

The psychophysics of texture segmentation.

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Abstract

Julesz considered texture discrimination as the “royal road” to understanding preattentive (subconscious) pattern discrimination. A distinction was made between image-driven preattentive processes and task-dependent attentive (conscious) processes in vision, resulting in three decades of successful research into the structure of early visual processes. Here we will consider the conflict inherent to texture segmentation tasks: the need for global analysis of textural properties, on one hand, and the requirement for texture border localization, as a marker for object boundary, on the other hand. Current models assume four essential processing stages: (1) Local filtering followed by a pointwise nonlinearity (feature extraction), (2) Spatial integration (averaging) followed by local inhibition (gradient detection), (3) integration of gradients across different filter scales and orientations and (4) Decision stage. Though successfully implemented, these models fail to account for some specific cases (asymmetric performance) where textures with equal power spectra have to be discriminated. Models have to be also modified to account for learning phenomena in texture based tasks. Recent experimental results indicate that ‘early vision’ processes can learn new spatial configurations by using simple local learning rules, thus allowing for global shape properties to affect segmentation performance.

Introduction

Texture segmentation involves breaking an image into different regions having some internal regularities. The first attempt to understand perceptual processes involved in texture segmentation was made by Julesz (1962), who also constrained the problem to early vision. Technically, this was made possible by using meaningless high contrast random dot patterns, exposed briefly (for less than 160 msec and followed by visual noise) so as to avoid eye movements. It is assumed that shortening stimulus duration does not affect acuity so much as it avoids high level (top-down) processes having a high degree of complexity. Experimental results show that human observers can locate some texture boundaries within this brief presentation time even when visual attention is not available for the task (Braun & Sagi 1990). Most experiments involving textures were designed to find the differences that make textures discriminable, or their boundary (when put next to each other) detectable. Theories of texture perception differ in the similarity measure they adopt to predict discrimination. Since textures can be only statistically defined (within a given area), the task of texture border localization imposes contradicting demands on the mechanisms involved, and probably involves processes operating on different scales. Different scientific approaches to human texture segmentation differ in the scale they adopt for the problem. Early texture models attempted to define global texture properties that would enable discrimination between two given textures. Julesz (1962) defined the problem in statistical terms thus using global concepts to account for human performance. Only later, after discovering the limitations of global accounts (Julesz 1980), along with the introduction of local geometric features into the texture process (Beck 1982; Caelli & Julesz 1978; Julesz 1981), was the emphasis shifted to local processes. However, these local “feature” or “texton” detectors were assumed to be followed by a global process, which computes their global statistics (Julesz 1981; Treisman 1985). Global statistics can be useful for texture discrimination, however, segmentation requires border localization and thus some recovery of the lost location information by a top-down, probably attentive, process. As texture segmentation and boundary localization seem to be carried out without visual attention

(Braun & Sagi 1990) and without any detailed ‘feature’ processing (Sagi & Julesz 1985; Nothdurft 1993), models assuming global statistics of local features should be rejected. Later theories assumed a local “textural gradient” detection stage, thus avoiding global processes (Beck 1982; Nothdurft 1985ab; Sagi & Julesz 1985, 1987), or transferring it to the final decision stage (Rubenstein & Sagi 1990) and keeping a simple feed-forward design. These recent theories of texture segmentation assume a few processing stages which are not strictly local. The different processing stages involve integration over different spatial extents, with the range of interaction increasing hierarchically.

A theory of texture segmentation

Here we assume two filtering stages with a nonlinearity in between (Bergen & Adelson 1988; Fogel & Sagi 1989; Landy & Bergen 1991; Malik & Perona 1990; Rubenstein & Sagi 1990; Sutter, Beck & Graham 1989). At the first filtering stage the classical spatial filters (Daugman 1980; Wilson & Bergen 1977) are being used. Second stage filters are defined as linear spatial filters and in most implementations are assumed to perform isotropic local bandpass filtering on a scale somewhat larger than that of first stage filters. Using well defined linear filters as major ingredients makes the analysis of these models simpler and allows for quantitative predictions. These models can be designed to account for human performance on psychophysical tasks. I emphasize the psychophysical task since it plays a major role in the success of any model and it is being ignored in most models. Modeling the psychophysical task was made possible by the availability of a large amount of psychophysical data from Four-Alternative-Forced-Choice (4AFC) experiments carried out by Gurnsey and Browse (1987). Rubenstein and Sagi (1990) added a simple decision stage to the two filtering stages in an attempt to model the 4AFC task and to derive percentage of correct response as model prediction. Their model assumes four processing stages (Figure 1):

Insert Figure 1 about here

1. Filtering: The input image is being filtered by localized spatial-frequency

and orientation selective filters like Gabor filters. A pointwise nonlinear operation is being applied at the filters' outputs. Possible nonlinearities may include squaring of filter output to provide an energy measure (Turner 1986; Fogel & Sagi 1989), a compressive nonlinearity (Caelli 1985) or both (Rubenstein & Sagi 1990). The output of this stage consists of a large number of filtered images (maps).

2. Gradient detection: Each filter map is being filtered again using a low resolution isotropic bandpass filter. A classical center-surround (DOG) filter can be used here. This second stage of filtering can be viewed as a two stages process: energy integration across space (averaging), resulting in a 'texture energy' measure, followed by a gradient detection (local inhibition). This filtering operation results in enhanced activity in locations where local filter energy changes.
3. Combination stage: All filter maps are combined into one master map where gradients from all maps are represented. The combination process may not necessarily imply summing up responses across maps, however, it does imply the loss of identity or label of individual maps.
4. Decision stage: Given the responses generated by the previous combination stage, a decision has to be reached in order to fulfill the psychophysical task.

All model processing stages are based on current knowledge of the visual system, however the application of this knowledge to problems involving texture discrimination and search is controversial.

The first filtering stage

The first stage consisting of spatial filters is being objected by popular feature-based theories (Julesz 1989; Treisman & Gelade 1980). In addition, data from search experiments support the notion that orientation and spatial-frequency are processed separately and can be conjoined only by attentive processes (Walters, Biederman & Weisstein 1983), while our model predicts a conjoined processing of both dimensions. However, these experiments were using the Treisman and Gelade

(1980) search paradigm where nontarget elements are of two types, thus producing irrelevant feature gradients in the background. This would confuse the decision making stage since it relies on gradient information only and not on filter label. Sagi (1988), using a modified stimulus without background gradients, showed that the conjunction of orientation and spatial-frequency can be effortlessly detected.

The second stage of filtering

Evidence for a second stage of filtering comes from experiments concerning the perceived contrast of suprathreshold patterns (Cannon & Fullenkamp 1991; Chubb, Sperling & Solomon 1989; Sagi & Hochstein 1985) and the detection of low contrast targets in the presence of spatially displaced masks (Polat & Sagi 1993). This stage can be viewed as consisting of local inhibitory connections between adjacent spatial filters having similar properties. These connections are assumed to operate above filter threshold only and their spatial range scales with filter size so that they connect filters separated by a distance of at most six times their typical wavelength (Polat & Sagi 1993; Sagi 1990). Polat and Sagi (1994a) also showed that second stage interactions are not isotropic but rather concentrated along the first stage filter orientation and a direction orthogonal to it. Note that at this stage only filters having similar properties are connected to each other, thus gradients are measured for each filter type separately. It is still possible that filters with different properties interact. Rubenstein and Sagi (1993), using periodic Gabor textures, found some evidence for non-isotropic excitatory interactions between filters having orthogonal orientations. These interactions seem to extend over a range somewhat larger than the in-between-same-type excitatory interactions. Interactions between spatially adjacent filters of different orientations can contribute to the detection of orientation gradients and are consistent with the experimental results of Nothdurft (1985ab, 1991, 1993). In the model described here in-between-different-type filter interactions are not assumed.

The combination stage

The end product of the second filtering stage (stage 2 above) consists of many filter gradient maps, each indicating local energy changes within a specific

spatial-frequency and orientation band. This representation contains labeling of both the locations and the identity (the specific band) of gradients. In order to account for the insensitivity of the texture segmentation process for feature identity (Sagi & Julesz 1985) we have to collapse all maps into a single master map where each location signals a combined local gradient value. Experimental evidence supporting the existence of a master map comes also from studies showing interference in tasks involving two or more maps (Nothdurft 1993; Pashler 1988; Sagi 1991; Wertheim 1981). This end product has similar properties to that of a feature gradient map, although without performing local comparisons between detectors having different feature values (there is no direct measurement of local orientation differences). The saliency map suggested by Koch and Ullman (1985) represents a similar concept.

The decision stage

Finally, we need a decision stage in order to generate a response, a stage that is a necessity in all psychophysical models. This stage is task dependent and has access to the combined map only. Detection of a texture target can be carried out by looking for above threshold activity in the combined map, localization of a texture target can be performed by looking for the location having highest activity (strongest gradient). This stage is the only stage having access to all locations in the visual field and thus has the ability to perform global computations. These computations may involve assigning different weights to different locations according to the statistical reliability of the activity at the different locations. However, since filter labels (orientation and spatial frequency) are lost in the previous stage, there is no way to differentially weight different filter maps (Sagi 1991).

Insert Figure 2 about here

Theory prediction and experimental data

The success of the model can be judged according to its ability to predict human performance on texture discrimination tasks. We claim that linear filters with the nonlinearities introduced in stages 1 and 4 can replace the geometric feature detectors suggested before (Caelli & Julesz 1978) to account for the discriminability of iso-second order statistics textures. Turner (1986) showed that some texture pairs having the same second order statistics, and hence power spectra, may produce filter responses (Gabor energy) with different first order statistics. Fogel & Sagi (1989) used the Gabor energy measure to compute filter response differences between target and background elements in search tasks. Calculations based on this energy measure were applied to stimuli used by Kröse (1987) and were compared with Kröse's experimental data yielding an excellent correlation. However, among the twelve target-background pairs tested one was found to be an exception; the model predicted no discrimination while psychophysically the pair was discriminable. This pair, consisting of triangular and arrow shaped elements (Figure 2), was shown to generate texture pairs having iso-dipole statistics (Caelli & Julesz 1978) and, as can be appreciated from the energy curves in Figure 2, have the same energy only when *energy is averaged across all orientations*. The failure of the Fogel and Sagi (1989) computations to account for this specific iso-dipole case resulted from the use of global energy averages; since orientation was randomized across space in the Kröse (1987) experiments energy was averaged across all orientations without taking into account local energy variations. Once local energy variations are considered, one can base detection on the observation that the target energy differs from its neighboring elements' energy in most occasions. Thus local energy differences can contribute to the detection process. However, once gradients are considered one may expect false gradients to occur between adjacent background elements, forcing us to use a decision rule which separates signal from noise.

Insert Figure 3 about here

Rubenstein and Sagi (1990) analyzed the statistical distribution of local en-

energy gradients in connection with the signal detection problem posed by the psychophysical task. In particular they modeled the Four-Alternative-Forced-Choice task used by Gurnsey and Browse (1987). In this task the observer had to indicate the display quadrant in which the foreground texture was most likely to appear. Gurnsey and Browse (1987) tested 18 texture pairs in psychophysical experiments, taking every pair twice by using each pair member as foreground element and background element in turn (totaling 36 cases). Most importantly, they found that exchanging pair members between foreground and background can have a dramatic effect on psychophysical performance. Since this exchange does not affect the energy difference at the foreground-background border, this finding may be taken as evidence against any spatial gradient-based model, including ours. However, as noted above, energy differences at the foreground-background border have to be considered in respect to energy differences existing in the background (the signal detection problem), thus performance should depend on background properties allowing for the foreground-background symmetry to be broken. Rubenstein and Sagi (1990) found that the most important source for background variability is the orientation randomization employed in most texture experiments. Using Gabor energy distributions across orientation at different spatial frequencies, they were able to model the Gurnsey and Browse (1987) findings (Figure 3). The computations of this model rely heavily on the conjoined dependence of filter response on spatial-frequency and orientation. What is relevant for discrimination is the low-frequency part of the energy spectra where filter wavelength is approximately equal to texture element size. At this wavelength different elements have different energy distribution across the orientation spectra, and in most cases these distributions have different averages. Figure 2 shows a case where the average energies across orientations are equal but the energy variance is different, thus the element having a flat energy curve will create a uniform background while the other one will create a noisy background (when randomly oriented). Since most textures used by Gurnsey and Browse (1987) are best discriminated by the same range of spatial frequencies the model predictions are not very sensitive to the assumptions made on the combination map (processing stage 3). While the Rubenstein and Sagi (1990) analysis considers the signal-in-noise problem within a single map

(both signal and noise are in the same filter map), the combination stage predicts that detection is affected by noise in other maps. Recent experimental results indicate also the existence of inter-map interactions (Rubenstein & Sagi 1993).

Something is still missing

While the histograms depicted in Figure 3 show a nice qualitative fit between theory and data, some critical problems are still left open. Asymmetry in performance exists also in cases where texture elements orientation is not randomized. For example, consider the detection of tilted line segments (foreground) in a background of vertical line segments, here, an exchange of the foreground and background elements produces a decreased performance level (Treisman & Gormican 1988; Foster & Ward 1991). Size based texture segmentation shows also an asymmetric performance, with the larger texture elements being more salient (Gurnsey & Browse 1989). Texture targets generated from open forms (broken circles, arrows as in figure 2) are easier to detect when coupled with closed forms (circles and triangles, respectively) (Treisman & Gormican 1988; Williams & Julesz 1992). The existing two-stage-filtering models can account for discrimination in these cases but not for asymmetries. The signal-in-noise framework allows for asymmetries even when no external noise is introduced into the system (e.g, orientation variability) by assuming internal noise that depends on the specific input. Thus, vertical lines may generate less internal internal noise than tilted lines as would be expected from their finer internal representation, and large texture elements may produce more noise than small ones (it is also possible that low frequency filters are noisier than high frequency filters). In the same way, broken shapes may be expected to generate more internal noise than closed ones. As for now, this assumption is not supported by independent experimental evidence. More than that, consider the triangle-arrow pair depicted in Figure 3 which produce asymmetric performance with an advantage for the arrows in the foreground. This asymmetry holds with or without orientation randomization (Rubenstein & Sagi, in preparation), while orientation variability would predict an advantage for triangles when in the foreground (see in Figure 3 where the triangle energy spectrum is more variable along the orientation dimension). Thus,

if internal noise is the source of asymmetry in these cases, it should be powerful enough to override the noise resulting from the orientation variability. Williams and Julesz (1992) suggested, when using closed circles and open circles as texture elements, that broken forms tend to be closed by ‘subjective contours’. This ‘subjective closure’ would be more distractive when operating on open circles in the background due to their higher frequency of occurrence (background area is assumed to be larger than foreground area). While this account for closed/opened form asymmetry is very attractive, it is difficult to see how it can be applied to the general case, in particular to shapes like arrows (Figure 2).

One interesting aspect of the Williams and Julesz (1992) data is that the same asymmetry exists for stimuli consisting of only two elements, pointing toward a non-texture type of asymmetry, or for some attentive sources. Attention may also be involved in orientation (and size) based asymmetries, as these asymmetries occur only for small orientation differences (Sagi & Julesz 1987) and thus can be viewed as a threshold phenomenon. As most texture experiments described in the literature do not monitor observers attention, it is possible that visual attention plays an important role when texture pairs differ by a small change on one parameter (orientation, size or gap length). Braun (1993) showed, using a dual task paradigm, that detection of a small target within an array of somewhat larger distractors depends on the availability of attentive resources, while the reversed task can be performed without attention. Using a similar paradigm, Rubenstein and Sagi (in preparation) could demonstrate the involvement of attention in gap/closure-based segmentation tasks, but not in triangle/arrow-based texture segmentation tasks. Sireteanu and Rettenbach (1993) showed, using reaction time experiments, that orientation-based asymmetries and closure-based asymmetries disappear with practice, when keeping the orientation difference (or gap size) constant. It would be interesting to see how practice improves performance on orientation, size and gap (closure) based segmentation and to examine the correlation between discrimination thresholds and asymmetry.

While second stage filters proved to be very useful in modeling the segmentation process, there is no clear evidence supporting a specific or a unique filter

type. The default structure assumes an isotropic DOG (summation and inhibition) type spatial filter operating on first stage filter maps (Malik & Perona 1990; Rubenstein & Sagi 1990), however, there is no direct psychophysical evidence to support this filter type. Contrast detection experiments support non-isotropic second stage filters where integration of first stage filters activity is performed along the first stage filter principal orientation and, to a somewhat less extent, in a direction orthogonal to it (Polat & Sagi 1994a). Data from these contrast detection experiments can be modeled by assuming either excitatory or inhibitory interactions (or both), though later experiments (Polat & Sagi 1994b) favor excitatory interactions. Texture segmentation experiments suggest summation along the first stage filter principal orientation, in addition to sideways excitatory interactions with orthogonal filters (Rubenstein & Sagi 1993). Some models (Landy & Bergen 1991; Malik & Perona 1990) assume both within map inhibition and between maps inhibition, though in these models the inter-map inhibition can be replaced by some nonlinear transducer function. It is certainly possible that the visual system employs different types of second stage filters and that first stage filters may interact in different, not necessarily simple, ways. It is also possible that these interactions have some adaptive properties and change according to the task and stimulus type.

Perceptual learning in preattentive vision

Surprisingly enough, although practice effects are generally known, little research has been published on learning effects in simple visual tasks (Ball & Sekuler 1982; Fiorentini & Berardi 1980; Ramachandran & Braddick 1973). Fiorentini and Berardi (1980) describe practice effects in tasks involving phase discrimination. They found learning to be specific for orientation, spatial frequency and location (hemifields), implying a low level site for the neuronal changes; however, this learning effect showed inter-ocular transfer, implying neural modifications at a processing level where the information originating from the two eyes is already combined. Karni and Sagi (1991) examined performance improvement for a task involving detection of texture gradients. The task involves either detection of

the three disparate lines (differing in orientation from the background) or identification of the global orientation created by these three lines (being vertical or horizontal). These tasks were shown to be preattentive or inattentive in the sense that they do not rely on any attentive resources (Braun & Sagi 1990). In such an experiment the target appears in a random location so that observers are forced to collect information from a relatively large visual field. On the other hand, the relevant information is local in the sense that observers have to detect orientation gradients. Also note that although an identification task is being used, the task does not involve pattern identification (of local elements) but rather an identification of a structure defined by feature gradients which, in turn, is the limiting factor in the task. This situation is quite different from the one in the learning studies described above, in which observers were presented with spatially uniform stimuli where any part of the visual field can be used for the task. This procedure allows for attention to be focused, directed and to be used. Our situation can be better described as a task where observers have to detect a small signal of an unknown location within a larger field of noise.

The main finding of Karni and Sagi (1991) is that learning is specific for:

1. Location in the visual field. Learning does not transfer from one quadrant to another.
2. Background orientation but not target orientation. Once observers have learned one target orientation, they can perform as well for the orthogonal orientation. This is not true for background orientation.
3. Eye. Learning does not transfer between eyes.

The above properties of the learning phenomena imply that learning takes place at an early stage of visual processing, at a level similar to that of spatial filters or of their lateral interactions. The structure that is being modified is local, has orientation specificity and is monocular. These constraints do not leave us much choice in identifying the physiological correlate to the modified structure. Monocular and orientation-selective cells have so far been found so far only in some layers of visual area V1 (Zeki 1978). More so, cells at this level of processing

were also found to be sensitive to orientation gradients as implied by our task (Van Essen et al 1989; Gallant et al 1994). Though the actual changes occur at the preattentive level of processing, they are probably gated (Karni & Sagi 1990) or controlled (Ahissar & Hochstein 1993, 1994) by some task-dependent process, or by cognitive set (Shiu & Pashler 1992).

Another interesting feature of the texture learning data is the time course of learning (Karni & Sagi 1993). The results show improvement over a time period of four to five days, although our observers performed a few hundreds of trials on each daily session. This is quite a slow time course compared with the earlier studies mentioned above. However, once observers learned the task they could maintain their improved level of performance for at least three years without further practice. Even more interesting is the observation (Karni & Sagi 1993) that observers do not improve much during each daily session and up to eight hours after a training session (except for a fast phase of learning at the beginning of their training, which is local but shows interocular transfer). This implies some incubation period in which changes induced by the repetitive performance of the task takes place. During this period of eight hours, the observers were not doing any activity related to the psychophysical task, however in most cases the time interval between two sessions included night sleep. In later experiments, observers were tested in the evening, before sleep, and then again in the morning after sleep. Experimental results show that observers do not improve significantly performance of the task if deprived of REM (dream) sleep, while deprivation of other sleep stages (slow wave sleep) only minimally affects consolidation (Karni et al 1992). It should be noted that REM deprivation affects performance only for tasks that are being learned (or being consolidated), while tasks that are already learned are not affected by sleep deprivation. This recent result may contribute to our understanding of the biological mechanisms involved in memory consolidation.

We suspect that the learning phenomena we observed involve modification at the filter level or at a level where adjacent filters interact (second stage filters). Modifications at the lateral interaction level can increase inhibition between adjacent filters and thus reduce the response level for the background, and noise in

general. This increased inhibition is also consistent with the general principle of ‘redundancy reduction’ where the sensory system tries to ignore redundant information (Barlow 1990). Evidence for plasticity at the level of filter interactions (connections) is provided by lateral masking experiments.

Plasticity of lateral interactions

While texture experiments can be considered as the “royal road” to understanding preattentive pattern discrimination, a finer method is required for exploring detailed neuronal interactions. Polat and Sagi (1993) used a lateral masking paradigm to explore spatial interactions. In these experiments observers had to detect the presence of a Gabor target when flanked by two high contrast Gabor patches (masks) at variable separations. Results showed a decrease of target sensitivity at small target to mask separations, and an increase of target sensitivity at larger separations, up to six times targets’ wavelength. In later experiments, we allowed observers to practice on the lateral masking experiments for a few weeks. The effect of practice is strikingly uniform across observers; all of them increased their enhancement range, up to 20 times the target wavelength, practically showing interactions on all distances tested (Polat & Sagi 1994b). This learning phenomena was also found to be monocular, that is, practicing with one eye did not generate any range increase for the other eye. In addition, the range increase was found to be specific for spatial frequency and orientation. Thus, it is reasonable to assume that the increase in interaction range, as observed in our lateral masking experiments, occurs at the same level of processing as texture learning, probably at a level corresponding to visual area V1.

The long range interactions obtained after a few weeks of practice may imply the existence of long range connections in the cortex. However, this is probably not the case. The data can be better explained by assuming a chain of connections, where activity from distal regions can spread through intermediate cells to the target cell. This chain can be developed only continuously, that is, longer range interactions can not be developed before intermediate range interactions take place (Polat & Sagi 1994b). Moreover, the chain can be broken by repetitive

stimulation of an intermediate region. This implies that neighboring elements in the chain must be activated during the same period of practice in order to develop their connections, while activation of only one of them, without the other, may reduce the connection efficacy. Thus we can induce new associations by introducing correlations between the Gabor masks and dissociations by breaking these correlations. In light of these findings we should view preattentive vision as an associative feedback network, rather than as a feed-forward system capable of increasing sensitivity due to repetitive stimulation.

Conclusion

Thirty years after the pioneering study of Julesz (1962) we seem to have reached a good understanding of processes underlying human texture perception. As we are entering now the fourth decade of texture research, we will probably see more quantitative models of texture segmentation, producing a better understanding of texture perception and of the architecture underlying preattentive visual processes. But probably the most unexpected outcome of this research is the recent finding that preattentive vision is not a rigid sensory module. The picture emerging from the studies described here is of a dynamic visual system in which early representations keep changing as the environment changes. The high degree of plasticity we observed raises the possibility that almost any pattern of spatial interactions can be obtained in early vision by direct or indirect connections. Global shape properties, as closure and figure/ground assignment, may be captured by this system via chains of connections, as indicated by the recent findings of Kovács and Julesz (1993). Reaching an understanding of the visual system and of texture perception will therefore involve understanding the learning rules of the system and the constraints put on it by the system architecture. As these learning rules are expected to apply to brain processes in general, we can view the study of texture discrimination as the royal road to understanding, not only preattentive pattern discrimination, but, cognitive processes in general.

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Figure captions

Figure 1: A model for texture segmentation. See text for description.

Figure 2: Gabor energy distribution of two texture elements used by Caelli and Julesz (1978) to demonstrate effortless discrimination of textures having identical power spectra. Gabor energies were computed using pairs (sine and cosine) of Gabor signals of different orientations and wavelength, and texture elements of size 17x17 (as in Rubenstein & Sagi 1990). Note that the two elements differ in the way energy is distributed across the different orientations (at longer wavelength). Only when energies are averaged across all orientations (or space when in textures), are elements' energies equal at all wavelengths.

Figure 3: The predictions of the Rubenstein and Sagi (1990) model (circles) compared with the experimental data (histogram bars) of Gurnsey and Browse (1987). The figure (from Rubenstein & Sagi 1990) is presented in groups of two elements, representing a particular stimulus. Each histogram rectangle represents the psychophysical performance level with the element depicted below it in the foreground and the adjacent element in the background. Filled circles represent the prediction obtained by selecting the spatial frequency yielding the highest performance for each pair ($r=0.8$). The open circles represent predictions for Gabor filters having only larger wavelength ($r=0.83$). The model accounts for performance asymmetries whenever they are significant. Note that pair 13 is an elongated version of the pair depicted here in Figure 2, thus producing lower performance levels; however, experimental asymmetry seems to exist.