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Specific Effects of Spatial-frequency Uncertainty and Different Cue Types on Contrast Detection: Data and Models*

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If the spatial-frequency of sinusoidal signals in a contrast-detection experiment varies randomly from trial to trial, then performance is decreased compared with that in a situation where it remains constant. This spatial-frequency uncertainty effect can more or less be compensated by presenting informative cues shortly before each trial. *Single-band*, as well as *multiple-band* models, have been proposed to explain the uncertainty and cuing effects. While the latter assume that under uncertainty multiple channels are monitored simultaneously, the former propose that in each trial a single, but sometimes inappropriate, channel is selected for monitoring. Until now it is open which of these models is valid. Therefore, psychometric functions were collected under different conditions of spatial-frequency uncertainty. It appears that the size of the uncertainty effect varies with spatial-frequency. This result can be explained by a multiple-band model, as computational analysis reveals. Copyright © 1996 Elsevier Science Ltd.

Spatial-frequency uncertainty   Cuing   Multiple-band models   Contrast detection   Signal detection

INTRODUCTION

The spatial-frequency selectivity of the human visual system has led to the conception that it operates as a local spatial-frequency analyzer, i.e. that each retinal location is processed simultaneously by multiple channels, each tuned to a specific range of spatial-frequencies and orientations [*cf* DeValois & DeValois (1988); Graham (1989)]. Different methods, such as subthreshold summation [e.g. Graham *et al.* (1978); Watson (1982)], contrast masking [e.g. Legge & Foley (1980); Wilson *et al.* (1983)], and adaptation [e.g. Blakemore & Campbell (1969); DeValois (1977)] have been applied to investigate bandwidth, sensitivity, and other properties of the presumed individual channels.

Usually, the task in such experiments is to detect certain signals, and the extent to which the observers' performance depends on such factors as the signals' contrast or the properties of other simultaneously presented stimulus components is then examined. An observed performance modulation is thought to reflect corresponding properties of the channels in the visual system.

However, detection performance is not only affected by stimulus parameters or the state of the early sensory system. Also, the state of higher, cognitive levels, such as the observers' knowledge about the signals they have to respond to, modulates signal-detection behavior. This can easily be demonstrated by introducing uncertainty, i.e. by presenting signals with attributes varying randomly across trials. In these cases detection performance or speed of response are usually reduced compared with situations where the attributes are fixed.

Such *uncertainty effects* have been found for various attributes such as phase [e.g. Burgess & Ghandeharian (1984a)], direction of movement [e.g. Ball & Sekuler (1981)], location [e.g. Burgess & Ghandeharian (1984b); Davis *et al.* (1983); Posner *et al.* (1980); Swensson & Judy (1981)], and spatial-frequency [e.g. Davis *et al.* (1983); Hübner (1996); Kramer *et al.* (1985)].

For interpreting the uncertainty effects, two functional stages of processing have been distinguished: a coding stage and a decision stage [*cf* Shaw (1984); Sperling & Dosher (1986)]. In the coding stage the stimulus is transformed into an internal representation, while in the decision stage this representation is used for determining the response. An important question is: "Are decision processes or also coding processes affected by uncertainty?".

To be more specific, assume that in a signal-detection experiment with a 2AFC (two-alternative forced-choice) procedure the value of a certain signal parameter is

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chosen randomly for each trial from M possible values. Assume further that for each of the M values there exists a corresponding sensory channel which encodes and transmits the information and whose output represents either the signal plus noise or noise alone. Then, in the signal-plus-noise interval one channel transmits the signal-plus-noise while the remaining channels transmit only noise. In the noise interval, on the other hand, all channels transmit noise alone. For deciding in which interval the signal was present, the output of at least one of the channels for each interval must be processed and the results compared in a certain way. In respect to such a situation, one can ask [e.g. Davis *et al.* (1983)] whether the uncertainty merely affects the processing of the channels' output (decision stage), or also the characteristics of the individual channels (coding stage).

For investigating this and related questions it can be very useful to consider ideal-observer models [*cf* Swets (1984)], i.e. quantitative models which represent the optimal behavior for the situation under consideration. By contrasting ideal and human performance, and by rendering the ideal model's behavior suboptimal, one might gain insight into the human visual system.

There are two main classes of formal models which have been employed for explaining uncertainty effects: *single-band* and *multiple-band* models [*cf* Graham (1989); Hübner (1993a,b); Pelli (1985)]. The single-band models assume that only the output of one channel can be monitored at a time. Since under uncertainty the observers do not know in advance which channel transmits the signal, they are monitoring a noise-alone channel in some trials, which leads to a decrease in overall performance.

The multiple-band models, on the other hand, assume that the output of several channels can be processed simultaneously. In this case a rule for transforming the multiple outputs into a single decision variable must be adopted. For instance, a possible strategy is to choose that interval in which the maximum output occurred (Creelman, 1960). Another procedure would be to combine the outputs for each interval linearly and to choose the interval with the largest value [see Green & Swets (1966) for more details].

The multiple-band models with a maximum-output rule predict a decrease in performance under uncertainty, because the "false-alarm" rate, i.e. the probability that a channel in the noise interval produces the maximum output, increases with the number of monitored channels [*cf* Swets (1984)]. If the linear-combination rule is applied, then performance also decreases, but this time because the amount of effective noise is increased.

Notice that these models assume uncertainty to produce a performance reduction solely by influencing the decision processes, i.e. without the sensitivity of the individual channels being affected. That this assumption holds for the detection of luminance increments under location uncertainty has been suggested by Shaw (1984). A similar hypothesis has also been proposed for the effects of spatial-frequency uncertainty (Davis *et al.*, 1983).

If it were also necessary to model a reduction of channel sensitivity, then this could be accomplished, for instance, by increasing the bandwidth of the individual channels, for which a further decrease in performance would be predicted (Hübner, 1993a,b).

Important with respect to uncertainty are also cues, which, when presented shortly before each trial, can more or less compensate for the uncertainty effect. Here, a similar question arises: given uncertainty, do cues reduce the uncertainty effect by also improving sensitivity of the individual channels or by only affecting the decision process?

Cuing has mainly been investigated in the domain of spatial uncertainty [for an overview see Kinchla (1992)]. In respect to the detection of luminance increments it has been proposed that cues improve performance by only affecting the decision process (Müller & Findlay, 1987). However, there are other results showing that cues can also improve sensitivity (Bashinski & Bacharach, 1980; Downing, 1988; Hawkins *et al.*, 1990; Müller & Humphreys, 1991).

If one considers the effects of cues, then it is important to distinguish different cue types. Mainly, symbolic and sensory cues have been distinguished. While symbolic cues provide only indirect information about the signal, sensory cues specify the signal by providing its attributes directly [*cf* Johnston & Dark (1986)]. Assume that we want to cue the spatial-frequency of a sinusoidal grating of a fixed spatial extension. Then we can employ a symbolic cue by presenting, for instance, a digit which indicates the number of cycles of the subsequent target grating. On the other hand, a sensory cue could be a grating of the same spatial-frequency as the target.

Usually, sensory cues are more efficient for reducing uncertainty effects than symbolic cues (Hübner, 1996; Jonides, 1981; Müller & Humphreys, 1991). A possible hypothesis for explaining the efficiency differences is that symbolic cues affect merely the decision process, whereas sensory cues also affect encoding by preactivating or priming the sensory channels [*cf* Müller & Humphreys (1991)]. In a recent paper Hübner (1996) compared the efficiency of several cue types for reducing spatial-frequency uncertainty. There turned out to be no clear-cut dividing line between the efficiency of symbolic and sensory cues. Thus, there seems to be a continuum of cuing efficiency.

Single- or multiple-band models can be used to explain both the cuing effects and the differences between different cue types. For the single-band models one could assume that cues help the observers to choose a more or less appropriate channel to monitor. While this mechanism merely affects the decision process, one could additionally propose that certain cues also reduce the bandwidth of this channel. On the other hand, for multiple-band models one could assume that the number of monitored channels decreases with increasing cue efficiency.

The aim of the present paper is to investigate the mechanisms responsible for spatial-frequency uncertainty and cuing effects by means of ideal-observer analysis. As has been mentioned, several mechanisms are potential candidates for explaining uncertainty and cuing effects. Thus, the objective was to determine which one is valid. Fortunately, it has been shown that psychometric functions, collected under different uncertainty conditions, can be useful for distinguishing between the mechanisms. Their slope and threshold parameters vary characteristically with uncertainty [*cf* Hübner (1993a,b)] for the different mechanisms. While the single-band models predict that the thresholds increase but the slopes decrease with increasing uncertainty, the multiple-band models predict increasing thresholds as well as increasing slopes.

The effect of bandwidth modulation on the slope of the psychometric functions depends on the specific filter model assumed for the individual channels. While for the so-called *energy-detector* model the psychometric functions steepen slightly with increasing bandwidth, they remain parallel for a *matched-filter* model [for details see Hübner (1993a,b)].

The approach of considering psychometric functions has already been successfully applied to modeling the mechanisms that produce frequency uncertainty in auditory perception (Hübner & Hafter, 1995). Thus, a similar method is applied here to visual signal-detection. Psychometric functions were collected under conditions with and without spatial-frequency uncertainty, as well as under several cuing conditions. The results obtained are analyzed by means of ideal-observer models.

METHODS

Apparatus

The stimuli were presented on a 19"-color-monitor (MIRO, Type GDM-1965). The monitor had a resolution of 1280×1024 pixels and was connected to a MIRO-TIGER graphics-board with a refresh rate of 75 Hz (non-interlaced), resident in an IBM-compatible personal computer (PC). The PC also served for controlling stimuli presentation and response registration.

The space-average luminance for each gray level was measured (with an L 1000 photometer from LMT LICHTMESSTECHNIK, Berlin) and the data were used to create a gamma look-up table to relate the required luminances to the corresponding 256 gray levels.

Stimuli

Signals were vertical sinusoidal gratings. The stimuli subtended *ca* 2.66 deg horizontally and vertically (256×256 pixels) and were viewed binocularly from a distance of 144 cm with a chin rest and natural pupils. Five different spatial-frequencies were employed: 0.75, 1.88, 4.14, 9.02, and 18.8 c/deg. To obtain psychometric functions, five signal levels were used which ranged from 1 dB below threshold, i.e. from –1 dB (SL) (sensation level), to 3 dB above threshold, i.e. to 3 dB (SL), in 1-dB steps. The space average luminance of the signals was 41 cd/m^2 which was identical to that of the homogeneous background.

Since we are interested in processes which are located at higher stages of the visual pathway, one-dimensional (vertical) static white noise was added to the signals to overwhelm the effects of photon noise and of peripheral internal noise sources [*cf* Geisler (1989)].

The noise was produced and its spectral density calculated analogously to the method employed by Burgess and Ghandeharian (1984a): pseudo-random numbers (Box–Müller method) were used to construct white noise in a band of 0–48 c/deg. Since the number of gray levels was limited, the values were truncated at ± 3.2 SDs. The 256 gray levels were distributed over a luminance range of 0.314–82 cd/m^2 which corresponds to a *luminance-modulation range* in Michelson-contrast $((L_{\max} - L_{\min})/L_{\max} + L_{\min}))$ of 0.99. The standard deviation of the noise was 0.099 modulation units or 8.16 cd/m^2. Since the noise power was flat from 0 to 48 c/deg, the resulting (one-sided) noise spectral density N_0 was 2.04×10^{-4} ($0.099^2/48$). In each trial, individual noise samples were drawn for each of the intervals.

Cues

Four different cue types were employed: iconic; rotated; phase; and symbolic. The iconic cues were identical to the signals but presented without noise and with a contrast of 0.6. Rotated cues were 90 deg rotated iconic cues, and phase cues were similar to the iconic cues but had counter phase. The symbolic cues were digits corresponding to the number of cycles of the signal. The individual characters of the digits subtended *ca* 0.6 deg $\times$ 0.4 deg.

Procedure

A *spatial* 2AFC-method was employed, i.e. signal plus noise and noise stimuli were presented simultaneously on the screen. Either the signal plus noise occurred at the left and the noise at the right of the fixation point (i.e. center of the screen), or vice versa. There was no spatial separation between the two stimulus fields.

The task of the subjects was to indicate, by pressing one of two buttons, which stimulus field contained the signal. There was no time limit for response. A trial started with a fixation mark which consisted of two short horizontally centered vertical lines (with a length of about 1 deg), one presented above and the other below the stimulus fields. The subjects were instructed to fixate the midpoint between the two lines. A tone started simultaneously with the fixation mark and was presented for 200 msec to mark the beginning of the trial.

After a random time interval with a uniformly distributed duration between 400 and 800 msec, a cue was presented for 106 msec (under conditions with cues). To avoid any negative interaction between cues and signals [see Hübner (1996)], the iconic, rotated, and phase cues were centered horizontally on the display and presented above (adjacent) the stimulus field. Only the symbolic cues were also vertically centered. A 400 msec time interval separated the cues and the stimuli which were presented for 106 msec. The fixation lines remained up to the end of stimulus presentation. If the response had not been correct, an acoustic feedback was given. Two thousand milliseconds after the subject's response the next trial started.

A transformed 1-up-2-down 2AFC-procedure (Levitt, 1970) was used to measure in a preliminary test the thresholds of the individual spatial-frequencies. By averaging the last six out of ten reversal points, estimates, corresponding to 70.7% correct responses, were obtained. Three such adaptive tracks were randomly interleaved for each spatial-frequency and the median of the estimates was taken as threshold. For one subject the threshold for the highest spatial-frequency was above the level producable with our equipment. Therefore, a spatial-frequency of 14.29 c/deg was used instead of 18.8 c/deg for that subject. In what follows, this lower spatial-frequency will be treated in the same way as the higher one for the other subjects without being further mentioned.

The thresholds obtained with this staircase procedure were used to determine the contrast corresponding to the SL for each stimulus for each subject. The method of constant stimuli was then employed with these levels to collect the data for the psychometric functions for the different conditions.

In addition to the conditions corresponding to the different cue types, in which the spatial-frequencies were always randomized, there was also a condition with blocked spatial-frequencies and no cues, and a randomized no-cue condition, i.e. a condition with randomized spatial-frequencies and no cues. All conditions consisted of 10 blocks each comprising 100 trials. In each block there were four trials for each combination of level and spatial-frequency, except for the blocked condition. Altogether, each subject produced 40 responses per level and spatial-frequency in each condition.

The blocked condition was run first to enable the subjects to become familiar with the different spatial-frequencies. If learning effects for a certain spatial-frequency were observed, then the blocks were repeated until a steady level of performance was reached. In the next step the 10 blocks with randomized spatial-frequencies and without cues were run. Finally, the blocks for the different cue types were randomly intermixed in each session, which consisted of four to five blocks.

Subjects

The author and three paid persons served as subjects (aged 21–38 yr; three male, one female). All subjects had normal or corrected-to-normal acuity.

RESULTS

The psychometric functions, averaged across subjects and spatial-frequencies, for the different conditions are depicted in Fig. 1. For comparison, each function for the cue conditions is presented together with that for the blocked and the randomized no-cue condition, respectively.

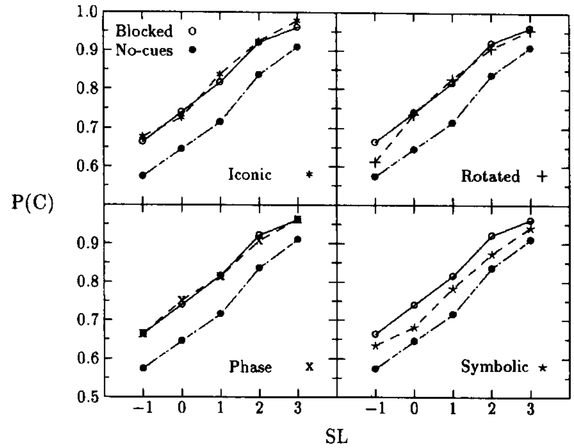

FIGURE 1. Psychometric functions for the different conditions. Percentage of correct responses $P(C)$ as a function of the contrast in sensation level (SL) units. The data were accumulated across subjects and spatial-frequencies. For comparison, each panel contains the functions for the condition with blocked spatial-frequencies and for the condition with randomized spatial-frequencies and no cues. For further details concerning the different conditions see the text.

As can be seen, the iconic, phase, and rotated cues counterbalance the spatial-frequency uncertainty completely. The symbolic cues, on the other hand, could not reduce uncertainty entirely. A Wilcoxon test (matched-pair signed-ranks) with the 20 data pairs of the subject's psychometric functions (five levels times four subjects) reveals that the performance in the blocked condition is significantly higher than that in the symbolic cue condition ($T = 16.5$, $N = 18$, $P < 0.01$). Nevertheless, the symbolic cues still improved detection performance significantly, compared with the randomized no-cue condition ($T = 13$, $N = 19$, $P < 0.01$).

For the purpose of examining the psychometric functions of the individual spatial-frequencies they were plotted separately. Since the logarithm of the signal-to-noise ratio should be used as unit on the abscissa, the SLs had to be transformed to signal energy. This transformation was obtained by applying equations (3) and (4) (see the next section). In order to average the psychometric functions across subjects, the mean contrast thresholds for each spatial-frequency (0.0395, 0.0545, 0.0669, 0.0834, 0.1738) were used to calculate the respective signal energies.

The psychometric functions for the blocked (single-frequency) condition averaged across subjects are shown in the top panel of Fig. 2. As in Hübner (1996), the thresholds increase monotonically with spatial-frequency. This result differs from that usually obtained with gratings of a fixed spatial extent, where the thresholds are nonmonotonic [*cf* DeValois & DeValois (1988)]. This difference is probably due to the external noise. The more sensitive the visual system is to a certain

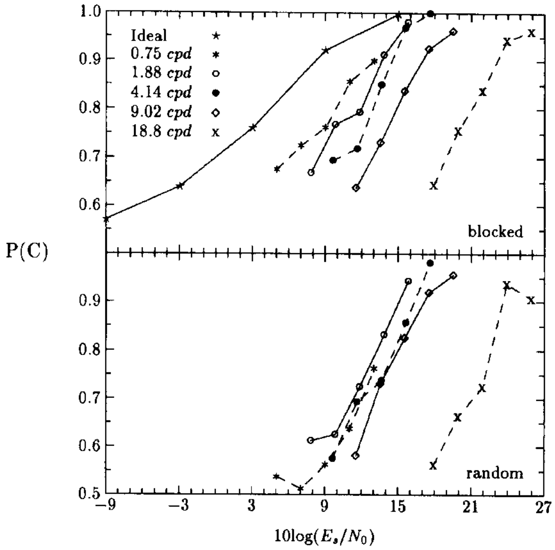

FIGURE 2. Psychometric functions, averaged across subjects, for the different spatial-frequencies. The upper panel shows the functions for the condition with blocked spatial-frequencies and the lower those for the condition with the randomized spatial-frequencies and no cues. The left-most function in the upper panel represents the behavior of a matched filter.

spatial-frequency, the larger is the corresponding masking effect of the noise. Thus, external white noise has a counterbalancing effect and eliminates nonmonotonicities in spectral sensitivity [*cf* Green *et al.* (1959)]. Interestingly, increasing thresholds were also found with gratings of a fixed number of cycles [e.g. Banks *et al.* (1987)].

Apparently, also the slopes of the psychometric functions vary with spatial-frequency. For quantifying the variation, i.e. to obtain estimates of the slopes and thresholds, logistic functions were fitted to the individual data by minimizing χ^2 with a search algorithm [PRAXIS; Gegenfurtner (1992)]. The estimated slopes and thresholds averaged across subjects are given in Tables 1 and 2, respectively. It appeared that the individual slopes increase linearly with the logarithm of spatial-frequency ($r = 0.52$, $P < 0.05$).

An interesting question is whether the effect of the spatial-frequency uncertainty was homogeneous across spatial-frequency. For comparison, the psychometric functions for the randomized no-cue condition are given in the lower panel of Fig. 2. As can be seen, the uncertainty effect differs considerably across the spatial-frequency range. While the detection performance for the lowest spatial-frequency is dramatically reduced such that the corresponding psychometric function is even shifted to the right of that for the next higher spatial-frequency, the functions for the highest spatial-frequencies are hardly affected by uncertainty. The mean thresholds obtained by fitting logistic functions to the individual data can also be seen in Table 2. The mean differences between the thresholds for the blocked and randomized no-cue condition are: 2.58; 1.05; 0.822; –0.016; 0.821. Thus, the largest effects occurred for the lowest spatial-frequency and the smallest for that of 9.02 c/deg. If we subject the individual threshold values of the blocked and randomized no-cue condition to a repeated-measure analysis of variance (ANOVA) with condition and spatial-frequency as factors, then the factors condition [$F(1,3) = 85.0$, $P < 0.01$], and spatial-

TABLE 1. Means of the estimated slopes [in *P(C)/SL* units] for the different conditions and spatial-frequencies

c/deg	0.75	1.88	4.14	9.02	18/14	$\bar{x}$
Blocked	0.0695 (0.0101)	0.0881 (0.0107)	0.1054 (0.0197)	0.1108 (0.0157)	0.1167 (0.0188)	0.0981 (0.0073)
No cues	0.1575 (0.0358)	0.1088 (0.0110)	0.1148 (0.0125)	0.1437 (0.0351)	0.1415 (0.0213)	0.1333 (0.0110)
Iconic cues	0.0809 (0.0122)	0.1449 (0.0263)	0.1208 (0.0251)	0.0857 (0.0053)	0.0993 (0.0094)	0.1063 (0.0089)
Rotated cues	0.1080 (0.0232)	0.1563 (0.0426)	0.1297 (0.0160)	0.1833 (0.0728)	0.1210 (0.0131)	0.1397 (0.0171)
Phase cues	0.0816 (0.0191)	0.1226 (0.0047)	0.1007 (0.0124)	0.1017 (0.0292)	0.0962 (0.0279)	0.1005 (0.0088)
Symbolic cues	0.0701 (0.0206)	0.0856 (0.0089)	0.1348 (0.0249)	0.1087 (0.0272)	0.1509 (0.0503)	0.1100 (0.0136)

The corresponding standard errors are given in parentheses. The last column shows the estimated thresholds averaged across subjects and spatial-frequencies.

TABLE 2. Means of the estimated thresholds (in *SL*) for the different conditions and spatial-frequencies

c/deg	0.75	1.88	4.14	9.02	18/14	$\bar{x}$
Blocked	0.3621 (0.3084)	0.0112 (0.1723)	–0.0058 (0.3826)	0.2659 (0.2102)	–0.0446 (0.4618)	0.1177 (0.1070)
No cues	2.9423 (0.2370)	1.0593 (0.2839)	0.8159 (0.1207)	0.2498 (0.1582)	0.7762 (0.3601)	1.1687 (0.2339)
Iconic cues	0.0799 (0.2440)	–0.0876 (0.1915)	–0.2462 (0.3779)	–0.2114 (0.1734)	–0.0173 (0.1435)	–0.0965 (0.0996)
Rotated cues	0.6433 (0.3727)	0.0146 (0.5538)	–0.0015 (0.1428)	–0.2713 (0.0610)	0.4261 (0.3371)	0.1622 (0.1552)
Phase cues	0.3960 (0.2819)	0.2517 (0.2211)	–0.1331 (0.2413)	–0.6190 (0.3841)	0.0902 (0.1705)	–0.0028 (0.1345)
Symbolic cues	1.1563 (0.5171)	0.2491 (0.4598)	0.6041 (0.2269)	0.2010 (0.5046)	0.4457 (0.3787)	0.5312 (0.1886)

The respective standard errors are given in parentheses. The estimated thresholds averaged across subjects and spatial-frequencies are shown in the last column.

frequency [$F(4,12) = 10.4$, $P < 0.001$] are significant. Moreover, there is a significant interaction [$F(4,12) = 6.96$, $P < 0.01$]. An explanation for the spatial-frequency specific uncertainty effects will be given later.

The slopes for the randomized no-cue condition do not increase systematically with spatial-frequency (see the means in Table 1). To investigate whether there are slope differences between the conditions, the individual slopes were subjected to an ANOVA with condition and spatial-frequency as factors. Neither the factors nor the interaction turned out to be significant. However, the condition factor failed only shortly [$F(5,15) = 2.78$, $P < 0.057$]. Since there were large differences between the standard errors of the means, the assumptions of the ANOVA might not be met. Therefore, the most interesting comparison, that between the blocked and the randomized no-cue condition, was repeated with a *t*-test for paired comparisons, and revealed that the slopes in the latter condition are significantly larger [$t(19) = 2.31$, $P < 0.05$].

DISCUSSION AND MODELS

The results reveal that detection performance is decreased under spatial-frequency uncertainty, which agrees with other studies [e.g. Davis *et al.* (1983)]. However, the finding that the uncertainty effect varies to such an extent across spatial-frequencies is surprising and has not, to the knowledge of the author, been observed before. This differential effect may be due to the presentation of external noise, since this is the main difference from most of the earlier studies.

The results further demonstrate that the application of sensory cues can entirely compensate for the effects produced by spatial-frequency uncertainty, while presentation of the symbolic cues was less helpful in improving detection performance. This replicates the results of Hübner (1996), where similar differences between the cue types were observed.

How can the observed differential uncertainty and cue effects be explained? An attempt at answering this question is made in the following discussion by applying ideal-observer models. In this respect the collected psychometric functions are quite helpful, since their pattern of slopes and thresholds limits the number of appropriate models (Hübner, 1993a,b).

Generally, it is assumed that an ideal observer monitors in each interval of a 2AFC-task the output of spatial-frequency channels whose number depends on the specific experimental conditions. The output of each channel is considered as a random variable representing either signal plus noise or noise alone. As already mentioned in the Introduction, if there is more than one relevant channel, then the different outputs are combined in a certain way to form a single decision variable for each interval. To decide in which interval the signal had occurred, the ideal observer chooses that interval in which the decision variable had its largest value [for details see Green & Swets (1966); Hübner (1993a,b)].

In order to construct a computational model to explain the experimental results, one has to specify in detail how the stimuli are transformed into the channel output, how many channels are monitored under each condition, and finally, if there are several relevant channels, how their outputs are combined to obtain a decision variable.

For convenience, the models will be fitted to the averaged (across subjects) data, since the slope and threshold relations within and between the different conditions are rather similar across subjects. Also, if we fit logistic functions to the averaged psychometric functions, then we get, for instance, as slopes for the blocked condition (with increasing spatial-frequency): 0.0622; 0.0897; 0.1089; 0.1101; 0.1112, and for the randomized no-cue condition: 0.1575; 0.1088; 0.1148; 0.1437; 0.1415; 0.1333. These estimates are rather similar to the mean values given in Table 1.

First, a model explaining the data for the blocked condition will be constructed, which is then considered as a basis for modeling behavior under the other experimental conditions.

Blocked condition

Since in the blocked condition the spatial-frequency of the signal is constant across trials, an optimal strategy is to monitor only that channel which corresponds to the spatial-frequency of the signal. But how can a channel be specified? A widely used method is to employ a matched filter or a cross correlator [e.g. Burgess & Ghandeharian (1984a); Hauske *et al.* (1976)]. In both cases, a stored version (template) of the expected signal is matched with the stimulus by convolution or cross-correlation, respectively.

One could assume that for each employed sinusoidal signal there exists a corresponding matched filter. However, different from our human observers, whose sensitivity decreased with increasing spatial-frequency, the sensitivity of a matched filter does not change across spatial-frequencies, given a fixed spatial extension of the signal. What matters is solely the amplitude of the signals [see Hübner (1993b) for details]. To introduce a spatial-frequency dependent sensitivity one could assume that the effect of the signal is proportionally attenuated, or that an increasing amount of internal noise is added somewhere along the visual pathway. However, such manipulations shift the functions parallel to higher thresholds, which is inconsistent with our data. In the top panel of Fig. 2, the psychometric function of an ideal matched-filter is shown, which has an estimated slope of 0.025. It is obvious that the empirical functions are not parallel to this curve. Even the function for the lowest spatial-frequency, which seems quite parallel, has a slope of 0.031.

Another possibility is to assume that the bandwidth of the channels increases with spatial-frequency, which is equivalent to assuming that the effective spatial extension of the filter decreases. This assumption is quite reasonable, since it is known that the detectability of gratings increases only up to a critical number of cycles, which is constant for medium and high spatial-frequencies [e.g. Howell & Hess (1978); Robson & Graham (1981)]. This result corresponds to the physiological fact that the receptive-field size of cortical neurons is smaller for higher spatial-frequencies [e.g. DeValois *et al.* (1982)]. Unfortunately, this assumption also predicts parallel psychometric functions (Hübner, 1993b). Thus, a single matched filter seems to be inappropriate to model the detection behavior in the present experiment.

One way to use the matched-filter model for predicting increasing slopes would be to assume *intrinsic uncertainty*, which is equivalent to assuming a multiple-band model. By intrinsic uncertainty is meant that even though a single spatial-frequency is presented within a given block, the subject is nevertheless uncertain which channel to monitor and might thus monitor multiple channels. This assumption predicts an increase in threshold and slope like the usual multiple-band models [*cf* Pelli (1985)]. For adjusting the location of the psychometric functions precisely, one could additionally assume some internal noise. In this connection it should be mentioned that nonlinear transducer functions have also been proposed for modeling the specific form of the psychometric functions for contrast detection [e.g. Foley & Legge (1981); for an overview see Graham (1989)].

Here, however, an energy-detection model is preferred to model the behavior, since it can predict a systematic increase in threshold and slope by simply assuming a single band with increasing bandwidth (Hübner, 1993a). An energy detector is an ideal observer who is not phase sensitive (Green & Swets, 1966). Although it has been suggested that the visual system is phase sensitive [e.g. Burgess & Ghandeharian (1984a)], this might not be the case under all circumstances, and it certainly does not hold for high spatial-frequencies (DeValois & DeValois, 1988).

The percentage of a correct answer $P(C)$ for a single-band energy-detector can be calculated by [*cf* Hübner (1993a)]:

$$P(C) = \Phi(z) \tag{1}$$

where Φ is the cumulative Gaussian distribution and z is given by:

$$z = \frac{\varepsilon(X_s) - \varepsilon(X_n)}{\sqrt{\mathrm{var}(X_s) + \mathrm{var}(X_n)}} \tag{2}$$

In this equation X_n denotes the decision variable for the noise interval with expected value $2WT$ and variance $4WT$. The random variable X_s represents signal plus noise with expected value $2WT + 2E_s/N_0$ and variance $4WT + 8E_s/N_0$. The term T denotes the size of the stimuli which was 2.66 deg in the present experiment, and W represents the bandwidth (i.e. the filterwidth in the spatial-frequency domain), which is considered as a free parameter. The same noise spectral-density N_0 as in the experiment was used. Observe that for the energy detector the variance of the signal-plus-noise sample increases with energy.

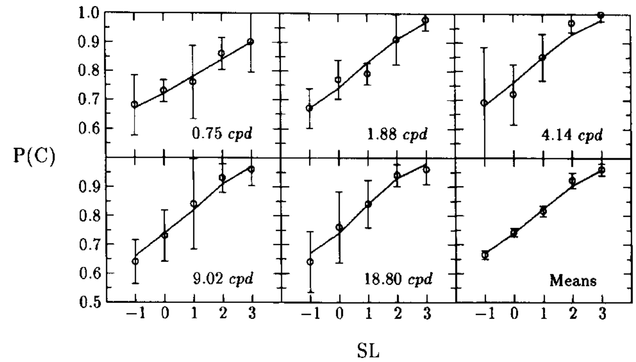

FIGURE 3. Psychometric functions for the condition with the blocked spatial-frequencies fitted with a single-band energy-detection model. The bars indicate the 95% confidence interval.

The energy of the signals was computed by:

$$E_s = 2.66\frac{A^2}{2}, \tag{3}$$

where the amplitude A was calculated from the threshold R by:

$$A = R10^{SL/10}. \tag{4}$$

Bandwidth W and threshold R are considered as free parameters for each psychometric function. The above-mentioned search algorithm [PRAXIS; Gegenfurtner (1992)] was used to fit this model to the averaged psychometric functions obtained under the blocked condition. Bandwidth and threshold were searched simultaneously for all functions until χ^2 was a minimum, where only those points corresponding to data points were estimated.

The result, as can be seen in Fig. 3, is quite good [$\chi^2(14) = 1.6771$, $P > 0.995$]. The values for R are (as contrast, with increasing spatial-frequency): 0.0118; 0.0197; 0.0239; 0.0216; 0.0270. The values for W are: 0.233; 4.648; 9.619; 8.237; 20.492.

If logistic functions are fitted to the theoretical psychometric functions in the same manner as to the empirical data, then a t-test for paired observations revealed no significant deviations between the estimated theoretical and empirical threshold and slope parameters (thresholds: $x_{emp} = 0.0781$, $x_{mod} = 0.0588$, $t(4) = 0.969$, $P > 0.38$; slopes: $x_{emp} = 0.0964$, $x_{mod} = 0.0906$, $t(4) = 1.72$, $P > 0.16$).

Our analysis shows that the energy-detection model fits the data very well. Apart from one reversal between 4.14 and 9.02 c/deg, the threshold (R) and bandwidth (W) parameters increase with spatial-frequency. Thus, compared with an ideal observer, the human observers can be characterized by stating that their channels' bandwidths increase with spatial-frequency. Additionally, there is some attenuation, also increasing with spatial-frequency, along the visual pathway, which is expressed in the increase in the parameter R. It is important at this point not to confuse the internal threshold parameter R of the model and the threshold parameter obtained by fitting a logistic function to a psychometric function. The latter is also affected by the bandwidth parameter W.

The model suggested here for describing the behavior in the blocked condition can be considered as a general model for signal-detection behavior in situations without spatial-frequency uncertainty. Therefore, the model is also suitable for explaining behavior under sensory-cue conditions, since sensory cues prevent any uncertainty effect.

Symbolic cue condition

Under spatial-frequency uncertainty the presentation of symbolic cues could not entirely compensate for the uncertainty effects, i.e. detection behavior was still decreased compared with that in the blocked condition. That the symbolic cues were nevertheless helpful can be seen from the fact that they improved detection performance significantly compared with the no-cue condition.* How can their effect be explained? Since the slopes of the psychometric functions did not decrease compared with those of the blocked condition, the symbolic cues obviously did not lead to monitoring a single but inappropriate or slightly mistuned (with respect to spatial-frequency) channel [see Hübner (1993a,b)].

One could speculate that symbolic cues helped to reduce the number of monitored channels, but that the reduction was not optimal, i.e. that more than one channel was monitored. However, it is rather difficult to formulate this assumption precisely, since several question have to be answered. For instance: how far does the reduction process proceed? Which channels are still monitored?

Alternatively, one can consider the hypothesis that the symbolic cues led to monitoring a single channel, but that the channel's bandwidth was increased compared with that in the blocked condition [*cf* Hübner & Hafter (1995)]. This hypothesis implies, on the one hand, that sensory cues not only reduce the number of attended channels but that they also reduce the bandwidth, i.e. that they also affect the coding process. On the other hand, it also implies that in the blocked condition there is some kind of selfcuing. This means that the signal at trial t serves as cue for the signal at trial $t + 1$, thereby not only reducing the uncertainty at the decision level but also the bandwidth of the relevant channel.

Corresponding to this hypothesis, a model with a single parameter a was considered. The parameter simply modifies the widths W_i, $i = 1,\ldots,5$ proportionally for all channels, i.e.:

$$W_i^{\text{symbolic}} = aW_i^{\text{blocked}}, \tag{5}$$

where the threshold (R) and width parameters of the model for the blocked condition were used.

Fitting this model simultaneously to all five psychometric functions for the symbolic cue condition was quite successful [$\chi^2(23) = 7.83$, $P > 0.995$], and revealed a parameter value of $a = 1.707$. The result is depicted in Fig. 4. There were no significant deviations of the slopes and thresholds of the fitted logistic functions from their empirical counterparts [thresholds: $x_{\text{emp}} = 0.5374$, $x_{\text{mod}} = 0.445$, $t(4) = 0.679$, $P > 0.5$; slopes: $x_{\text{emp}} = 0.1003$, $x_{\text{mod}} = 0.089$, $t(4) = 1.79$, $P > 0.14$].

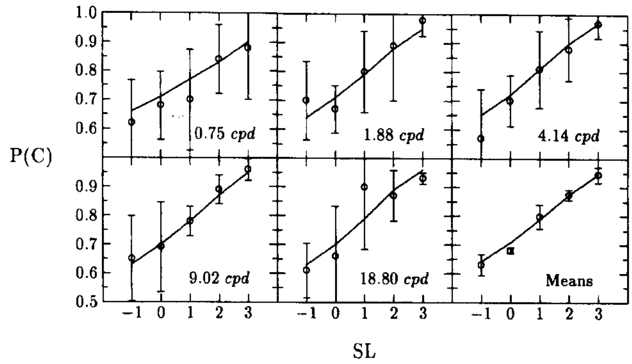

FIGURE 4. Psychometric functions for the condition with the symbolic cues fitted with a single-band energy-detection model. The bars indicate the 95% confidence interval.

Thus, the 25 data points could be fitted well by a rather simple model with a single parameter, given the energy-detector model obtained from the blocked condition.

Randomized no-cue condition

In this section a model is constructed for explaining performance in the randomized no-cue condition. Since the psychometric functions for this condition are steeper than those for the blocked condition, a single-band model can be rejected and a multiple-band model seems to be appropriate [*cf* Hübner (1993a)]. Of the various multiple-band models which have been proposed for modeling different aspects of the visual system, such as for the processing of multiple-component stimuli [e.g. Legge & Foley (1980); for a overview see Olzak & Thomas (1986)], those are of interest here, which can be employed for explaining spatial-frequency uncertainty.

For instance, Kramer *et al.* (1985), who also found increasing slopes under spatial-frequency uncertainty, considered several such multiple-band models with different combination rules for the filter outputs. However, they assumed all monitored channels to have the same characteristic. If this assumption does not hold, as for the data to be considered here, comparing the predictions for various rules is very intricate. Therefore, only one decision rule was considered: the weighted sum of the filter outputs, with weights g_i $i = 1,\ldots,5$, which led to a decision variable X^* of the form:

$$X^* = \sum_{i=1}^{5} g_i X_i. \tag{6}$$

This combination rule is similar to the sum-of-outputs rule which provided the best overall fit for the data of Kramer *et al.* (1985).

It was further assumed that the filters which do not

*One reviewer argued that the reduced efficiency of the symbolic cues, compared with that of the other cues, might be due to masking, because only the symbolic cues were presented at the same position as the stimuli. Although I cannot definitely rule out this explanation, given the other results obtained with symbolic cues, as mentioned in the Introduction, it seems highly unlikely that masking is responsible.

correspond to the signal frequency behave as in the noise interval. Therefore, the expected value of X^* for the noise interval is:

$$E(X_n^*) = 2T\sum_{i=1}^{5} g_i W_i, \tag{7}$$

and that for the signal-plus-noise interval:

$$E(X_s^*) = 2T\sum_{i=1}^{5} g_i W_i + 2g_s E_s/N_0, \tag{8}$$

where g_s denotes the respective weight of the signal channel.

In an initial step it was assumed that the spatial-frequency filters do not overlap and, consequently, do not produce correlated outputs. In this case the outputs can be treated as independent random variables with variance:

$$\mathrm{var}(X_n^*) = 4T\sum_{i=1}^{5} g_i^2 W_i \tag{9}$$

for noise, and:

$$\mathrm{var}(X_s^*) = 4T\sum_{i=1}^{5} g_i^2 W_i + 8g_s^2 E_s/N_0 \tag{10}$$

for signal plus noise. The resulting z-value for this model is:

$$z = \frac{g_s E_s/N_0}{\sqrt{2T\sum_{i=1}^{5} g_i^2 W_i + 2g_s^2 E_s/N_0}} \tag{11}$$

While threshold and width parameters for each channel were taken from the model for the blocked condition, only the weights g_i for each filter were considered as free parameters. The weights were normalized such that they always summed up to one. This normalization should reduce the parameter space. On the other hand, it also reduced the variance of the decision variable compared with a simple summation rule.

Although the overall fit with this model was relatively good [$\chi^2(19) = 9.1984, P > 0.95$], the thresholds obtained by fitting logistic functions to the data are overestimated and the slopes are systematically underestimated [thresholds: $x_{emp} = 1.21$, $x_{mod} = 1.58$, $t(4) = 6.56$, $P < 0.01$; slopes: $x_{emp} = 0.1188$, $x_{mod} = 0.0940$, $t(4) = 3.27$, $P < 0.05$].

Even though normalization of the weights already reduces the variance of the decision variable, the model fit suggests that it is still too large. How can this overestimation of variance be explained? One reason could be that the channels are not independent. If the frequency-response functions of neighboring channels overlap, then the fact that the variance of the decision variable is overestimated can be explained by assuming that the channel outputs are negatively correlated, possibly due to mutual inhibition. In this case, one would have to subtract twice the absolute amount of the covariances from the overall sum of the individual variances to obtain an appropriate variance estimation. However, such a cross-channel correlation is rather difficult to model. Thus, to keep the model relatively simple, the amount of channel overlap was estimated by assuming a certain filter shape and employing the individual filter widths. The estimates W_i reflect the equivalent bandwidth, i.e. the area under the filter function divided by the function's maximum height. If one further considers the area under the overall envelope of the five overlapping filters as a measure of the effective noise, then, by integrating from 0 to 50 c/deg, it appears that it is only 62.2% of the sum of the individual filter areas.

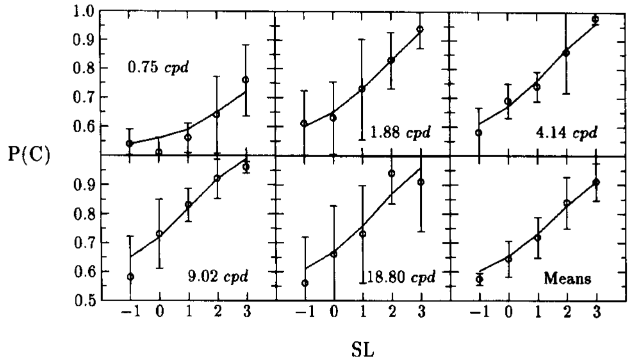

FIGURE 5. Psychometric functions for the condition with randomized spatial-frequencies and no cues fitted with a multiple-band energy-detection model. The bars indicate the 95% confidence interval.

By decreasing the variance of the decision variable accordingly, the fit improved [$\chi^2(19) = 5.77, P > 0.995$], and there were no significant threshold and slope differences [thresholds: $x_{emp} = 1.21$, $x_{mod} = 1.23$, $t(4) = 0.18$, $P > 0.8$; slopes: $x_{emp} = 0.1188$, $x_{theo} = 0.0970$, $t(4) = 2.52$, $P > 0.07$].

The obtained weights g_i are: 0.225; 0.212; 0.163; 0.273; 0.127.

The curves for the individual psychometric functions fitted by this model are depicted in Fig. 5. As can be seen, even the fit to the data for the lowest spatial-frequency is rather good.

In this model it has been assumed that the characteristic of the individual channels is identical to that in the blocked condition. However, although this assumption finally led to a good fit, it is inconsistent with the conclusions drawn in the last section. There is no reason to assume that the filters are narrower in the randomized no-cue condition than in the symbolic cue condition.

If we assume that in the randomized no-cue condition the width of the individual channels was identical to that in the symbolic cue condition (i.e. the width parameters of the blocked condition times 1.707), then this would increase the variance. This modification makes it necessary to calculate the amount of effective noise, i.e. the area under the envelope, again, which now turned out to be 41.8% of the sum of the individual channel widths. This modification leads to almost identical results.

CONCLUSION

The empirical results show that, when the task is to detect sinusoidal gratings in white noise, the thresholds as well as the slopes of the psychometric functions increase with spatial-frequency. This suggests that an energy-detector model might be more appropriate for describing the behavior of the individual spatial-frequency channels than a matched-filter model.

It has further been shown that spatial-frequency uncertainty leads to higher thresholds and steeper psychometric functions compared with detection under certainty. This fact excludes traditional single-band models for modeling the uncertainty effect and favors multiple-band models [*cf* Hübner (1993a)].

Unexpectedly, it turned out that the size of the uncertainty effect varied considerably across spatial-frequencies. Nevertheless, a multiple-band model, where the outputs of the individual channels were linearly combined to construct a single decision variable, could fit the data quite well.

Although the estimated value of the weight (g) for the channel with the smallest uncertainty effect is the largest, it is obvious that the obtained weight pattern is not the main reason for the differential uncertainty effect. Rather, the characteristic of the individual channels seems to produce most of the variation. The effect-size differences can easily be understood if one considers the individual channels' contribution to the effective noise.

For simplicity, compare only two channels: one for the lowest and one for the highest spatial-frequency. Because the bandwidth of the channel for the lowest spatial-frequency is rather small, it is highly sensitive. This means that in a single-band condition (no uncertainty) only a small signal amplitude is needed to obtain a certain signal-to-noise ratio. On the other hand, the channel for the highest spatial-frequency is less sensitive, since its bandwidth is broader, and a high signal contrast is needed to obtain the same signal-to-noise ratio. If, under uncertainty, the output of both channels is added, then the same amount of noise is effective, independent of the spatial-frequency of the signal.

Now assume that the low spatial-frequency signal with its low contrast is present. In this case the relatively large amount of noise contributed by the high spatial-frequency channel would lead to an extremely low signal-to-noise ratio compared with the single-band condition, and to a corresponding performance reduction. If, on the other hand, the signal with the high spatial-frequency with its high contrast is present, then the signal-to-noise ratio and the corresponding performance is hardly affected by the small amount of extra noise contributed by the low spatial-frequency channel. This asymmetry can explain the large effect-size differences.

The presentation of cues indicating the spatial-frequency of the signal in the subsequent trial significantly reduced the spatial-frequency uncertainty effect. Particularly effective in this respect were the sensory cues. Since they were presented at a different location in the visual field as the signals, and since the rotated and phase cues were also highly effective, it can be concluded that sensory cuing takes place at higher stages in the visual pathway, where spatial-frequency is coded independently of phase and orientation [*cf* Burbeck & Regan (1983); Bradley & Skottun (1984); Heeley *et al.* (1993); Magnussen *et al.* (1990)], and also independently of retinal coordinates (Burbeck, 1987).

Although the symbolic cues also appreciably reduced uncertainty, they were less effective than the sensory cues. This could indicate that the symbolic cues affected merely the decision process, whereas the sensory cues additionally affected stimulus coding by decreasing the width of the sensory filters. Unfortunately, the considered models for the randomized no-cue condition provide no strong support for this view. The model with the smaller filters fitted the data similarly well. Thus, the question of whether the cues affect the coding or the decision process cannot definitively be answered.

These difficulties encourage one to generally question the assumption that two stages are sufficient to describe the results, and to consider alternative interpretations. One possibility is to introduce an additional stage where the outputs of spatial-frequency channels, which are assumed to process the stimuli in parallel (coding stage), are selected (selection stage) into the visual short-term memory (VSTM). The selected information is then used to determine the response (decision stage). Such a *late-selection* model has also been proposed by Müller and Humphreys (1991) in connection with spatial uncertainty.

Within this framework, cues can be thought of as improving the selection process. The more relevant information a cue provides the more precise the selection process will be and, consequently, the less noise will be selected. For instance, to utilize symbolic cues, the subjects have to rely on the spatial-frequency information recalled from long-term memory. This information should be less precise than that provided by the sensory cues which can directly be stored in the VSTM and might be nearly perfect [*cf* Magnussen *et al.* (1990, 1991)]. Reduced precision leads to the selection of some additional noise from neighboring channels.

Such a conception would also be in line with the model fitted for the symbolic cue condition. One would merely have to assume that the additional noise is proportional to the filter width of the cued channel.

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