

A computational model of periodic-pattern-selective cells

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In: J. Mira and F. Sandoval, editors, *Proceedings of the International Workshop on Artificial Neural Networks, IWANN'95*, Torremolinos (Málaga), Spain, June 7-9 1995, volume 930 of *Lecture Notes in Computer Science*, (Berlin: Springer-Verlag, 1995), pages 90-99.

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Abstract: A computational model of so-called grating cells is proposed. These cells, found in areas V1 and V2 of the visual cortex of monkeys, respond strongly to bar gratings of a given orientation and periodicity but very weakly or not at all to single bars. This non-linear behavior is quite different from the spatial frequency filtering behavior exhibited by the other types of orientation selective cells. It is incorporated in the proposed model by using an AND-like non-linearity to combine the responses of simple cells and compute the activities of so-called grating subunits which are subsequently summed up. The parameters of the model are adjusted to reproduce the results measured by neurophysiologists with different visual stimuli. The proposed computational model of a grating cell is used to compute the collective activation of sets of such cells, referred to as cortical images, induced by natural visual stimuli. On the basis of the results of such simulations we speculate about the possible role of grating cells in the visual system and demonstrate the usefulness of grating cell operators for some computer vision tasks, such as automatic face recognition and document processing.

Keywords: Grating cells, visual cortex, computational model, texture analysis, face recognition, document processing

1 Introduction

Extensive neurophysiological studies in the past fifty years have led to the accumulation of considerable knowledge of the visual system of primates. The functional description of classes of visual neurons makes a major part of this knowledge. The discoveries of the center-surround organization of the receptive fields of retinal ganglion cells [5] and of the orientation selectivity of the majority of neurons in the primary visual cortex [3] are major milestones in the development of this area.

These neurophysiological discoveries were followed by model building aiming at a precise quantitative description of the functional behavior of visual neurons. For instance, the concept of a receptive field function which specifies the response of a visual neuron to a light spot stimulus as a function of position has successfully been applied to describe the behavior of retinal ganglion cells and simple primary cortical cells, enabling one to predict their responses for arbitrary visual stimuli. Such models are the basis of computer simulations in which the collective activation of many cells are computed and visualized giving an opportunity for improved insights into the function of the visual system [10]. They are also important for building artificial vision systems which would perform like natural systems.

Recently Von der Heydt et al. [12] reported on the discovery of a new type of orientation selective neurons in areas V1 and V2 of the visual cortex of monkeys which they named *grating cells*. Similarly to other orientation selective neurons, such as the so-called simple, complex and hyper-complex cells [4], grating cells will respond vigorously to a grating of bars of appropriate orientation, position and periodicity. In contrast to other orientation selective cells, grating cells

respond very weakly or not at all to a single bar. This non-linear behavior is quite different from the spatial frequency filtering behavior exhibited by the other types of orientation selective cells. In particular, the behavior of a grating cell cannot be explained by weighted spatial summation (linear filtering), followed by half-wave rectification as in the case of simple cells (see Section 2). Neither can their behavior be explained by three-stage models (linear filtering, rectification, summation) used for complex cells [11].

Most grating cells reported in [12] start to respond when a grating of a few bars (2 to 5) is presented. In most cases the response rises linearly with the number of additional bars up to a given number (4 to 14) after which it quickly saturates and the addition of new bars to the grating causes the response to rise only slightly or not at all and in some cases even to decline. Similarly, the response rises with the length of the bars up to a given length after which saturation and in some cases a decline (end-stopping) is observed. The responses to moving gratings are unmodulated and do not depend on the direction of movement. The dependence of the response on contrast shows a switching characteristic, in that turn-on and saturation contrast values lie pretty close. (The most sensitive grating cells start to respond at a contrast of 1% and level off at 3%.)

The above properties suggest that the primary role of grating cells is to signal periodicity in oriented textures, ignoring other details (such as contrast). On the other hand, their relatively narrow bandwidth for both spatial frequency (median of 1 octave) and orientation (about 20°) causes this type of cells to be activated relatively rarely (as compared to other orientation selective cells) by natural visual stimuli. Therefore, the role of grating cells needs to be clarified. One approach to this problem adopted in this study is to construct a computational model of a grating cell and use it to compute the collective activation of many such cells with different preferred orientations and periodicities, covering the visual field, induced by natural visual stimuli. On the basis of the results of such simulations we speculate about one possible role of grating cells in the visual system and demonstrate the usefulness of grating cell operators for some computer vision tasks.

2 A computational model of grating cells

Grating cells are found in the same cortex area (V1) as simple cells and similarly to simple cells show orientation selectivity. On the other hand they show a more complex non-linear behavior. These facts may suggest that grating cells receive input from simple cells. Although this is a speculation which is not proven experimentally, we propose a model in which the responses of simple cells are used to compute the responses of grating cells. (This is similar to the speculation that complex cells may receive inputs from simple cells [4]). In this model there are three layers where the first layer consists of simple cells and the last one of grating cells (see Fig.1). The intermediate layer plays an auxiliary role; in reality the units of this layer, to be referred to here as *grating subunits*, may correspond to dendrites of grating cells.

We use the following model (for a similar model with a different parametrization, see e.g. [2]) to compute the response r of a simple cell characterized by a receptive field function $g(x, y)$ to a composite visual signal $s(x, y)$, $(x, y) \in \Omega$ (Ω - visual field domain):

- (i) An integral

$$\tilde{s} = \iint_{\Omega} s(x, y) g(x, y) \, dx dy \quad (1)$$

is evaluated in the same way as if the receptive field function $g(x, y)$ were the impulse response of a linear system and

- (ii) the result \tilde{s} is submitted to half-wave rectification (more generally to thresholding) and

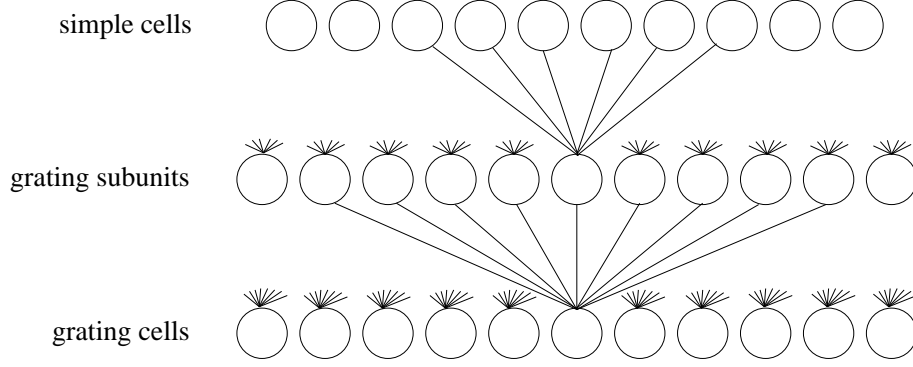


Figure 1: Schematic representation of a computational model of grating cells: grating cells (bottom layer) carry out spatial summation of inputs which they receive from a layer of intermediate cells, called the grating subunits, which combine inputs from simple cells (top layer) in an AND-like way.

local non-linear normalization as follows:

$$r = 0 \quad \text{if} \quad \tilde{s} \leq 0. \quad (2)$$

$$r = \log\left(1 + \frac{\tilde{s}}{a}\right) \quad \text{if} \quad \tilde{s} > 0, \quad (3)$$

where a is the average luminance in the receptive field of the concerned neuron.

As to the particular form of the function g , it has been the subject of neurophysiological research for more than thirty-five years. In particular, the receptive fields of simple cells were found to consist of a number of oriented alternating parallel excitatory and inhibitory zones. We use the following family of functions to model simple cells:

$$g_{\xi, \eta, \sigma, \gamma, \Theta, \lambda, \varphi}(x, y) = e^{-\frac{(x')^2 + \gamma^2 y'^2}{\sigma^2}} \cos\left(2\pi \frac{x'}{\lambda} + \varphi\right) \quad (4)$$

$$x' = (x - \xi)\cos\Theta - (y - \eta)\sin\Theta$$

$$y' = (x - \xi)\sin\Theta + (y - \eta)\cos\Theta$$

where the arguments x and y specify the position of a light spot in the visual field and $\xi, \eta, \sigma, \gamma, \Theta, \lambda$ and φ are parameters whose effect on the function g is explained in more detail in [10]. In this study, we use functions g with values of the phase parameter $\varphi = 0$ and $\varphi = \pi$ which correspond to symmetric receptive field functions with one central excitatory lobe surrounded by two inhibitory lobes (to be referred to as center-on functions in analogy with retinal ganglion cell responses, Fig.2a) and one central inhibitory lobe and two excitatory side lobes (to be referred to as center-off functions, Fig.2b), respectively.

Substituting a receptive field function $g_{\xi, \eta, \sigma, \gamma, \Theta, \lambda, \varphi}(x, y)$ in eqs.1-2, one can compute the response $r_{\xi, \eta, \sigma, \gamma, \Theta, \lambda, \varphi}$ of a simple visual cortical cell modelled by this function to an input image $s(x, y)$. In the following we skip the parameters γ and σ , since, as neurophysiological research has shown [1], γ varies in a very restricted domain — we take a constant value of $\gamma = 0.5$ — and σ is closely related with λ in that the ratio $\frac{\sigma}{\lambda}$ is relatively constant on the population of all simple cells — in this case we take $\sigma = 0.5\lambda$. Hence, instead of $r_{\xi, \eta, \sigma, \gamma, \Theta, \lambda, \varphi}$ we shall write in the following for short $r_{\xi, \eta, \Theta, \lambda, \varphi}$.

Next, a quantity $q_{\xi, \eta, \Theta, \lambda}$ is assigned to each grating subunit of the intermediate layer. One such subunit is taken for each distinct combination of the parameter values. The concerned quantity is computed as follows:

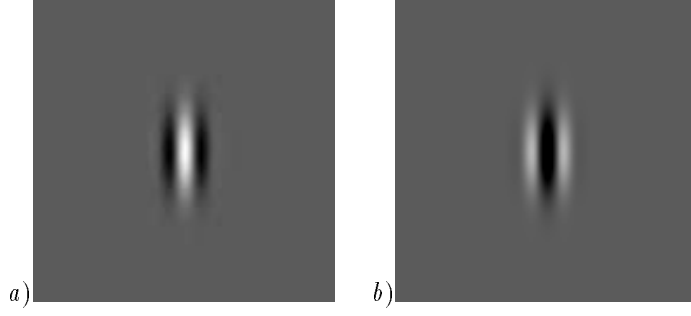


Figure 2: An example of symmetric center-on (a) and a center-off (b) simple cell receptive field functions. The values of the other parameters are $\xi = 0, \eta = 0, \gamma = 0.5, \Theta = 0, \lambda = 2\sigma$ and $\sigma = 0.0625L$ (L - image size). White and black colors indicate excitatory and inhibitory areas, respectively.

Let

$$M_n(\xi, \eta) = \text{Max}\{r_{\xi', \eta', \Theta, \lambda, \varphi_n} \mid \xi', \eta' : n \leq \frac{2(\xi' - \xi)}{\lambda \cos \Theta} < n + 1, \quad n \leq \frac{2(\eta' - \eta)}{\lambda \sin \Theta} < n + 1\} \quad (5)$$

$$\begin{aligned} n &= -3, -2, -1, 1, 2, 3 \\ \text{where } \varphi_n &= 0 \text{ for } n = -3, -1, 2 \\ \text{and } \varphi_n &= \pi \text{ for } n = -2, 1, 3 \end{aligned}$$

and let

$$M(\xi, \eta) = \text{Max}\{M_n(\xi, \eta) \mid n = -3, -2, -1, 1, 2, 3\} \quad (6)$$

The above quantities are related to the activities of simple cells along a line segment of length 3λ passing through point (ξ, η) in orientation Θ . This segment is divided in intervals of length $\frac{\lambda}{2}$ and the maximum activity of one sort of simple cells, center-on or center-off, is determined in each interval. $M_{-3}(\xi, \eta)$, for instance, is the maximum activity of center-on simple cells in the corresponding interval of length $\frac{\lambda}{2}$; $M_{-2}(\xi, \eta)$ is the maximum activity of center-off simple cells in the next interval, etc. Center-on and center-off simple cell activities are alternately used in alternate intervals. $M(\xi, \eta)$ is the maximum among the above interval maxima. The response $q_{\xi, \eta, \Theta, \lambda}$ of a grating subunit in point (ξ, η) is computed as a binary-valued function as follows:

$$\begin{aligned} &\text{if } (M_n(\xi, \eta) \geq \rho M(\xi, \eta) \text{ for } n = -3, -2, -1, 1, 2, 3) \\ &\text{then } q_{\xi, \eta, \Theta, \lambda} = 1 \\ &\text{else } q_{\xi, \eta, \Theta, \lambda} = 0 \end{aligned} \quad (7)$$

where ρ is a threshold parameter with a value smaller than but near 1 (e.g. $\rho = 0.9$).

Roughly speaking, the concerned grating cell will be activated if center-on and center-off cells of the same preferred orientation (Θ) and spatial frequency ($\frac{1}{\lambda}$) are alternately activated in intervals of length $\frac{\lambda}{2}$ along a line segment of length 3λ centered on point (ξ, η) and passing in direction Θ . This will be the case if three parallel bars with spacing λ and orientation Θ of the normal to them are encountered. In contrast, the condition is not fulfilled by the simple cell activity pattern caused by a single bar or two bars. At this point, an explanation is due of a question why this condition is applied on responses of simple cells and not on the pixels

of an input image. If applied on the pixels of the input image, periodicity of three crests and three troughs along a line with orientation Θ passing through point (ξ, η) will be detected. This periodicity need however not be due to a system of three parallel bars. Experiments with checkerboard patterns (see Fig.12D in [12]) in which the direction of the periodicity of the checks does not coincide with the normal to the diagonals — this is the case when the aspect ratio of the checks is different from 1 — have shown that grating cells detect the periodicity of the diagonals (which evidently resemble bars in the response they elicit) rather than the periodicity of the checks.

Finally, the grating cells sum the responses of the grating subunits in their receptive fields. The response $w_{\xi, \eta, \Theta, \lambda}$ of a grating cell whose receptive field is centered on point (ξ, η) and which has a preferred orientation Θ of the normal to the grating and periodicity λ is computed as follows:

$$w_{\xi, \eta, \Theta, \lambda} = \int G_{\lambda}(\xi - \xi', \eta - \eta') q_{\xi', \eta', \Theta, \lambda} d\xi' d\eta' \quad (8)$$

where G_{λ} is a Gaussian function with radius 5λ at half amplitude. This means that the responses of all grating subunits which detect three bars are summed up in the receptive field of a grating cell. This provision is made to model the summing properties of grating cells with respect to the number of bars and their length as well as their unmodulated responses with respect to the exact position (phase) of a grating.

3 Computed cell responses

Von der Heydt et al. [12] describe the responses of grating cells for different visual stimuli. We next turn to the question of how the model presented above performs for the set of visual stimuli used by Von der Heydt et al. The aim is to validate the model and to find the values of its parameters for which it will optimally approximate the behavior of grating cells.

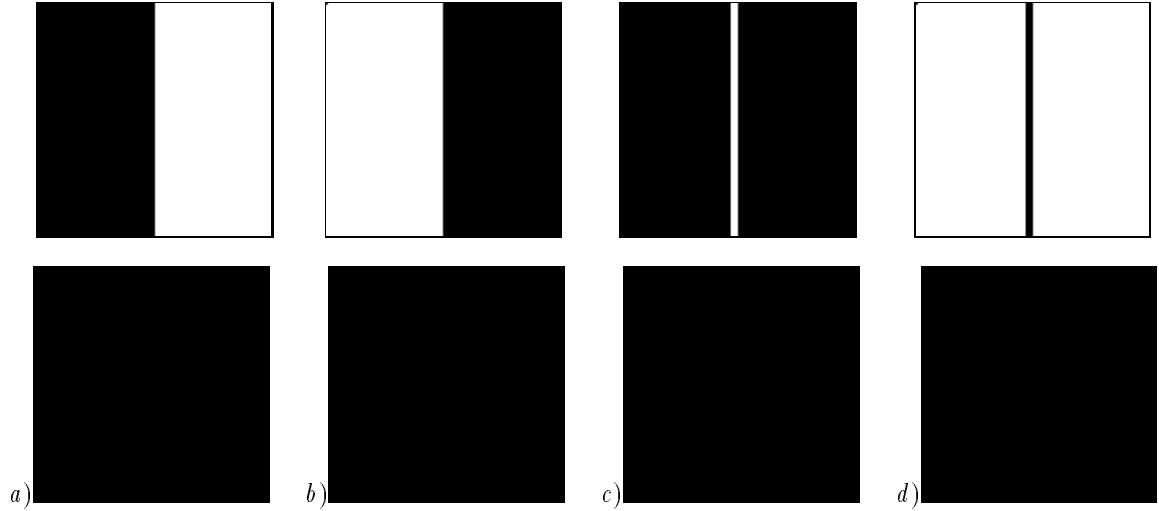


Figure 3: Input visual stimuli (first row) and computed grating cortical images (second row). None of the cells is activated (black and white mean no activity and strong activity, respectively). The simulated grating cells have vertical preferred orientation, $\Theta = 0$, and periodicity of $\lambda = 0.03125L$ (L - image size).

In Fig.3 the upper row of images shows a set of input visual stimuli for which the responses computed according to the above presented model are visualized in the respective images of the

lower row. This presentation form of computed grating cell responses needs an explanation, since it differs from the one used in neurophysiological experiments (compare with Fig.1 in [12]). Each pixel (ξ, η) in an image of the lower row of Fig.3 represents the computed activity $w_{\xi, \eta, \Theta, \lambda}$ of a grating cell with preferred orientation Θ of the normal and periodicity λ and a receptive field centered at point (ξ, η) . The intensity of the pixel, i.e. its gray value, specifies the computed activity (i.e. firing rate) of the cell for the respective input image. The computed activities of the grating cells which have the same preferred orientation Θ and periodicity λ but differ in the position of their receptive fields are thus represented together in one image. We refer to such images as *cortical images*, or more precisely *grating cell cortical images* to distinguish them from *simple cell cortical images* as used in our previous works [6, 7, 8, 9].

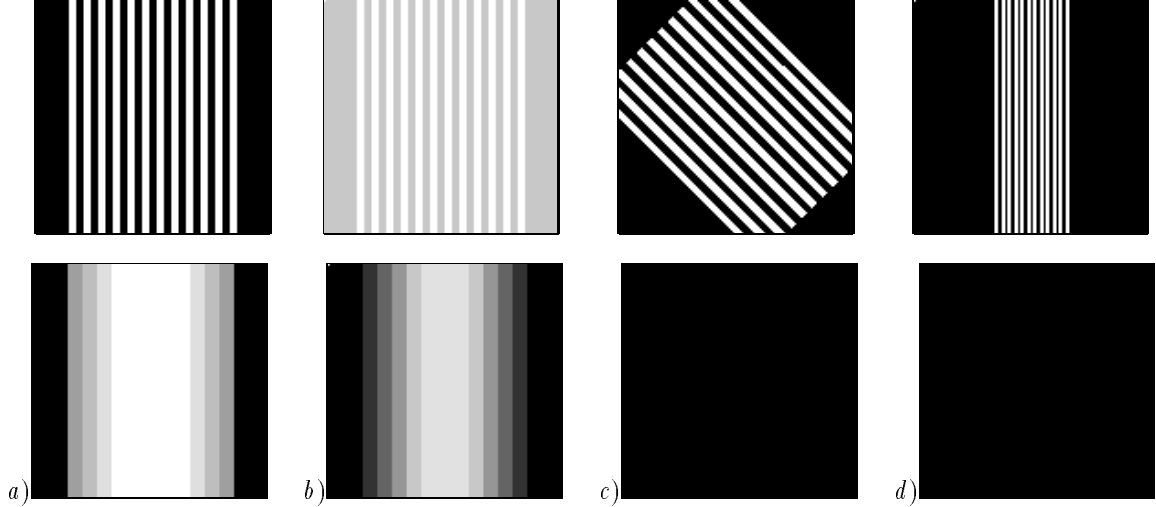


Figure 4: Input visual stimuli (first row) and computed grating cortical images (second row). The simulated grating cells have vertical preferred orientation, (orientation of the normal $\Theta = 0$), and periodicity of $\lambda = 0.03125L$.

In the particular case shown in Fig.3, grating cells with vertical preferred orientation are simulated; although the oriented stimuli in the input images have the same orientation as the preferred orientation of the cells and although they have enough spectral power in the spatial frequency domain for which the cells are selective, none of the cells is activated. In contrast, many cells are activated by a grating of bars with the proper orientation and periodicity (Fig.4a-b). Bar gratings of periodicity (Fig.4c) and orientation (Fig.4d) which differ substantially from the preferred periodicity and orientation of the simulated grating cells fail to activate them.

Fig.5 illustrates the behavior of the grating cell model when a checkerboard pattern (Fig.5a) is presented. In this simulation a model of grating cells with vertical preferred orientation ($\Theta = 0$) and periodicity λ equal to the periodicity of the checkerboard in horizontal orientation is used. The simulated cells would respond to one isolated row of checks, but as can be seen from Fig.5c, the cells do not respond when the checkerboard pattern is presented as a whole. (Real grating cells do not respond in this case either - see Fig.12B in [12].) This is due to the fact that the simple cells whose responses are used in the model integrate the intensity along the columns of the checkerboard and are not activated as shown in Fig.5b. In this way the model is made sensitive for periodicity of bar gratings but not to mere periodicity along a line.

Fig.6 illustrates the behavior of the grating cell model when a rotated checkerboard pattern (Fig.6a) is presented. In this case a model of grating cells with vertical preferred orientation ($\Theta = 0$) and periodicity λ equal to the periodicity of the *diagonals* of the checkerboard in

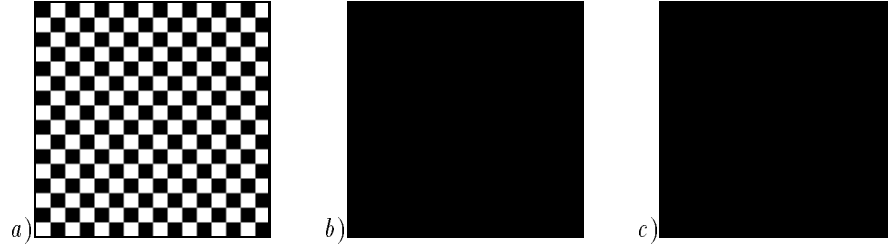


Figure 5: A checkerboard input stimulus (*a*) and a cortical image (*c*) comprising the responses of simulated grating cells with vertical preferred orientation and preferred periodicity equal to the periodicity of the checkerboard in horizontal orientation. The middle image (*b*) shows the corresponding simple cell cortical image used to compute the grating cell cortical image on the right (*c*).

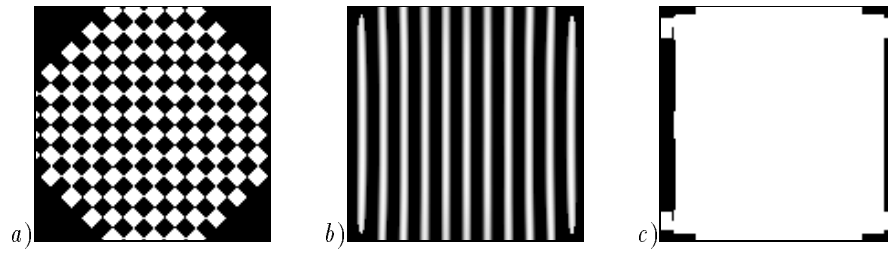


Figure 6: A rotated checkerboard input stimulus (*a*) and a cortical image (*c*) comprising the responses of simulated grating cells with vertical preferred orientation and preferred periodicity equal to the periodicity of the checkerboard diagonals in horizontal orientation. The middle image (*b*) shows the corresponding simple cell cortical image used to compute the grating cell cortical image on the right (*c*).

horizontal orientation is used. Similar to their biological counterparts (compare with Fig.12D in [12]), the simulated grating cells detect the periodicity of the diagonals, although perceptually one would rather give preference to the periodicity along the rows and columns.

4 Experiments with natural images

We now apply the grating operators proposed above on an image of a human face (Fig.7a), one of the most commonly encountered type of visual patterns in the practice of man.

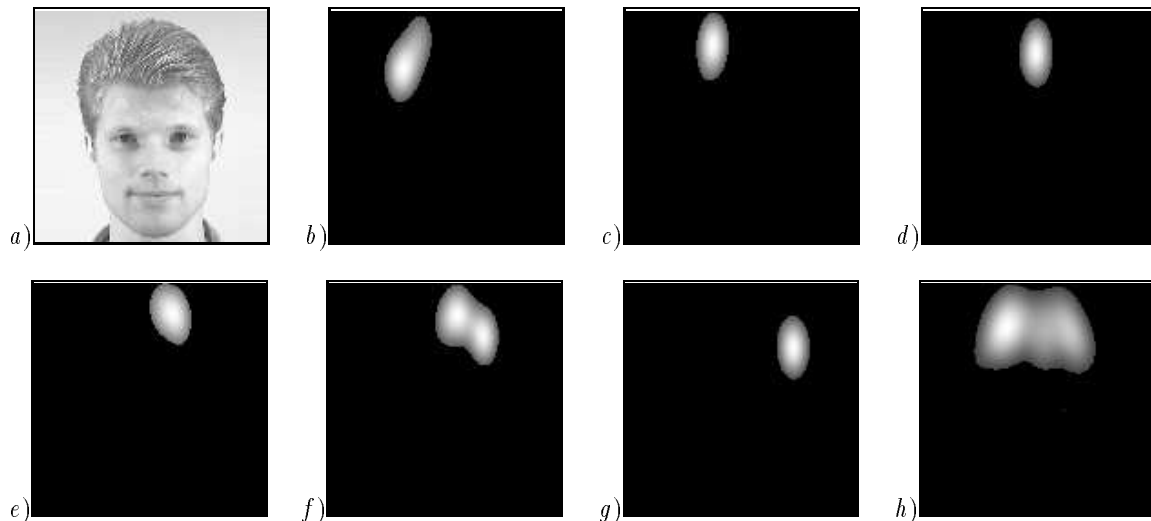


Figure 7: An input image (a) and a number of grating cell cortical images (b-g) obtained from it using different preferred orientations and periodicities. The superposition of 64 such images is shown in bottom-right position (h).

Figures 7b through 7g show grating cell cortical images obtained from the input image shown in Fig.7a by applying grating cell operators with different preferred orientations and periodicities. Different operators produce activity in different areas of the hair according to the orientation and periodicity of the hair bunches. The superposition of 64 grating cortical images as resulting from the use of 16 orientations and 4 periodicities is shown in Fig.7h. As can be seen from this composite cortical image, the area of activity quite well coincides with the texture of the hair. Similar results are obtained with other natural scenes such as forests, fields, etc. — grating cell operators act as detectors of oriented texture areas. Since the orientation and spatial frequency bandwidths of the proposed grating cell operators are not very narrow — 20° and 1 octave at half amplitude, respectively — activity is caused not only by perfectly oriented periodic stimuli: the bandwidth allows for a certain spread in orientation and distance and thickness of the constituting bars and lines.

Fig.8 illustrates the usefulness of grating cell operators for document processing. Two problems often encountered in this area are to separate pictures and figures from text and to determine the orientation of the text. When a bank of grating cell filters is applied on such a document image, the filter which has the proper orientation and spatial frequency will produce the strongest response and allow to identify text areas and the orientation of the text lines. Narrowly tuned grating cell filters allow to determine text orientation with great precision, much more unambiguously than ‘classical’ methods such as the Hough transform.

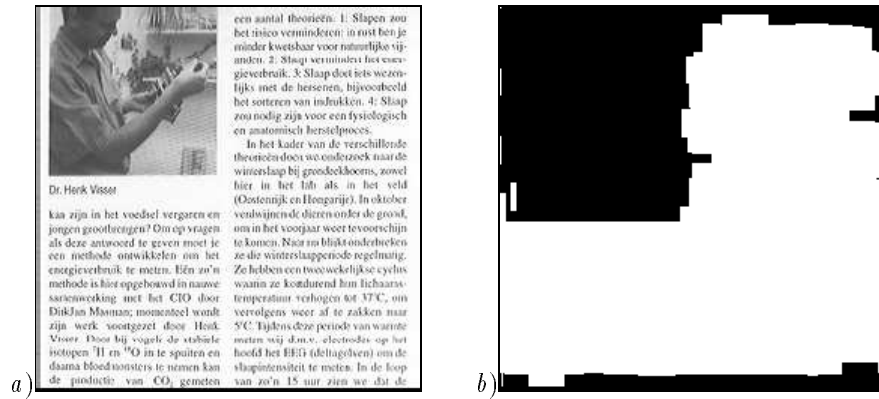


Figure 8: A useful application of grating cell operators in document processing: a filter with appropriate orientation and periodicity allows to identify text areas.

In a future work we will report on the relation of the parameters of the model to the bandwidth properties of grating cells.

5 Discussion

For vision applications it is often necessary to mask out information which is of lesser importance for a given task. Areas of constant illumination, for instance, are less important for many computer vision tasks concerning the form of objects. As a matter of fact such areas are completely characterized by their illumination and contour. Edge detecting operators, such as the operators modelling simple and complex cortical cells as well as retinal ganglion cells, extract intensity transitions, such as edges, from an image, discarding constant illumination information. In this way, edge detection operators separate form information from other visual information.

Similarly to constant illumination, texture is another type of information in natural scenes, which is of lesser interest with respect to form as represented by edges and contours. Perceptually, texture areas are quite similar to areas of constant illumination; in fact fine texture areas appear as areas of constant illumination in low resolution images. One can easily observe this effect by looking at a texture and slowly closing one's eyelids — when the gap between the eyelids becomes small enough the texture area appears as an area of constant color and illumination. In contrast to areas of constant illumination, textures are not suppressed but are rather enhanced by edge detection. As a result, texture information and form information cannot be separated from each other by edge detection. An edge detector applied on the face image shown in Fig.7a, for instance, would enhance the contours of the face and other important form clues, such as the mouth, the eyes, the brows, etc., but at the same time it will enhance a tremendous number of edges in the hair. (This was a major problem in our previous works on biologically motivated face recognition [6, 7, 8, 9].) Additional processing will be needed to separate the form clue edges from the texture edges.

In contrast, a grating cell operator will enhance a system of parallel or semi-parallel lines which are close together, arranged equidistantly or semi-equidistantly. In this way, such an operator can enhance texture areas, in particular when oriented textures are encountered, but will discard isolated lines and edges. This gives the opportunity to effectively separate oriented texture information from form clue information, as present in single lines, edges and contours. Fig.7 is a good illustration of this idea. One may speculate that this is one of the possible roles of grating cells in biological vision. At this point a question may arise of whether it would not be more efficient for form information extraction to take edge and line detection operators which

enhance isolated edges and lines but do not respond to gratings of lines. It is worth noting that in their study Von der Heydt et al. have actually found such cells [12], but in the referred study their attention was focussed on grating cells. Another, and possibly the main, role of grating cells is encoding of oriented texture information. With respect to the larger receptive fields of these cells as compared to simple and complex cells, such an encoding would be more efficient than an encoding based on simple cells. This may be an explanation of the fact that grating cells are less frequently found in areas V1 (4%) and V2 (1.6%). Finally, as proposed by Von der Heydt et al. [12] some textures may be of vital importance for an animal (e.g. a bunch of bananas for a monkey) which requires effective and quick visual mechanisms for their proper classification.

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