Biol. Cybern. 79, 413–425 (1998)

Biological Cybernetics

Detection of aperiodic test patterns by pattern specific detectors revealed by subthreshold summation

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Received: 16 December 1996 / Accepted in revised form: 9 June 1998

Abstract. The hypothesis that the visual system detects, under certain conditions, stimulus patterns by means of filters matched to these patterns (Hauske et al. 1976) may be challenged by the argument that other coding mechanisms like spatial frequency channels, Gabor or Hermite filters mimick the behaviour of matched filters, a view supported by the finding of non-linear contrast-interrelationship functions (CIFs), as determined in superposition experiments. In this paper we argue that an overall non-linear CIF does not contradict the hypothesis of detection by a single matched filter: we find that the sensitivity functions determined in our experiments can be separated into two components reflecting (i) a bandpass filter and (ii) a filter characterised by the spectrum of the test-pattern.

1 Introduction

The visual system may be conceived as a neural network composed of subunits acting as "channels'. Hauske, Wolf and Lupp (1976) proposed the hypothesis that channels matched to certain stimulus patterns exist and were the first to provide threshold measurements, arrived at by an adaptation of the superposition method of Kulikowski and King-Smith (1973), supporting the hypothesis; Hauske, Lupp and Wolf (1978) elaborated the hypothesis and presented more data.

The model of Hauske et al. (1976) has been criticised as being implausible as a *general* model of pattern detection since it is uneconomical to have special detectors for each possible pattern; pattern detection mechanisms should be multipurpose systems responding to a variety of patterns. Graham (1989) claimed that data supporting the model could alternatively be explained particularly in terms of models of detection by probability summation, e.g. probability summation among spatial frequency channels (Sachs et al. 1971; Graham 1977, 1980; Watson 1982), or probability summation among channels defined by DOG functions, like Wilson and Bergen (1979). Models that may be considered hybrid models of feature detection and detection by probability summation, e.g. Daugman (1984); Jaschinski-Kruza and Cavonius (1984); Ross et al. (1989); Du Buf (1992, 1994) may also be taken as competing with the matched filter model; however, quantitative tests of the claim that models like these are indeed equivalent to the matched filter model do not seem to exist.

However, the matched filter model becomes interesting again if one takes processes of perceptual learning into account (Beard et al. 1995; Poggio et al. 1992; Kirkwood et al. 1996); indeed, it is possible to show that Hebb's rule (Hebb 1949; cf. Hertz et al. 1991) together with the suplementary condition that synaptic weights should not become infinite implies that a neuron will turn into a matched filter for a certain stimulus aspect with probability 1 (Oja 1982; Nachtigall 1991). This does not yet mean that the human visual system actually behaves this way, but it appears to be worthwhile to explore to what extent data may be found that support the matched filter model.

The purpose of this paper is to present further data concerning the matched filter hypothesis and to discuss some conditions which – it seems – have to be satisfied if the superposition method is to reveal detection by matched filters. Additionally, we note some properties of parameter estimates that may blur the image of the channels involved in the detection task as generated by the superposition method. In summary, we may say that our experimental results suggest that for the matched filter model to fit the data, the stimulus patterns have to be small and the experimental situation has to be such that cognitive processes like attentional focussing, usually not taken into account by models of elementary detection processes, generate no additional variance in the data.

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2 Theory

2.1 Notation, definitions and assumptions

2.1.1 Notation

Stimulus patterns will be defined as $s = m_t s_t + m_b s_b$, where s, s_t and s_b define luminance as functions of the retinal coordinate x; we restrict ourselves to one-dimensional patterns. s_t will be called the test pattern, s_b the background pattern. m_t and m_b are Maxwell contrasts, defined by $m = (l_{\max} - l_{\min})/2l_0$, with $l_{\max}$ and $l_{\min}$ the maximum and minimum luminance, respectively, and l_0 the average luminance.

A channel is some subsystem of the visual system; we restrict ourselves to linear channels. Let r be the response of a channel C to the input s. We write $r = L(s)$, L an operator representing the channel C. Then $r = m_t L(s_t) + m_b L(s_b)$; $h_t := L(s_t)$ and $h_b := L(s_b)$ will be called the unit responses of the channel C to s_t and s_b, respectively, because they are the responses of C to s_t and s_b with contrast equal to 1. r, h_t and h_b are functions of x.

2.1.2 Matched filters and matched channels

We make use of the standard definition of a matched filter: let u be a signal with Fourier transform U, and let the signal be processed by a linear system with system function V. The system is matched to the signal u, if $V(\omega) = aU^*(\omega)\exp(-j\omega x^+)$, where U^* is the complex conjugate of U, $\omega = 2\pi f$, f – in our case – a spatial frequency, and x^+ the position of maximum output of the system; a is some proportionality constant and $j = \sqrt{-1}$ (cf. Papoulis 1981).

In order to apply the notion of a matched filter to the visual system, one has to consider the possibility that the site of the filter is cortical, i.e. the filter responds to a signal that results from the stimulus pattern s being passed through the retina, the lateral geniculate nucleus, etc. These stages will be called a pre-filter; the pre-filter may be represented by a system function $G(\omega)$. Let u_t be the response of the pre-filter to the stimulus pattern s_t, and let the Fourier transform of s_t and u_t be given by S_t and U_t, respectively. Then $U_t(\omega) = G(\omega)S_t(\omega)$. Let us assume that u_t is detected by a filter matched to u_t. The system function of this filter is then $V_t(\omega) = a_t U_t^*(\omega)e^{-j\omega x^+} = a_t(G(\omega)S_t(\omega))^* e^{-j\omega x^+}$ (see Fig. 1). The filter will be referred to as a matched channel for s_t.

Let us consider the matched channel for $s_t(x) = s_{0t}(x - x_0)$, i.e. for a pattern differing from a given, foveally presented pattern s_{0t} only by a shift with respect to the x-axis. From measurements of the line spread function (LSF) of the visual system, it is known that the shape of the LSF depends upon the retinal location (e.g. Hines 1976; Wilson and Giese 1977). Correspondingly, we assume that the pre-filter described by G depends upon x_0, and so we write $G(\omega, x_0)$. Note that we allow for the special case $G(\omega, x_0) \equiv G_0$, G_0 a constant independent of ω, perhaps even of x_0, i.e. we allow for the possibility that there is no separation into a pre-filter and a cortical filter. The matched filter for the shifted pattern $s_t(x) = s_{0t}(x - x_0)$ with Fourier transform S_t is defined by $U_t^*(\omega, x_0) = a_t G^*(\omega, x_0) S_t^*(\omega) e^{-j\omega x_0^+}$, where x_0^+ is the locus of maximum output of this filter. Since $S_t(\omega) = S_{0t}(\omega)e^{-j\omega x_0}$, the system function of the matched channel is then given by

$$W_t(\omega, x_0) = a_t |G(\omega, x_0)|^2 S_{0t}^*(\omega) e^{j\omega(x_0 - x_0^+)} \tag{1}$$

Note that a_t is a free parameter in (1) related to the energy of the signal (Papoulis 1981, chapter 6). Figure 1 shows the corresponding cascade.

2.1.3 Contrast interrelation

Suppose that a pattern $s = m_t s_t + m_b s_b$, i.e. a superposition of the patterns $m_t s_t$ and $m_b s_b$, is presented with the contrasts m_t and m_b assuming values such that the probability of detection of s equals a certain constant p_0, e.g. $p_0 = 1/2$ or $p_0 = 3/4$. We may write $m_t = \phi(m_b)$, expressing the fact that for a fixed value of p_0, the contrast m_t has to assume a certain value depending upon that of m_b once m_b has been fixed. ϕ will be called a contrast-interrelationship function (CIF). The indices t and b may be dropped if there is no possibility of confusion: we may put $m = m_b$, $\phi(m) = m_t$.

While for s_t an arbitrary – e.g. a bar or a sawtooth – pattern will be chosen, s_b will define a sinusoidal grating. It will be shown (Sects. 2.2 and 2.3) that under certain conditions the unit response h_b to s_b of a matched channel C_t for s_t – provided such a channel exists – turns out to be proportional to the system function of C_t, and h_b is found via the experimental determination of CIFs for the composite pattern $s = \phi(m)s_t + ms_b$.

2.1.4 Dominance

Suppose there exists a set $\mathbf{D} = \{C_1, \ldots, C_n\}$ of channels which may become involved in the detection task. Let $F_k = 1 - P_k$ with P_k being the probability that the channel $C_k \in \mathbf{D}$ detects the pattern $\phi(m)s_t + ms_b$. Suppose there exists a channel $C_\mu \in \mathbf{D}$ and a corresponding interval of contrast values $M_\mu = \{m | 0 < m < m_{\mu+}\}$ for some $m_{\mu+} > 0$ such that for all $m \in M_\mu$, $F_\mu < 1$ and $F_k = 1$ for $k \neq \mu$. Then the channel C_μ is said to dominate the detection process on M_μ.

The idea behind the notion of dominance is that for a certain range, i.e. interval M_μ, of values of m, the effects

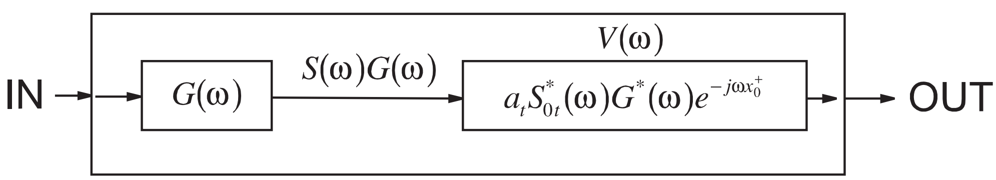

Fig. 1. The structure of a matched channel, the notation is given in the Fourier domain

of probability summation or non-linear pooling of channel activities do not exist or are at least negligible: for all $m \in M_\mu$, detection is by a certain single channel C_μ; C_μ will be called the dominating channel[1] for $s = m_t s_t + m_b s_b$.

2.1.5 Assumptions

We make the following assumptions:

A_1 (*Matched filter*) For stimulus patterns s_t as defined in sect. 3.1.2 (with s_{0t} representing the special case $x_0 = 0$), detection will be dominated by a single channel $C_\mu = C_t$, and C_t has the system function (1), i.e. C_t is a channel matched to s_t.

A_2 (*Detection*) The pattern will be detected with probability p_0 if

$$r_t = \phi(m)h_t + mh_b = c \tag{2}$$

c a certain constant, with $r_t = r_t(x_0^+)$, $h_t = h_t(x_0^+)$ and $h_b = h_b(x_0^+)$, and x_0^+ is the retinal coordinate at which the output of C_t is maximal.

Comments. A channel may be matched to a pattern without being dominant. However, our method of testing the hypothesis of detection by a matched channel presupposes that the channel is dominant in order to show up as a matched channel (see Sect. 2.3.1); while it is hard to assign a value to $m_{\mu+}$ in advance, it should be understood that $m_{\mu+}$ should be sufficiently large to allow for different values of $m < m_{\mu+}$ for which different values $\hat{\phi}(m)$ can be reliably estimated provided s_t and s_b are such that $\phi(m) \neq$ constant.

It is also implied that the matched channel is location-specific, i.e. is specific for the retinal position at which the pattern is presented. Hauske et al. (1976) appear to be the first who discussed detection of patterns with respect to (1). It should also be noted that the existence of a matched channel for an arbitrary pattern is not postulated; we only consider detection of patterns by a matched filter for each of the patterns employed in the experiment. □

2.2 Grating sensitivity of a channel matched to s_t

Let s_b be a sinusoidal grating, i.e. let either $s_b = \sin(\omega x)$ or $s_b = \cos(\omega x)$, with $\omega = 2\pi f$ and f the spatial frequency. Given appropriate conditions ($m = m_b$ has to be sufficiently small; if m is too large, the pattern s may be detected by a channel maximally sensitive to s_b and h_b is no longer the unit response of the channel C_t), the unit response h_b of C_t is the (harmonic) steady-state response of C_t. Clearly, h_b depends upon the value of ω. Since for an arbitrary linear system with system response W one has $L(e^{j\omega x}) = W(\omega)e^{j\omega x}$ (e.g. Hsu 1970, p. 124) one finds, making use of Euler's relations,

$$h_b(x;\omega) = \begin{cases} h_b^{\cos}(x;\omega) := L(\cos(\omega x)) = Re(W(\omega)e^{j\omega x}) \\ h_b^{\sin}(x;\omega) := L(\sin(\omega x)) = Im(W(\omega)e^{j\omega x}) \end{cases}$$

Substituting for W the expression for W_t given in (1), one has for $x = x_0^+$, i.e. for the point of maximum output,

$$h_b(x_0^+;\omega) = \begin{cases} a_t|G(\omega,x_0)|^2 Re[S_{0t}^*(\omega)e^{j\omega x_0}], & s_b(x) = \cos(\omega x), \\ a_t|G(\omega,x_0)|^2 Im[S_{0t}^*(\omega)e^{j\omega x_0}], & s_b(x) = \sin(\omega x), \end{cases} \tag{3}$$

with S_{0t} the Fourier transform of s_{0t} and S_{0t}^* its complex conjugate. Note that according to (1) the system function depends upon x_0^+; taking, as in (3), the response at x_0^+ implies that x_0^+ no longer shows up on the right hand side of (3), which again means that no specific assumptions about the value of x_0^+ have to be made. We will therefore simply write $h_b(\omega)$ when it is necessary to indicate the dependency of h_b upon ω. Thus the unit response $h_b(\omega)$ equals the system function of C_t. $h_b(\omega)$ will also be referred to as the grating sensitivity of C_t.

2.3 Estimation of channel characteristics

2.3.1 Estimation of the grating sensitivity

Assumption A_2 implies $\phi(m) = c/h_t - mh_b/h_t$ for $m \in M_\mu = M_t$ (since $C_\mu = C_t$), i.e. the linearity of the CIF on M_t. The parameters $\alpha_t := -h_b/h_t$, $\beta_t := c/h_t$ may be estimated from the pairs $(m, \hat{\phi}(m))$, where $\hat{\phi}$ is the experimentally determined estimate of ϕ corresponding to m. Further, $\beta_t = \phi(0) = m_{0t}$, m_{0t} the threshold contrast for s_t when presented without the background pattern s_b, and $m_{0t}h_t = c$. It follows that $\alpha_t/\beta_t = -h_b/c$. On the other hand, $\phi(m) = \beta_t + \alpha_t m$ implies $\alpha_t = (\phi(m) - \beta_t)/m$ and $\alpha_t/\beta_t = (\phi(m) - \beta_t)/(m_{0t}m) = -h_b/c$. Let $\hat{\alpha}_t$ and $\hat{\beta}_t$ be estimates of α_t and β_t, and let '$\hat{=}$' stand for 'is an estimate of'. We introduce the sensitivity estimates Φ_i, $i = 1, 2$:

$$\Phi_1(\omega, x_0) \stackrel{\text{def}}{=} -\frac{\hat{\alpha}_t(\omega)}{\hat{\beta}_t} \hat{=} \frac{h_b(\omega, x_0)}{c} \tag{4}$$

$$\Phi_2(\omega, x_0) \stackrel{\text{def}}{=} -\frac{\hat{\phi}(m;\omega) - \hat{m}_{0t}}{\hat{m}_{0t}m} \hat{=} \frac{h_b(\omega, x_0)}{c} \tag{5}$$

We have written $\hat{\alpha}_t(\omega)$ instead of $\hat{\alpha}_t$ in order to stress the fact that the slope α_t of the CIF depends upon ω, since h_b depends upon ω. $\hat{\beta}_t$ should be independent of ω.

Comments.

1. The calculation of Φ_1 requires the estimation of the slope α_t and the additive constant β_t of the linear approximation to a CIF, i.e. is based upon the determination of a part of a CIF. Therefore, Φ_1 summarises, for a given ω, threshold estimates $\hat{\phi}$ for different values of m. Φ_2, on the other hand, allows

[1] The definition of dominance may be relaxed somewhat, demanding only $F_\mu < F_k = 1 - \epsilon_k < 1$, where the ϵ_k are sufficiently small numbers such that the slope of the linear approximation ϕ_μ approximates $-h_{\mu b}/h_{\mu t}$ to a fair degree. However, such an approach would require a lengthy discussion of the resulting approximations, which is beyond the scope of this paper. We return to the question of dominance in the Discussion.

us to arrive at an estimate of $-h_b(\omega)/c$ on the basis of a single threshold determination $\hat{\phi}(m)$ for a given value of m (and ω), provided the estimate $\hat{m}_{0t}$ is available. One has to assume, of course, that the value of m is from an interval M_t upon which the CIF is linear. The advantage of using Φ_1 is that the estimates of $-h_b/c$ are more stable, being based on more measurements, and that the observed section of the CIF allows an appreciation of the requirement of linearity of this section which is necessary to allow the interpretation of Φ_1 being an estimate of $-h_b/c$. The clear advantage of using Φ_2 is speed of experimentation.

The equations (4) and (5) or equivalent versions of them may of course also be found in the work of Kulikowski and King-Smith (1973)[2] and Hauske et al. (1976).

2. If $\hat{\alpha}_t$ and $\hat{\beta}_t$ are determined as Least Squares estimates, they will be unbiased (Kendall and Stuart 1973, p 81); however, the quotient even of unbiased estimates need not be unbiased (Kendall and Stuart 1969, p 227).[3] A bias may, in particular, create the impression of a misfit of model and data even if the model is correct. The bias may, however, be negligible if the variances of the estimates $\hat{\alpha}_t$ and $\hat{\beta}_t$ (or, equivalently, $\hat{\phi}$ and $\hat{m}_{0t}$) are sufficiently small.
3. Like a_t, c is a free parameter in our model. Without further assumptions, neither a_t nor c can be estimated from the data; we will concentrate on the fact that according to (1) the system function W_t of a matched filter is proportional to the complex conjugate of the spectrum of the signal to which the filter is matched. We will comment upon the estimation of a_t in the Discussion.
4. If dominance of the detecting filter is lacking, a change of m to m' may imply that the detecting channel changes from C_t to C_t', or the mixture of detecting channels changes to another mixture. This will be the case when channels with similar responses to the stimulus pattern compete with each other under threshold conditions to the extent that in different trials the stimulus may be detected by different channels. Since there is practically no physical, in particular no physiological, system which is free of noise (Gardiner 1990), lack of dominance will most likely be due to detection by probability summation for all values of m, which again implies that for no value of m does the CIF reflect the characteristics of a single channel. □

Unfortunately, we do not know in advance whether a dominant channel exists for the stimulus patterns employed. Even if we knew, we still might not know the interval M_t. However, if the sensitivities Φ_i do reflect the spectrum of s_t according to (3) we may take this as support of the hypothesis of detection by a dominant, matched channel. If they do not, the detecting channel is either not matched, or not dominant, or neither matched nor dominant. A possible hint for the lack of dominance is that (i) the estimates $\hat{\beta}_t$ for different values of $f = \omega/2\pi$ show systematic deviations from $\hat{m}_{0t}$, i.e. depend upon f, and/or (ii) that the estimates Φ_1 and Φ_2 deviate from each other by more than experimental error.

2.3.2 Estimation of the pre-filter

The factor $a_t|G(\omega, x_0)|^2/c$ has to be estimated from the data in order to evaluate the matched-channel model. If $\Phi_i(\omega)$, $i = 1, 2$, is divided by either the real or the imaginary part of $S_{0t}e^{j\omega x_0}$, which again is known from the definition of the stimulus patterns, one obtains, according to (3), an estimate of $B(\omega; x_0) \stackrel{\text{def}}{=} a_t|G(\omega, x_0)|^2/c$, depending upon the phase (sine or cosine) of the background grating. Experimental error would imply different estimates for each phase of s_b. However, these estimates may be summarised into a single estimate $\hat{B}(\omega, x_0)$ of $a_t|G(\omega, x_0)|^2/c$, namely

$$\hat{B}(\omega, x_0) = \frac{a_t}{|S|}\sqrt{(\Phi_i^{\cos})^2 + (\Phi_i^{\sin})^2} \mathrel{\hat{=}} \frac{a_t}{c}|G(\omega, x_0)|^2 \qquad (6)$$

$|S|$ is the modulus of $S_{0t}^* e^{\omega x_0}$. Equation (6) follows directly from the definition of Φ_i, $i = 1, 2$.

One may then predict the observed sensitivities $\Phi_i(\omega, x_0)$ according to

$$\hat{B}(\omega, x_0) Re[S_{0t}^*(\omega)e^{j\omega x_0}] \mathrel{\hat{=}} \Phi_i^{\cos}(\omega, x_0)], \quad s_b = \cos(\omega x)$$

$$\hat{B}(\omega, x_0) Im[S_{0t}^*(\omega)e^{j\omega x_0}] \mathrel{\hat{=}} \Phi_i^{\sin}(\omega, x_0)], \quad s_b = \sin(\omega x) \qquad (7)$$

i.e. one has to multiply the estimate $\hat{B}(\omega, x_0)$ with either the real or the imaginary part of the spectrum of the stimulus pattern s_t in order to arrive at a prediction of the measured sensitivities $\Phi_i^{\cos}(\omega, x_0)$ or $\Phi_i^{\sin}(\omega, x_0)$. For given s_t, spatial frequency $f = \omega/2\pi$ and contrast m the value of $\Phi_i(\omega, x_0)$ was determined several times, so that the standard deviation of the lefthand side of (7) can be computed and indicated by error bars. The curve computed according to the lefthand side of (7) can then be directly compared with the values of $\Phi_i(\omega, x_0) = \Phi_i^{\cos}(\omega, x_0)$, or $\Phi_i(\omega, x_0) = \Phi_i^{\sin}(\omega, x_0)$, depending upon the phase of s.[4]

Note that the factor a_t/c does not have to be estimated when predictions for a given stimulus pattern are

[2] Kulikowski and King-smith (1973) introduced the contrast m_0, usually not from the interval C_t, such that $\phi_t(m_0) = \beta_t + \alpha_t m_0 = 0$. Then $1/m_0 = -\alpha_t/\beta_t = -h_b(\omega)/c$ according to (4); m_0 is the contrast of $s_b(\omega)$ necessary to lift the activation of C_t to threshold value if activated by a sinusoidal grating of frequency $f = \omega/2\pi$. Since the reciprocal of a threshold contrast is often called 'sensitivity' we have thus a further motivation for calling h_b (or h_b/c for our purposes) the spatial frequency sensitivity of C_t. Of course, m_0 is an extrapolated value.

[3] This follows from the fact that the expected value of a quotient does, in general, not equal the quotient of the corresponding expected values.

[4] Alternatively, one could have "predicted" $Re[S_{0t}^*(\omega)e^{j\omega x_0}]$ and $Im[S_{0t}^*(\omega)e^{j\omega x_0}]$ by $\Phi_i^{\cos}(\omega, x_0)/\hat{B}(\omega, x_0)$ and $\Phi_i^{\sin}(\omega, x_0)/\hat{B}(\omega, x_0)$. However, (i) quotients of estimates may be biassed (see Sect. 3, comment 2, and (ii) the standard deviation of these quotients is not known.

considered. $\hat{B}$ is proportional to $|G(\omega, x_0)|^2$; however, since a_t is specific for a pattern and therefore for the corresponding channel, the proportionality factor a_t/c will be different for different stimulus patterns.

3 Experiment

The experiment aimed at the determination of estimates of Φ_1 and Φ_2 in order to test the hypothesis of detection by matched filters. In particular, (i) estimates of Φ_1 and Φ_2 according to (4) and (5) were derived from threshold measurements (see Sect. 3.2), the equivalence of the Φ_1- and Φ_2-values and the linearity of the resulting approximation ϕ_t to ϕ was investigated; (ii) estimates of $a_t|G|^2/c$ were derived according to (7), and (iii) the matched filter hypothesis was tested by comparing the estimates Φ_i with the predictions of the matched filter model as expressed in (3).

The specific stimulus patterns with respect to which the individual tests were carried out will be given together with the corresponding results, see Sect. 4.

3.1 Method

3.1.1 Apparatus

Patterns were generated on a RAMTEK graphics computer and displayed on a MAG 17" screen with a resolution of 1280×1024 pixels and a pixel depth of 24 bits allowing for 256 gray levels to be displayed simultaneously. The amplitude response of the monitor was linearized using an electrical circuit that compressed the displayable range of contrasts to a small interval centered at the mean luminance of 6.5 cd/m^2. The linearity of the monitor's amplitude response was checked before each experimental session using a calibration program which determined the relationship between the digital gray value of the LUTs and luminance in cd/m^2 measured by an LMT 1003 photometer. The coefficient of determination of the regression line was in all cases greater than 0.98. The vertical scan rate of the monitor was 62 Hz at a horizontal frequency of 66 kHz. The room was darkened such that the illumination of the surround matched the illumination on the screen to a fair degree of approximation. Patterns were viewed monocularly at a distance of 150 cm. The subjects used a chin rest and an ocular with a lens for correction of myopia. The ocular limited the visible area of the screen to a field of 8×8 deg.[5] The subjects signalled the presence or absence of the stimulus by pressing a button on an external response box.

3.1.2 Stimuli

The stimulus patterns were defined as compound patterns

$$l(x) = l_0[1 + \sigma_t(x) + \sigma_b(x)] \tag{8}$$

[5] 'deg' is used for 'degrees of visual angle'.

where l denotes luminance and l_0 mean luminance. Further, $\sigma_t(x) = m_t s_t(x)$ and $\sigma_b = m_b s_b(x)$, where m_t and m_b are contrasts (see Sect. 2.1), and s_t and s_b are functions defining luminance distributions; s_t defines an aperiodic pattern and s_b a sinusoidal grating.

Consider the single sawtooth pattern

$$S_{\text{saw}}(x; x_k) = \begin{cases} 1 + (x - x_k)/\Delta x, & x_k < x \leq x_k \quad k = 1, \cdots, 5; \\ 0, & \text{else} \end{cases} \tag{9}$$

with $x_k = (k-1)\Delta x$, $\Delta x = 0.225$ deg. Each of the patterns $s_{\text{saw}}(x; x_k)$, $k = 1, \ldots, 5$ was employed as a test pattern.

The pattern defined for $x_1 = 0$ will be said to be foveally presented; its maximum is in the center of the fovea ($x = 0$).

The background pattern was defined by $\sigma_2 = m s_b(x)$ with

$$s_b(x) = \begin{cases} \sin(2\pi f), & \text{or} \\ \cos(2\pi f) \end{cases} \tag{10}$$

The grating patterns always subtended the total visible area of 8×8 deg. The relation between test and background pattern is shown in Fig. 2.

Note that $s_{\text{saw}}(x; x_2) = s_{\text{saw}}(x - \Delta x; x_1)$. Let $s_{\text{saw}}(x; x_2) \stackrel{\text{def}}{=} s(I)$ and define $s(II) \stackrel{\text{def}}{=} -s(I)$, $s(III) \stackrel{\text{def}}{=} s_{\text{saw}}(-(x + \Delta x))$, $s(IV) \stackrel{\text{def}}{=} -s_{\text{saw}}(-(x + \Delta x))$, see Fig. 3. From these patterns two more stimulus patterns may be defined: $s_{\text{saw}}^{\text{even}} \stackrel{\text{def}}{=} s(I) + s(III)$ and $s_{\text{saw}}^{\text{odd}} \stackrel{\text{def}}{=} s(I) + s(IV)$.

Eventually, stimulus patterns were defined either as a single vertical bar or as being composed of bars. Single bars are defined either as

$$s_{\text{bar}}(x) = 1 \textit{ for } x \in [0, \Delta x], \quad s_t(x) = 0 \text{ otherwise} \tag{11}$$

with $\Delta x = .225$ deg; such bars can be composed as a superposition of two sawtooth patterns, see Fig. 4.

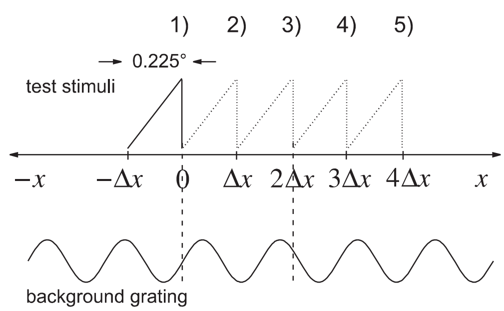

Fig. 2. Test stimuli and subthreshold gratings. Test patterns were constructed by shifting the test pattern at $x_1 = 0$ deg to positions $x_k = (k-1)\Delta x$, $k = 1, \ldots, 5$. All five resulting test patterns have the same amplitude spectra, but different phase spectra

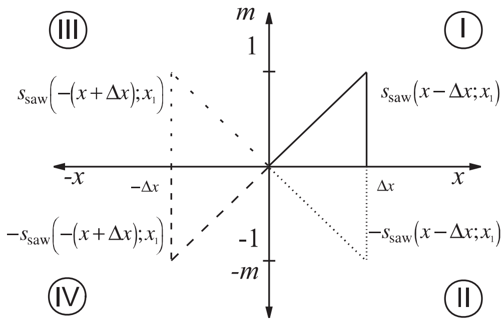

Fig. 3. Test patterns s_t generated from the pattern at position $x_2 = 0.225$ deg. This pattern will also be called $s(\mathrm{I})$. Mirroring this pattern on the y - axis (contrast) and the x - axis (location) produces the test stimuli $s(\mathrm{II})$, $s(\mathrm{III})$ and $s(\mathrm{IV})$

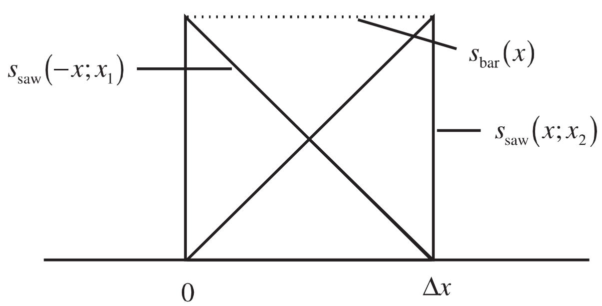

Fig. 4. A bar is given as the superposition of two appropriately chosen sawtooth edges, i.e. $s_{bar} = s_{saw}(-x;x_1) + s_{saw}(x;x_2)$

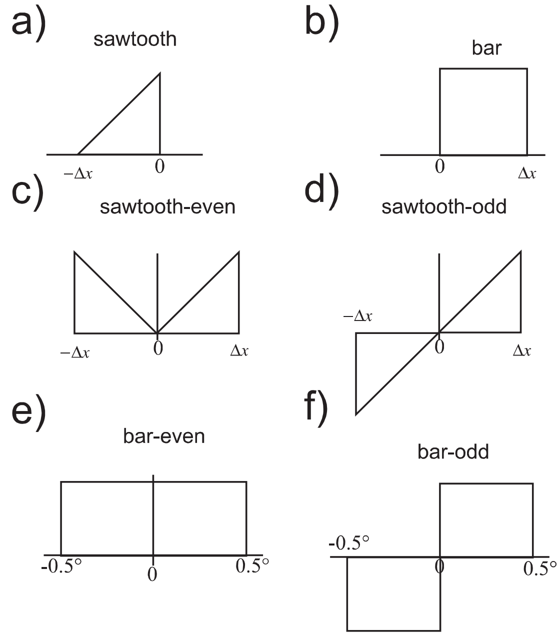

Fig. 5. Overview of the test stimuli used in the experiment. The sawtooth edge was presented at $x_1 = 0$ deg and at four further retinal positions, as shown in Fig. 2. All other stimuli were presented only at the single position $x_1 = 0$ deg as shown have. A comparison with Fig. 3 shows that $s_{saw}^{even} = s(\mathrm{I}) + s(\mathrm{III})$, $s_{saw}^{odd} = s(\mathrm{I}) + s(\mathrm{IV})$

Alternatively, patterns composed of bars are defined as

$$s_{bar}^{even} = \begin{cases} 1, & x \in [-.5, .5), \\ 0, & \text{otherwise} \end{cases} \qquad s_{bar}^{odd} = \begin{cases} -1, & x \in [-.5, 0), \\ 1, & x \in (0, .5], \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

see Fig. 5.

Thus, s_{bar}^{even} is a 1 deg wide vertical bar with midpoint at the fovea; since the pattern is even, its spectrum has no imaginary part. s_{bar}^{odd}, on the other hand, is an odd pattern with its centre at the fovea. The spectrum contains no real part.

3.2 Procedure

In order to determine threshold contrasts, a variant of the Method of Limits was employed. This variant may be characterised as follows:

1. The stimulus (either the test stimulus pattern alone or the superposition of the test stimulus pattern plus a background grating) is presented as a sequence of steps, where each step has a duration of 200 m. For given value of m_b, the sequence is either decreasing or increasing; in a decreasing sequence the contrast m_t ($m_t = m_{0t}$ if $m_b = 0$) is decreased, in an increasing sequence the contrast m_t is increased after each step until, after a certain step, the subject responds; the response signals that the pattern is no longer seen if the sequence decreases and that it has been detected if the sequence increases.
2. For fixed value of m_b of the background grating, the contrast m_t of the test pattern was, in a decreasing sequence, reduced by Δm, e.g. $\Delta m = 4.2 \times 10^{-4}$, from one step to the next, and increased by the same amount in an increasing sequence.
   In a decreasing sequence, the contrast of the pattern in the last step before the subject's response is the *lower value* $\hat{\phi}_l$. In an increasing sequence, the contrast of the pattern in the step before the subject's response is the *upper value* $\hat{\phi}_u$.
3. Decreasing and increasing sequences were taken in pairs, i.e. a decreasing sequence was followed by an increasing one and an increasing sequence by a decreasing one. The starting value of the contrast m_t for an increasing sequence was always $m_{tl} - .012$, where m_{tl} is the lower value determined in the preceding decreasing sequence. The starting value for a decreasing sequence after an increasing sequence was, analogously, $m_{tl} + .012$, where m_{tl} is now the upper value last determined.
4. The estimate Φ_1 was determined as follows. For the ith pair of sequences, the arithmetic mean $\hat{\phi}_i = (\hat{\phi}_{li} + \hat{\phi}_{ui})/2$ was computed. The estimates $\hat{\alpha}$ and $\hat{\beta}$ are LS-estimates from the pairs $(m, \hat{\phi}(m))$ with $\hat{\phi}(m) = \sum_i \hat{\phi}_i/8$.
   To determine Φ_2 the differences $\Delta_i \stackrel{\text{def}}{=} \hat{m}_{0t,i} - \hat{\phi}_i$, with $\hat{m}_{0t,i}$ the estimate of m_{0t} in the ith sequence, were determined for a given value of m. The difference $\Delta = \hat{\phi}_k(m;\omega) - \hat{m}_{0t}$ in (5) was then estimated as the arithmetic mean $\bar{\Delta}(m) = \sum_i \Delta_i/8$.

The standard deviation of the eight estimates will be used to indicate the estimation error.

3.3. Subjects

Two male persons served as subjects, both corrected myopes and experienced observers, one of them the author G.M. All the data reported were taken by the subject who was naive with regard to the purpose of the experiment; G.M. took only control measurements in order to confirm the qualitative nature of the curves.

4 Results

4.1 Linear approximation to CIFs

For all stimulus patterns employed in the experiment, a linear approximation of the CIF was determined. We present data in particular for $s_{saw}(x; x_2)$. Figure 6 shows sections of CIFs and the corresponding linear functions approximating the CIFs for various values of the spatial frequency $f = \omega/2\pi$. The square of the correlation (i.e. the coefficient of determination) between the m_i and the corresponding estimates $\phi_t(m_i)$ was generally about .98. Figure 6a in particular shows CIFs and the linear approximations for s_b in sine-phase, where the axes show the *normalised contrasts* $\tilde{m}$ and $\tilde{\phi}$, i.e. the x-axis shows $\tilde{m} = m/m_{0b}$ with m_{0b} the threshold contrast for the grating without the superimposed test pattern, and the y-axis shows $\tilde{\phi} = \hat{\phi}(m)/\hat{m}_{0t}$, $\hat{m}_{0t}$ an estimate of the threshold contrast of the test pattern s_t without the background grating. The overall non-linearity of $\phi(m)$ is obvious. For $f = 2c/deg$, ϕ can be approximated by a linear function ϕ_t over (at least) the range $(-.5, .5)$; for $f = 4c/deg$, the range of m-values (i.e. of M_t) is even larger. For this frequency the CIF may be taken to be parallel to the x-axis if the normalised contrast $\tilde{m}$ satisfies $-.5 < \tilde{m} < .5$, indicating that this frequency has no influence upon the detection of $s_{saw}(x; x_2)$ within the range of background contrasts employed (negative contrasts reflect a phase shift of the background grating by 180^0). For values of the normalised contrast in the neighbourhood of 1, however, the CIF becomes almost parallel to the y-axis [representing the normalised contrast of the test-pattern $s_{saw}(x; x_2)$]. Figure 6b shows the results for the cosine-phase. For the test patterns employed there exists an interval M_t of normalised contrasts containing m_{0t} upon which the linear approximation for the CIF holds. Altogether, we may assume that for each of the patterns employed, a corresponding interval M_t exists upon which detection is by a dominant channel.

4.2 Test of the matched-filter hypothesis

4.2.1 Matched filters at different eccentricities

The hypothesis that a given stimulus pattern is detected by a matched filter for this pattern implies that the sensitivities Φ_i, $i = 1, 2$ should reflect the spectrum of the pattern. We will present results for the stimulus patterns $s_{saw}(x; x_k)$, $k = 1, \ldots, 5$, employing (7) in order to predict especially the sensitivities Φ_2 corresponding to either the real or the imaginary part of the spectrum of the test pattern s_t. The test requires the determination of estimates of $a_t|G(f, x_{0k})|^2/c$, $x_{0k} = (k-1)\Delta x$, $f = \omega/2\pi$, for the different values of k. To illustrate, we

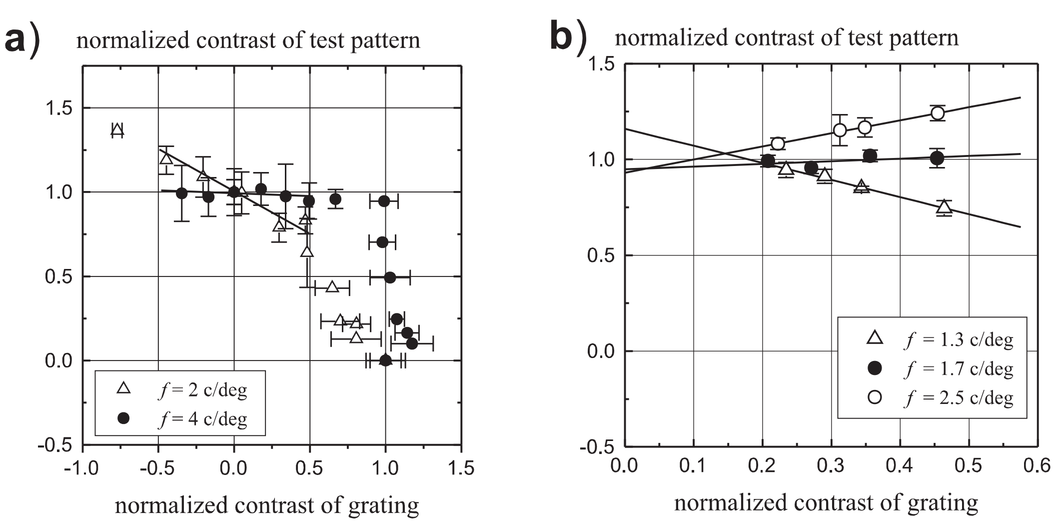

Fig. 6a,b. Contrast interrelationship functions in the normalized contrast space. **a** Recorded for the test pattern $s_{saw}(x; x_1)$, superimposed on sine gratings. The grating contrasts range from half the negative grating threshold contrast up to the positive threshold contrast for the grating alone. The curves are shown for two spatial frequencies (s key). Threshold contrast measurements for normalized grating contrasts $\tilde{m}$ greater than 0.5 were obtained by inverting the order of superposition (the gratings were superimposed on test patterns of constant contrast, the subject had to adjust the contrast for the grating until the compound pattern was at threshold). The linear functions are the regression lines for $\tilde{m} \in [-.5, .5]$ and are the linear approximations ϕ_t to ϕ; negative contrasts refer to background gratings shifted by 180°. **b** Same test patterns, superimposed upon cosine gratings well below threshold. The curves were measured only for positive grating contrasts

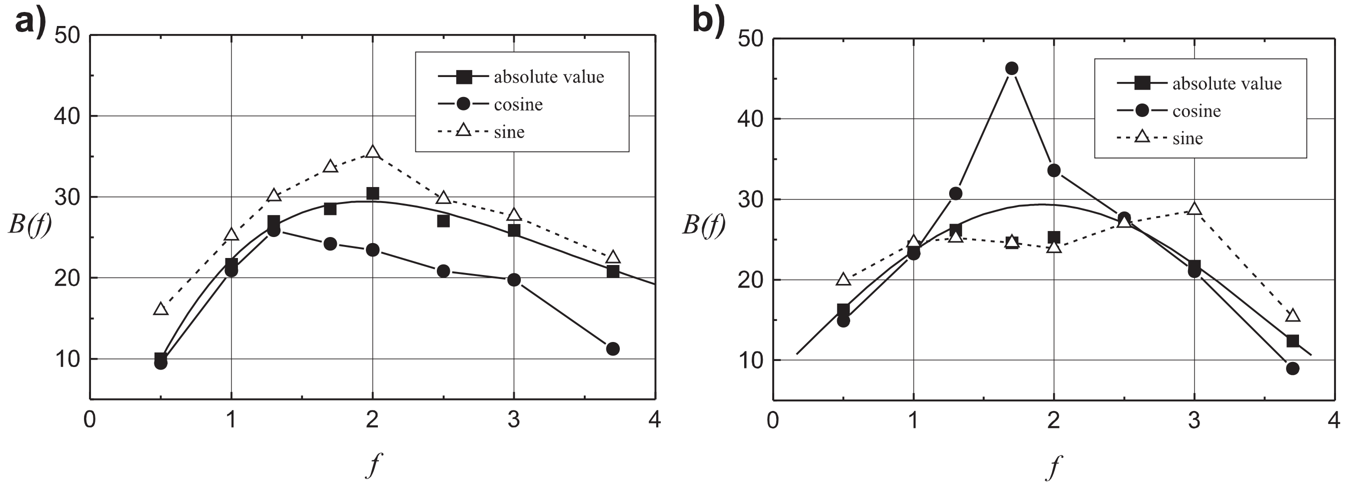

Fig. 7a,b. Values of $a_t|G|^2/c$, estimated according to (6) (*filled squares*), estimates based on $\Phi_2^{\cos}$ (*filled circle*), $\Phi_2^{\sin}$ (*open triangles*), for stimulus patterns at $x_1 = 0$ deg and $x_2 = .225$ deg, exhibiting band pass character. A third-order polynomial was fitted to represent all estimates (*solid line*)

present the results for the eccentricities 0 and $\Delta x = .225$ deg. Figure 7 shows the results, which correspond to those of Hauske et al. (1976): the data indicate a bandpass character of G.

As pointed out in Sect. 2.3.1, the grating sensitivity h_b, which is, according to (3), proportional to the system function of the detecting channel (provided the pattern is indeed detected by a matched filter as specified in Sect. 2.1.5), may be estimated either by Φ_1 or by Φ_2. Φ_1 requires the estimation of the parameters of the linear approximation of the CIF. This is time consuming and necessary only if one wants to explore the range of contrast values for which a linear approximation to the CIF is meaningful. In order to test the hypothesis of detection by a matched filter (i.e. assumptions A_1 and A_2), the estimation of Φ_2 is more parsimonius. We have tested the equivalence of Φ_1 and Φ_2 to make sure that Φ_2 may be used safely. Figure 8 shows the results of the test of the matched-filter hypothesis according to (7) for various values of x_k; Fig. 8b shows the points resulting from estimates Φ_1 and Φ_2, showing the excellent correspondence of the two estimates. One may say that within the precision of measurements, the data correspond to the matched-filter hypothesis.

4.2.2 Crossvalidation I: the effect of modulation sign

Consider the patterns $s(\mathrm{I})$ and $s(\mathrm{II})$ in Fig. 3. Obviously, $s(\mathrm{II}) = -s(\mathrm{I})$, and correspondingly the spectra of the two patterns also differ just by sign. Figure 9a gives the results for the sine- and Fig. 9b for the cosine-background. For the pattern $s(\mathrm{I})$ the data are compatible with the hypothesis of detection by a matched filter (c.f. Fig. 8). So if the predictions for $s(\mathrm{II})$ differ from those for $s(\mathrm{I})$ just by sign we may argue that the pattern $s(\mathrm{II})$ is also detected by a matched filter corresponding to this pattern.

Clearly, the sensitivity curves are mirror images of each other, supporting the hypothesis of detection by a matched filter for $s(\mathrm{II})$. Moreover, the results imply that we may assume that $a_t|G(\omega, x_0)|^2/c$ has the same value for $s(\mathrm{I})$ and $s(\mathrm{II})$.

4.2.3 Crossvalidation II: even and odd compound patterns

As already noted by Kulikowski and King-Smith (1973), Shapley and Tolhurst (1973) and Hauske et al. (1976), even test patterns are only affected by cosine-type gratings, and odd test patterns only interfere with sine-type gratings.

Let us consider the patterns $s_t^{\mathrm{odd}} = s(\mathrm{I}) + \mathrm{s(IV)}$ and $s_t^{\mathrm{even}} = s(\mathrm{I}) + \mathrm{s(III)}$ (referred to as "sawtooth-odd" and "sawtooth-even", respectivley, in Fig. 5), where $s(\mathrm{I})$, $s(\mathrm{III})$ and $s(\mathrm{IV})$ are as defined in Fig. 3, Sect. 3.1.2 Let S_t^{odd} and S_t^{even} be the Fourier transforms of s_t^{odd} and s_t^{even}, and let S_t be the Fourier transform of $s_t = s(\mathrm{I})$. We find that $S_t^{\mathrm{odd}} \equiv 2Im(S_t)$, $S_t^{\mathrm{even}} \equiv 2Re(S_t)$.

The data for s_t^{odd} are presented in Fig. 9c, those for s_t^{even} in Fig. 9d. The sensitivity estimates for $s(\mathrm{I})$ and $s_t^{\mathrm{odd}} = s(\mathrm{I}) + \mathrm{s(IV)}$ for sine-background and $s(\mathrm{I})$ and $s_t^{\mathrm{even}} = s(\mathrm{I}) + \mathrm{s(III)}$ for cosine-background agree as predicted by the matched-filter model, but the sensitivity estimates do not differ by a factor of 2. Now the size of the retinal area covered by each of the patterns $s(\mathrm{I})$ to $s(\mathrm{IV})$ is identical, and for reasons of symmetry we may assume that $a_t|G|^2/c$ assumes the same value for the four stimulus patterns. However, s_t^{odd} and s_t^{even} cover twice the area covered by an individual pattern. This may well mean that the values of a_t of the patterns $s(\mathrm{I})$ to $s(\mathrm{IV})$ differ from the values of a_t for the compound patterns, and consequently the estimates of $a_t|G|^2/c$ will differ. It follows that one cannot expect the sensitivity estimates for s_t^{odd} and s_t^{even} just to differ by a factor of 2 (or 1/2).

4.2.4 Crossvalidation III: bar patterns

Stimulus patterns may in principle be represented as linear superpositions of some other, appropriately chosen patterns. For instance, consider a vertical, rectangular bar. The bar is the sum of two sawtooth patterns $s_{\mathrm{bar}} = s_{\mathrm{saw}}(-x; x_1) + s_{\mathrm{saw}}(x; x_2)$ (see Fig. 4), and the spectrum of the bar pattern equals the sum of the spectra of the sawtooth patterns; we denote the sawtooth pattern by s_{saw}. Suppose that the bar-pattern is again detected by a matched channel for a bar of width Δx and position as defined in (11); then the (grating) sensitivity of the bar

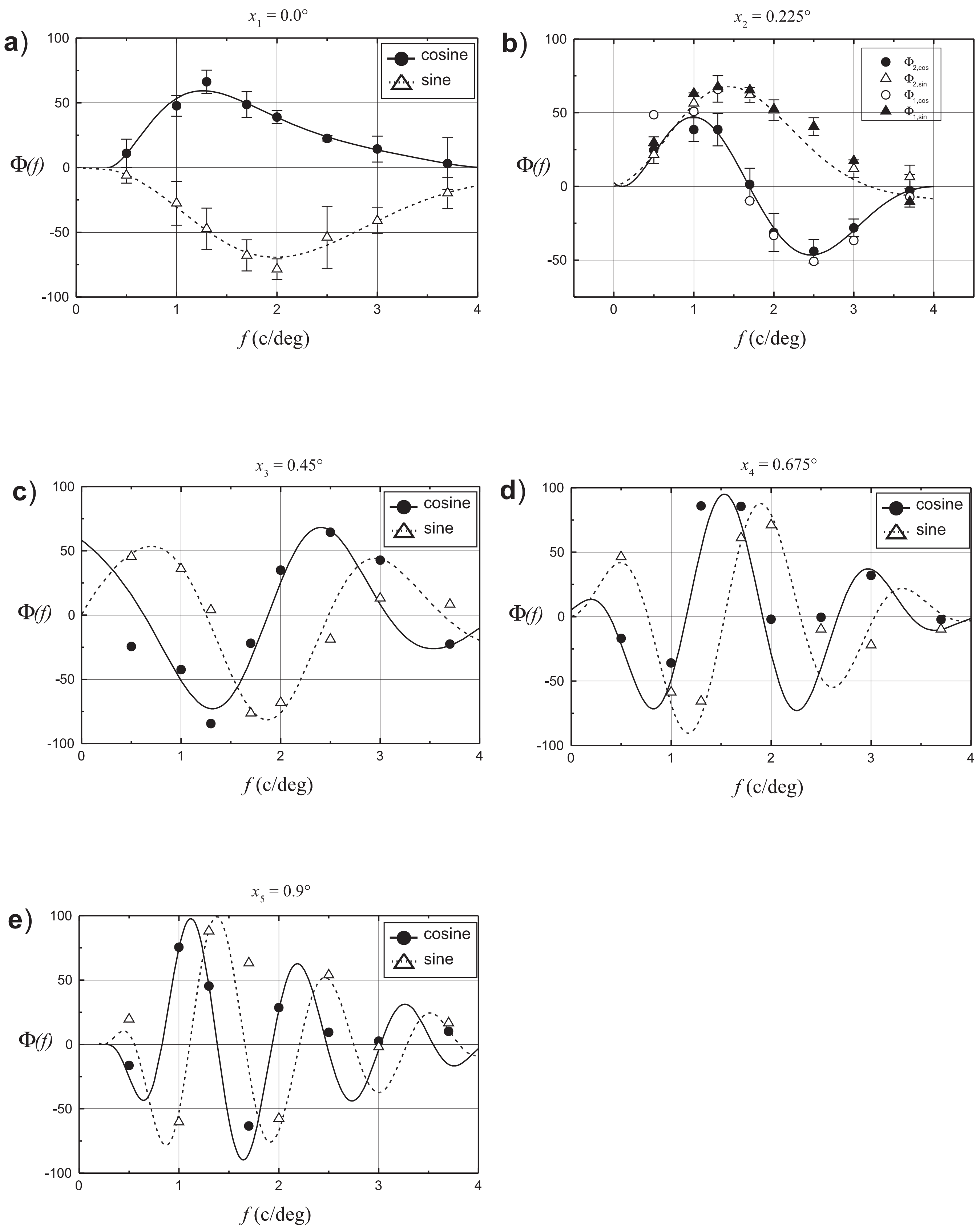

Fig. 8a–e. Sensitivity functions $\Phi_2(f)$, $f = \omega/2\pi$, for sawtooth patterns $s_{\mathrm{saw}}(x; x_k)$, $k = 1, \ldots, 5$; for background gratings in sine- (*open triangles*) and cosine-phase (*filled circles*). *Solid* and *dashed curves* are the predictions of the matched filter model. **b** additionally shows estimates based on Φ_1. *Apparently missing open symbols* are due to the fact that they represent data coinciding with the corresponding prediction. See text for further explanation

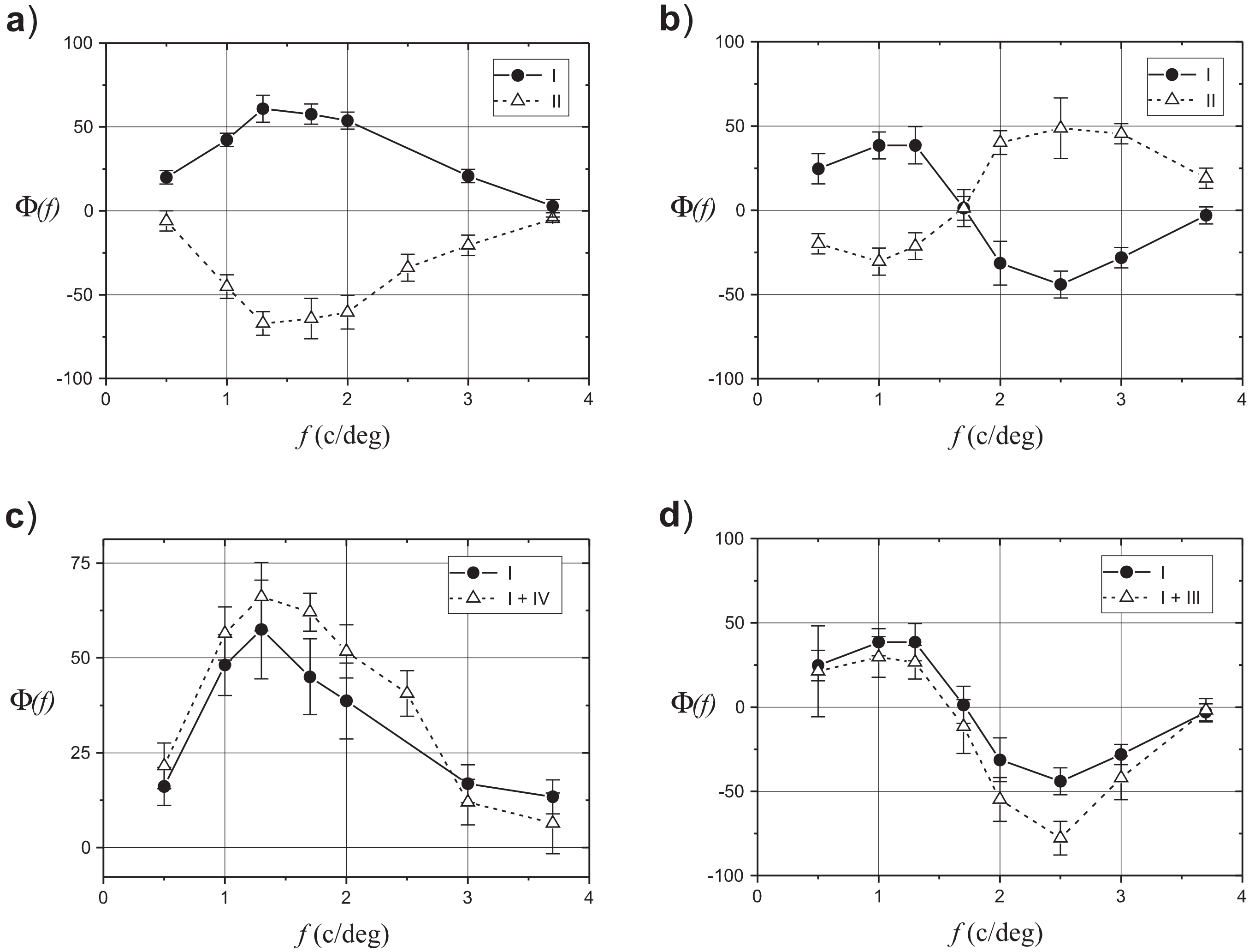

Fig. 9a. Sensitivity functions, for positive (*filled circles*) and negative (*open triangles*) modulations of the test stimulus for sine and **b** cosine background gratings. The corresponding stimulus pattern is given in the key. **c, d** Sensitivity functions for the same test stimulus (*filled circles*). **c** In addition, the pure odd stimulus $s_{\mathrm{saw}}^{\mathrm{odd}} = s_{\mathrm{saw}}(\mathrm{I}) + s_{\mathrm{saw}}(\mathrm{IV})$ (*open triangles*, s, key of Fig. 3), superimposed on sine gratings. **d** Sensitivity functions for the test pattern (*filled circles*) and the pure even test pattern $s_{\mathrm{saw}}^{\mathrm{even}} = s_{\mathrm{saw}}(\mathrm{I}) + s_{\mathrm{saw}}(\mathrm{III})$ (*open triangles*), for cosine background gratings

channel should be predicted by the sum of the corresponding sensitivities of the two sawtooth patterns.

Figure 10 shows the sensitivities, as measured for the bar (filled circles), for cosine- (a) and sine-gratings (b). The data are certainly compatible with the hypothesis of detection by a matched filter for this pattern. The open triangles in Fig. 10a,b are the predictions from the sum of the sensitivities of the two sawtooth patterns after multiplication by a factor $a_0 \approx 2/3$. The correspondance to the direct measurements for the bar is very good, – however, the price to be paid is the introduction of the factor a_0. One reason for having to introduce this factor could be that the factors a_t for bar pattern on the one hand and sawtooth patterns on the other (or their corresponding channels) differ.

Figure 11a shows the data and corresponding predictions of the matched filter model for a bar of width $\Delta x = .225^0$ at position $x_1 = .00$ (see Fig. 5b); the filled circles represent the measurements for the cosine-background grating, the open triangles those for the sine-background grating. The data are obviously compatible with the hypothesis of detection by a matched filter for the bar pattern.

Figure 11b contains the measurements and the corresponding prediction of the matched filter model for (i) $\Delta x = 1^0$ bar (“bar-even” in Fig. 5); since the pattern is even there are only measurements for s_b in cosine-phase (filled circles), and (ii) for a bar pattern also of $\Delta x = 1^0$ width (“bar-odd” see Fig. 5) with s_b just in sine-phase since the pattern is odd. For the “bar-even” pattern the data correspond to the predictions. This cannot be said for the “bar-odd” pattern. In order to exclude the possibility of faulty experimenting, the measurements were repeated at other times with different subjects; however, the result remains the same and may therefore be considered as systematic.

5. Discussion

We have presented data that are compatible with the matched filter model at least to some extent. Briefly, the

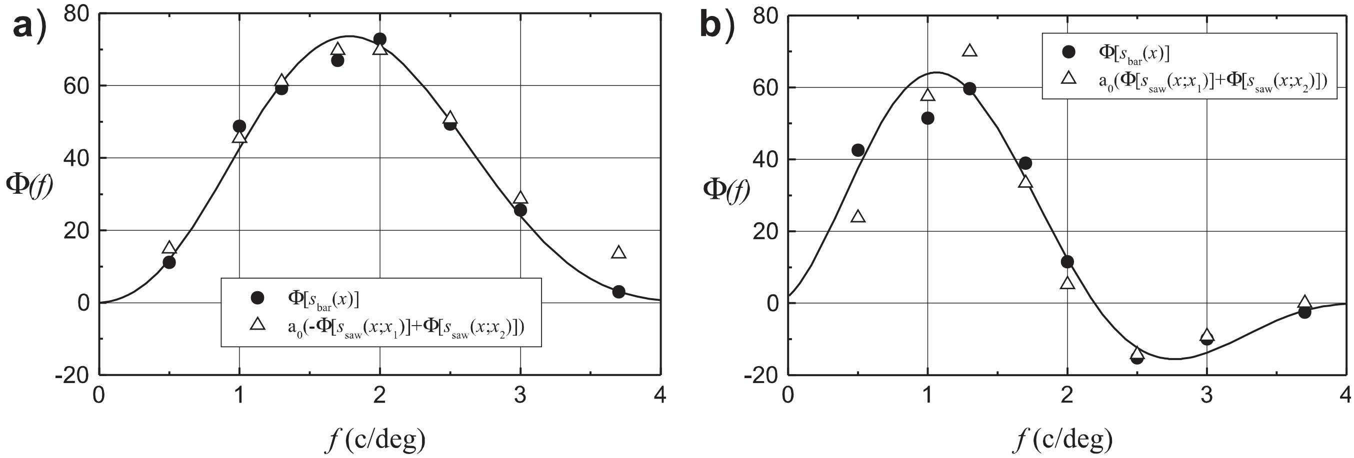

Fig. 10a,b. Predicting the sensitivities for a bar pattern from those for sawtooth patterns. *Solid line*: prediction of the matched-filter model, **a** sine-grating, **b** cosine-grating. The factor a_0 was found to be close to 2/3

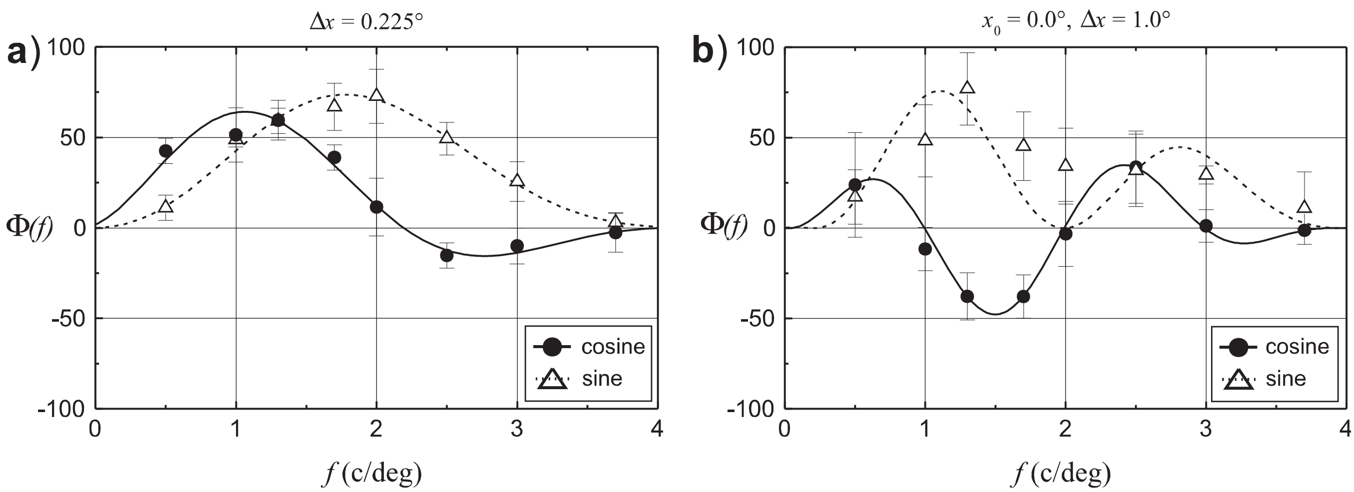

Fig. 11a. Sensitivity estimates $\Phi_2(f)$, $f = \omega/2\pi$, for a bar pattern $\Delta x = 0.225$ deg wide (see Fig. 5b) presented at $x_1 = 0.0$ deg (*filled circles*, cosine-background; *open triangles*, sine-background). **b** Sensitivity estimates $\Phi_2(f)$ for $s_{\text{bar}}^{\text{even}}$ (see Fig. 5e), superimposed on cosine gratings (*filled circles*), and $s_{\text{bar}}^{\text{odd}}$ (see Fig. 5f), superimposed on sine-gratings (*open triangles*), each with width $\Delta x = 1$ deg. *Dashed* and *solid lines* are the predictions of the matched filter model

model fits the data well if the stimulus pattern (i) covers a relatively small retinal area (here: .225 deg), and (ii) shows a definite ‘feature’ (here: an edge, defined by the sawtooth luminance distribution defined in Sect. 3.1.2, or two edges as found with the vertical bar of .225 deg width). The data conform with the model not only for a fixed position, e.g. the fovea, but also if the stimulus pattern is presented at different foveal positions.

There are some open questions, though. One refers to the factor a_t, introduced in (1) as a free parameter. If the system function of a matched filter is derived from a decision theoretical point of view (e.g. Peterson et al. 1954; Whalen 1971) one is led to the postulate that the impulse response h of the filter should be given by $h(x) = s(x_0^+ - x)$, s the stimulus to which the filter is matched, and x_0^+ the point of maximal response. This means that h is defined not only with respect to the form of s, but also with respect to its modulation. If we consider instead of s the pattern ms, m some real number representing contrast, the corresponding matched filter should be defined by mh. Clearly, the energy of s differs from that of ms. The factor a_t enters to account for the appropriate adjustment of the energy of the signal to which the filter is matched. So, if in particular s_t has unit contrast and the presented stimulus is ms_t, we would have to put $a_t = m$. This is the approach of Hauske (1988), who argued that if in particular the stimuli are presented with threshold contrasts m_{0t}, one should have $a_t = m_{0t}$. Although this assumption is plausible, we have not explicitly incorporated it. Firstly, if one assumes that matched filters exist as fixed units within the visual system, one would have to postulate that they also exist for different modulations of the same s; however, this seems to be a very wasteful way of wiring the system. If, on the other hand, one assumes that matched filters are formed, e.g. as a result of detection tasks, they will be formed with respect to the modulation actually occurring. However, the modulation varies between trials as a result of the fact that either m_{0t} – when there is no background grating – or $\phi(m)$ has to be determined experimentally (cf. Section 2). Possibly a_t will assume values near to the true value of m_{0t}, but whether this is indeed so is an additional hypothesis that has to be tested. On the other hand, our main aim was to test the hypothesis of the existence of matched filters, and with respect to this hypothesis, it is sufficient to test for the proportionality to the spectra of the test stimuli of the sensitivities Φ_i, $i = 1, 2$. We therefore decided not to suggest particular values of a_t.

The model does not fit for the bar-odd pattern $s_{\rm bar}^{\rm odd}$ of 1^0 width (see Fig. 11b). One may speculate that different matched filters – e.g. one for the bright and one for the dark bar – compete in the detection process, meaning that processes of attentional focussing may play a role in this process. Further research is necessary here. Also, for $s_{\rm saw}^{\rm odd}$ and $s_{\rm saw}^{\rm even}$ the data correspond qualitatively, but not in a strict, quantitative sense to the predictions of the matched filter model. These findings clearly restrict the generality of the matched filter model; since the model is supported for the smaller stimulus patterns, one may speculate that matched filters exist or form only for finer details; for related results, cf. Hauske et al. (1978). Again, further research is needed here.

We argued that dominance of the detecting channel C_μ – provided the stimulus pattern is indeed detected by a single channel – has to be an essential feature of C_μ if its characteristics are to be explored by the superposition method. Since for the smaller patterns the matched filter model is compatible with the data, one may argue that the detecting filters are dominant.

It is possible that certain subsystems of the visual system exist like the receptive fields (RFs) considered by Koenderink and van Doorn (1990) which could act like matched filters for appropriately chosen stimulus patterns. However, no such receptive field is likely to dominate the detection process simply because many functionally similar RFs exist, possibly arranged in a stack, and the overlap of activities of these RFs will imply some sort of pooling, probabilistic or otherwise, of their responses. In cases like this, the superposition method cannot reveal the matched filter properties of the RFs even if the RFs had this property (Mortensen et al., unpublished manuscript). An argument of this sort may also apply to Logvinenko's (1993) failure to demonstrate the matched filter property for spatial frequency channels; his data may also be contaminated by a bias of the sort discussed in Sect 2.3, comment 2.

The question of whether the superposition method allows us to identify matched filters under any circumstances also arises when another class of models is considered. For instance, von der Heydt, Peterhans and Baumgartner (1984) suggested a computational model of form processing incorporating cortical simple, complex and end-stopped cells, and Heitger, Rosenthaler, von der Heydt, Peterhans and Kübler (1992) showed how cortical simple, complex and end-stopped cells may cooperate to allow for the perception of complicated contours. The notion of a matched filter is not introduced in these models; however, with respect to the already mentioned work of Oja (1982) and Nachtigall (1991), one may speculate that networks of simple, complex and end-stopped cells exist behaving like matched filters for certain features. If, however, the subject's attentional focus can oscillate between different filters, the superposition method will yield a blurred picture of them which seemingly contradicts the matched filter hypothesis. The apparent breakdown of the matched filter model reported by Hauske et al. (1978) may be due to this fact. A more detailed discussion of this possibility is, however, beyond the scope of this paper.

It should be mentioned that Logvinenko (1995, 1996) takes a different path in order to interpret the findings from superposition experiments; he tries to derive the properties of channels from the convexity of CIFs. Since probability summation among channels does not seem to play a role in his model – at least he has not treated probability summation explicitly – his conclusions about the meaning of gradients of CIFs at $m_b = 0$ differ from ours.

In any case, threshold curves generated by the superposition method may be distorted by processes of quite a different sort: Hübner (1993) has argued that shifts of attention may even alter the tuning of spatial frequency channels, and attentional processes usually remain rather uncontrolled in experiments of the type reported here. It is possible that the psychophysical exploration of channels of the visual system – provided such entities exist at all – cannot be achieved, disregarding the cognitive aspects of stimulus detection.

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