Gabors. Our observers were less able to discriminate the mean orientation of second-order Gabors in the presence of first-order Gabors. This may reflect asymmetric interactions between two mechanisms or an interaction between first-order and second-order stages in one mechanism.

C. Experiment 3: Signal Choice

In the previous experiment, observers knew which type of Gabor contained the signal. In principal, they were able to use top-down processes to select the useful signal from the array. It is not clear, however, whether the selection was automatic and occurring at a low level or whether top-down processes were needed to segment the image. In this experiment, as in experiment 2, the arrays contained a signal distribution plus randomly oriented Gabors. When the signal Gabors were first order, the random Gabors were second order and vice versa. However, conditions with a first-order signal were randomly interleaved with conditions with second-order signal Gabors. All arrays contained the same number of both types of Gabor (32 of each), but which type contained the signal was randomly chosen on each trial (each with arrangement with $p = 0.5$). The observer did not know which type of Gabor contained the signal and which signals were randomly oriented; however, data from the two signal types were separated for analysis. Figures 6(a)–6(c) compare performance with 32 first-order signal Gabors (dashed curves, triangles) with performance with 32 first-order signal Gabors plus 32 random second-order Gabors (solid curves, diamonds). The presence of the random Gabors does slightly change the estimates of internal noise and number of samples, but this is not a significant change ($p < 0.05$, from comparison of the confidence intervals for the model parameters). Figures 6(d)–6(f) compare performance with 32 signal second-order Gabors alone (dashed curves, triangles) with performance with 32 second-order Gabors plus 32 random first-order Gabors (solid curves, diamonds). When the random Gabors are present, orientation discrimination thresholds are much higher than those for when the signal is presented alone. Estimates of internal noise are also much higher, and the estimated number of samples is much lower.

When observers do not know which order of Gabor is signal and which is randomly oriented noise, estimates of first-order mean orientation still seem immune to added second-order orientation (and its carrier). Observers do not seem, in this condition, as able to select only second-order orientation without top-down processes. This suggests that there is either a mismatch in the strength of the two signals or a bias toward one type of signal.

D. Experiment 4: Mixing First- and Second-Order Gabors

The visual system is able to estimate the mean orientation of arrays of both first- and second-order Gabors. This experiment was designed to investigate whether information from first- and second-order Gabors can ever be combined. In some situations it is to be expected that first- and second-order information provide similar information about a surface and combining information from the two sources would be advantageous. Recall that results from experiment 1 indicated substantial changes in sampling when the number of elements changed from 32 to 64 [see Figs. 3(b) and 3(d)] so that we could be confident that if subjects were combining across both first- and second-order patches then this would show up clearly in the parameters derived from the equivalent noise model. Observers judged the mean orientation of arrays containing 32 first-order plus 32 second-order Gabors, and the orientations of all the Gabors were drawn from the signal distribution as described in Section 2. If the visual system is not able to combine the first- and second-order Gabors, then the estimated number of samples from the combined array will be similar to the estimated number of samples from 32 first-order or second-order Gabors alone. Figure 7 shows the mean orientation discrimination thresholds for each σ of the distribution of Gabor orientations. Performance when there were first- and second-order Gabors combined (solid curves, diamonds) was close to performance with either the first-order or the second-order Gabors alone (dashed curves, triangles). It seems that the observers were unable to combine the information from first- and second-order Gabors, even though that would have improved their performance.

It is reasonable to ask what would be predicted if first- and second-order information was combined. One prediction is that the observer would produce the same per-

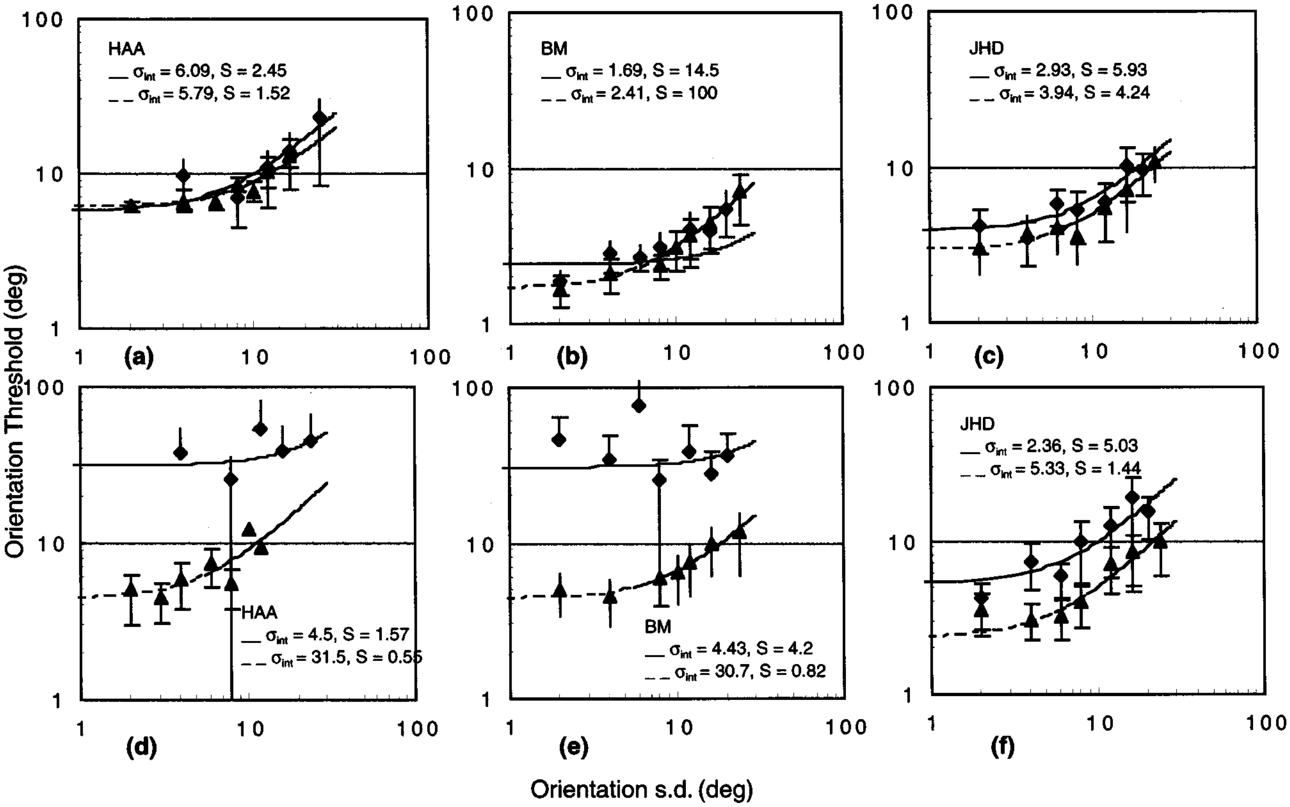

Fig. 6. Graphs comparing observers' performance judging the mean orientation of arrays of Gabors with, or without, randomly oriented noise Gabors of the opposite order being present. Observers did not know whether the first-order or second-order Gabors were the signal Gabors. Orientation thresholds were measured as the standard deviation of the distribution of orientations in the signal population increased. Each plot shows thresholds and the fitted model for performance when there were 32 signal Gabors (dashed curve, triangles) compared with 32 signal Gabors plus 32 noise Gabors (solid curves, diamonds). (a)–(c) Conditions when the signal was first order (noise was second order). (d)–(f) Conditions when the signal was second order (noise was first order).

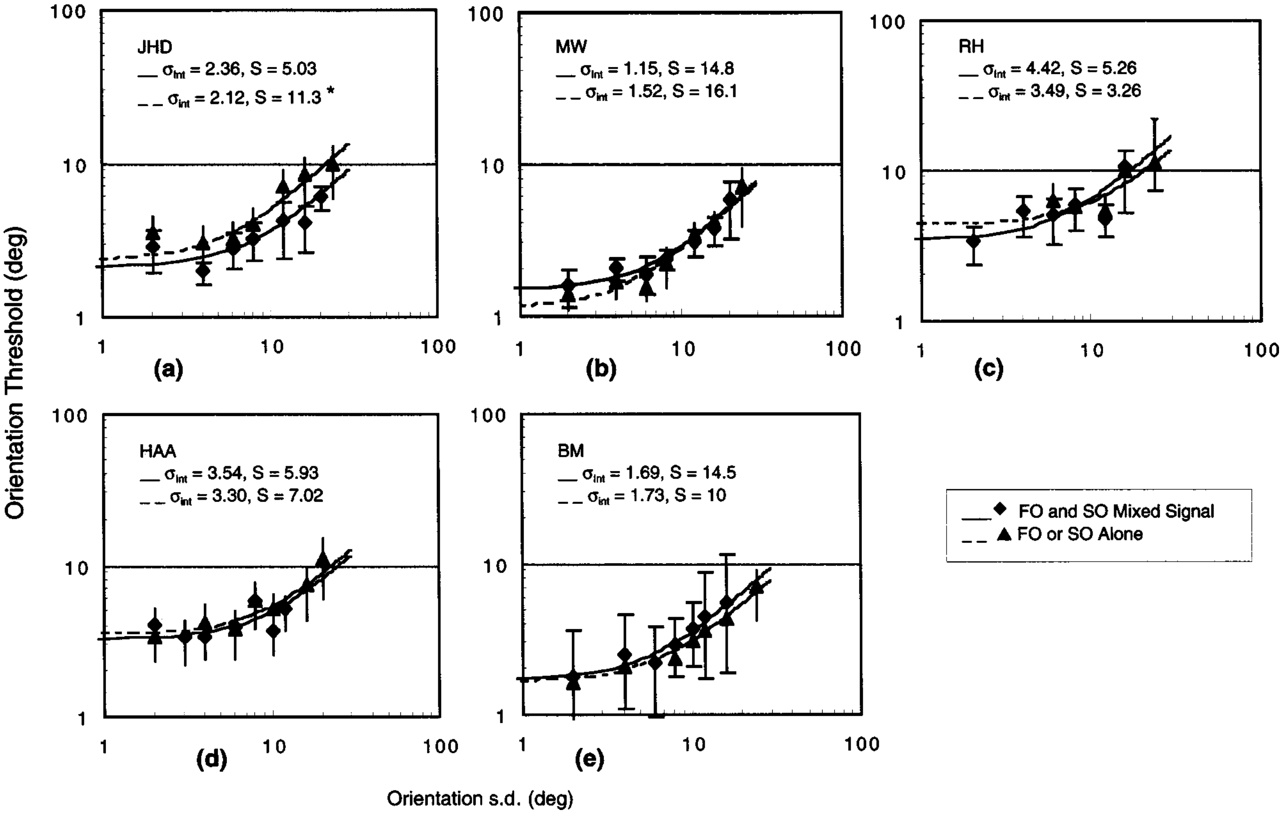

Fig. 7. Graphs of observers' performance judging the mean orientation of arrays containing either 32 first-order or 32 second-order Gabors (dashed curves, triangles) and their performance judging the mean orientation of arrays containing both 32 first-order and 32 second-order Gabors (solid curves, diamonds). Orientation thresholds were measured as the standard deviation of the distribution of orientations in the signal population increased. Each subplot shows a different observer's data. Performance in the mixed Gabor condition is compared with performance with 32 first-order Gabors for HAA, BM, and MW (naïve observer) and with 32 second-order Gabors for JHD and RH (see text).

formance as when they had 64 Gabors of one order. To make this assumption, one has to assume that there are both a perfect combination and an equal quality of information from both types of Gabor. Since we found that individuals had slightly different mean orientation performance for first- and second-order arrays of Gabors, these did not seem valid assumptions. From experiment 1 we do know, however, that for both first- and second-order Gabor arrays, as the number of Gabors increases from 32 to 64, the effective number of samples used by the visual system also increases. So, if the visual system were able to combine the mean orientation of first-order and second-order Gabors, we would expect the estimated number of samples to be greater for the mixed arrays than for 32 Gabors alone. We find that only one observer's (JHD) estimated number of samples is significantly greater ($p < 0.05$) for the mixed stimulus than for 32 Gabors alone (indicated by an asterisk on Fig. 7).

A second, related argument also supports the argument that the visual system is not combining the information from first- and second-order Gabors. The estimated internal noise of the observer reflects observers' performance with stimuli in the absence of external noise. Estimated internal noise is different for arrays of first- and second-order Gabors, although which one provides a lower estimate depends on the observer. If the visual system uses one type of Gabor, then we might expect that, given a combined stimulus, each observer should use the order of Gabors that gives the lower estimate of internal noise. Figure 7 plots thresholds and a fitted equivalent noise model for the combined stimulus with data from arrays of either 32 first-order or 32 second-order Gabors, whichever had the lower estimated internal noise. The estimated internal noise from the combined array is the same as the estimated internal noise from the array with only one order of Gabors. Furthermore, the estimated number of samples is also the same in these two conditions.

When presented with arrays of both first-order and second-order Gabors, where all the Gabors contain useful information, the visual system does not use information from both types of Gabor. The visual system may even estimate mean orientation from the order of Gabor that produces the lower internal noise.

4. DISCUSSION

We investigated whether observers could judge the mean orientation of arrays of Gabors, a task requiring that the visual system combine local estimates of orientation across space. Observers were able to judge the mean orientation of arrays of either first-order or second-order Gabors. When presented with arrays containing both first-order and second-order Gabors, observers were able to estimate the mean orientation of either first order or, to a lesser extent, second order, ignoring the other order. Observers seemed unable to effectively combine information from first- and second-order Gabors or to automatically select the Gabor type that contained the signal information.

Figure 8 shows four possible schema of how first- and second-order mean orientation could be estimated by the visual system. Each possible arrangement begins with filters tuned to the local first-order orientation, and the second-order channel also has filters tuned to the local second-order orientation (local processing). The last stage of each model is always an estimate of mean orientation. The right column of Fig. 8 summarizes whether this model is plausible given our data. First-order-only processing, suggested by the noncombination of information from multiple patches of second-order motion [Fig. 8(a)] and blind combination [Fig. 8(b)] are easily ruled out by our data. Observers can discriminate the mean orientation of arrays of first- and second-order Gabors [Fig. 8(a)] and can base their judgments on either order selectively [Fig. 8(b)]. Observers can use either first- or second-order Gabors but do not completely ignore first-order Gabors. This result seems inconsistent with an either–or process [described by Fig. 8(c)] by which the mean orientation of either first-order or second-order local information is computed; however, the second-order channel does also process first-order information (the carrier), which could explain this result. However, since the strength of the local signal was matched (in terms of the orientation discrimination of individual Gabor elements) for first and second orders, it is not clear on what basis the visual system would choose to use either first- or second-order local information.

Figure 8(d) shows separate first-order and second-order integrators for mean orientation. This allows the strength of the mean orientation output signal to be different for first- and second-order patterns. The two mean orientation estimates are subject to an OR combination before the final estimate of mean orientation. Which of the two mean orientation signals is used is controlled by the relative strengths of the outputs from first- and second-order integrators and by top-down modulating processes. Normally, the output of the first-order integrator is stronger or preferred. This scheme accounts for observers' ability to judge the mean orientation of arrays of either first- or second-order Gabors and to selectively exclude information from one or the other type of Gabor.

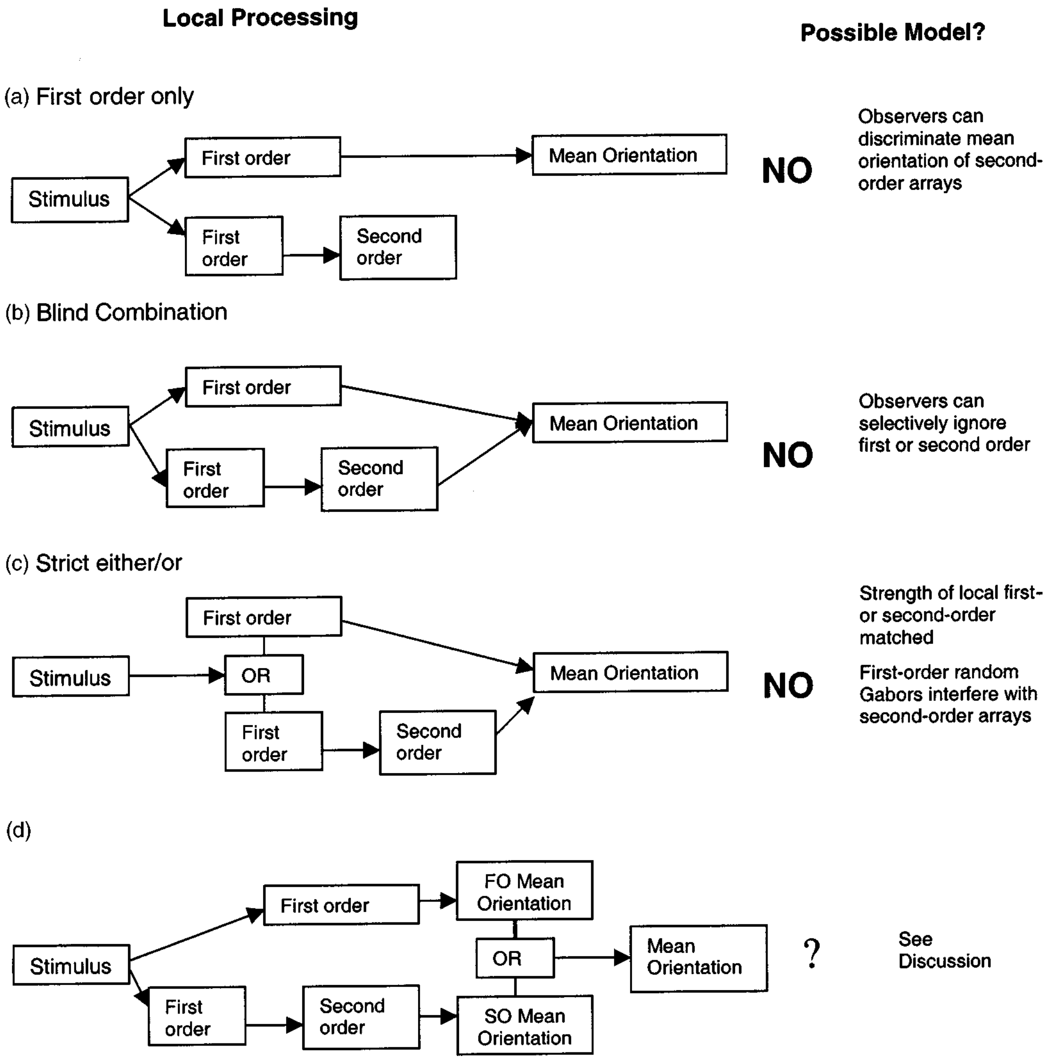

Fig. 8. Summary of possible mechanisms underlying the judgment of mean orientation.

Because the output of the first-order mean orientation unit is stronger or preferred, this accounts for observers' tendency to use only first-order Gabors when they did not know which order of Gabor carried the useful information. Furthermore, when observers were asked to ignore the first-order Gabors, they did this imperfectly because of the stronger signal or preference from the first-order mean orientation integrator and the processing of first-order structure by the first stage of the second-order channel. Similarly, when both first- and second-order Gabors signal the same mean orientation, performance is based on one type of Gabor, but it is possible that some information from the other type of Gabor can be accessed.

These results are relevant to three questions; each will be discussed in turn. First: Can second-order information be combined over space? Second: Is information from first-order and second-order stimuli analyzed separately by the visual system? Third: Does the visual system segment the image on the basis of the order of the signal?

A. Spatial Interactions between Second-Order Stimuli

It is clear from our results that second-order information from multiple patches can be combined over space. Smith and colleagues[14] have previously shown that the mechanism that processes second-order (contrast-defined) stimuli is capable of producing the same repulsion- and attraction-tilt illusions found for first-order stimuli. They proposed that the mechanism that processes second-order orientation, although being slightly higher in the processing stream, is of the same type of mechanism as the mechanism for first-order stimuli.

The tilt illusion is likely to be due to horizontal, inhibitory connections between orientation-selective cells.[35–37] The estimation of mean orientation may not involve inhibitory connections but is likely to involve lateral connections between multiple cells. It has been shown that there are considerable excitatory and inhibitory connections between orientation-selective cells. Furthermore, the nature of the interactions can depend to a large part on the exact properties of the stimulus.[37] Thus it seems likely that these same connections exist between cells responsive to second-order contrast-defined structure.

One finding seems to conflict with the idea that second-order orientation information is combined over space, and that is the failure of observers to identify contours of second-order elements.[16] It has been proposed that contours are analyzed by "association fields."[38] It is possible that association fields represent a process different from the lateral interactions involved in mean orientation estimation or the tilt illusion. Contour integration is sensitive to increasing levels of position uncertainty,[39] whereas judging mean orientation, almost by definition, discards information about the position of pattern elements. Furthermore, orientation is averaged over pattern elements, irrespective of polarity,[40] whereas previous studies found that elements of alternate polarity do not form contours as well as elements of the same polarity.[41,42] It is clear from the present findings that the visual system's failure to link oriented second-order elements into contours represents a special case failure of second-order processing rather than a general failure to undertake global operations on the orientation of spatially distributed elements. From a functional perspective, it may be that contour structure in natural images is largely conveyed by luminance information, whereas texture could be conveyed by a variety of cues including, but not limited to, contrast-defined and luminance-defined form.

B. Combination of First- and Second-Order Orientations

We also find that information from first-order and second-order patterns is available separately to the decision processes. Models of the first- and second-order visual mechanisms usually assume that information from the two types of stimulus is combined. For moving patterns, for example, when information from first- and second-order structures is low quality, the two sources can combine to improve spatial-frequency discrimination.[43] However, in other circumstances, such as when there is global motion of first- and second-order structures, the two sources of information do not combine to improve performance.[44]

For static patterns, several authors have shown that first-order and second-order orientation information interacts. These studies can be divided into two camps. First, there are studies that have investigated the interaction between luminance-defined and contrast-defined components of the same object, which might be considered to be interactions between the two stages of a filter-rectify-filter-type model. Second, there are investigations of interactions across space between separate first- and second-order contours. We will deal with these in turn.

First, the perceived orientation of a second-order envelope in a pattern is influenced by the orientation of its carrier.[45,46] In these studies, observers judged the orientation of the high-spatial-frequency first-order components or the low-spatial-frequency second-order component of the same patch. First- and second-order orientation information is not kept separate; indeed, it is inextricably connected, and it is unsurprising that there are interactions. The experiments reported here, however, addressed the interactions between first- and second-order patterns of the same spatial frequency but at different visual field loci, after the orientation of local second-order structure has been resolved.

When first-order and second-order modulations of the same spatial frequency are presented at the same visual field locus, second-order modulations will mask first-order modulations.[47] Similarly, both first-order and second-order modulations will bias the perceived orientation of the other type of modulation.[14] To account for the masking data, Schofield and Georgeson[47] proposed a two-pathway model with energy summation between separate first- and second-order pathways. A two-pathway model followed by a combination process also accounts for the tilt illusion between first- and second-order patterns[14]; one pathway processes only first-order information, and the other pathway processes first- and second-order information. Consistent with this, we find that observers are sometimes unable to completely ignore first-order random

Gabors when they are judging the orientation of second-order Gabors. Both first-order and second-order Gabors contain binary noise, which may be processed by the early stage of the pathway that processes second-order structure, adding to its internal noise. There are likely to be horizontal connections between cells in each pathway, as described above, but the two mechanisms may not be interconnected. Possible reasons for this are discussed in the Subsection 4.C.

C. Does Order Segment the Image?

Our results show that estimates of mean orientation seem to keep first- and second-order information separate. Even when it would be advantageous to do so, the observers do not fully combine the two sets of information.

The tilt illusion is reduced when the inducing and test patterns are clearly segregated.[48] This suggests that the segmentation of the image influences how orientation signals are combined. Taken with our results, this might suggest that the visual system has a tendency to segment first-order from second-order information.

It must also be considered that first- and second-order information may be segmented not because of specific processes for these types of pattern. Rather, this might arise from other processes. Patterns of different spatial frequencies are easily segmented. In our stimulus, only the first-order stimulus contained a low-frequency (luminance-defined)-oriented contour. Simple linear filters could easily discriminate between the two stimuli (although not resolve an oriented signal from the second-order stimuli). The output of these early filters could be used to determine whether orientation signals are treated as if they come from one object or are assigned to different objects. This would lead to the two types of pattern being treated as if they were separate image objects. The current experiments cannot distinguish between whether segmentation occurs on the basis of order directly or as a by-product of another stimulus attribute.

The fact that first- and second-order orientation signals are not combined across space with a common integrator may, however, follow from the statistics of natural images. Only if there is a strong correlation between like orientations of luminance- and contrast-defined features within the same region of the image would it be useful to combine such estimates.

D. Conclusion

We find that observers are able to judge the mean orientation of arrays of contrast-defined, second-order Gabors. It is likely that similar, but separate, processes underlie the estimation of mean orientation for first- and second-order patterns.

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