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# Implementation of an Orientation Selectivity Hierarchical Spatial Filter Using Diffusion Network

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**Abstract**

This paper describes a neural network which detects the edges of different orientation and spatial frequency in an image. The proposed neural network is useful for image analysis, feature extraction, and texture segmentation.

## 1 Introduction

It is well known that the mammalian visual cortex has cells with feature selectivity such as cells responding to specific orientations and directions of lines and edges in the visual field. Recently many findings have been reported which suggest that feature extraction functions depend on the visual experience during the early critical period [1], [2]. Several neural network models for orientation selectivity have been proposed to explain the development of the feature extraction mechanism [3]-[5].

Hubel and Wiesel [6] proposed a theory of visual information processing based on the receptive-field properties of neurons in the primary visual cortex. According to this theory, the cells are described, due to the limited extent of their receptive fields, as local-feature detectors. For example, cortical simple cells are detectors of bar or edge features. Always at the level of individual cells, other neurophysiological studies showed a pyramidal filtering property of the visual cells [7], [8]. In the cortex, the cells are not only highly selective to spatial frequency, but also highly orientation selective, which is not the case for the cells in the retina and lateral genicular nucleus.

One suitable model of the two-dimensional receptive field profiles encountered experimentally in cortical simple cells, which captures their salient tuning properties of spatial localization, orientation selectivity, and spatial frequency selectivity is the parameterized family of 2-D Gabor filters. This neural model was originally proposed in 1980 simultaneously by Daugman [9] in two-dimensional form and by Marcelja [10] in one-dimensional form.

Watson [11] proposed a cortex transform which maps an image into a set of image that vary in resolution and orientation. The cortex transform was designed to create several pyramids, one per selected orientation. Other band-pass filters with spatial frequency selectivity and orientation selectivity are QMF(quadrature mirror filter) [12], wavelet transform [13], etc..

On the other hand, Kwon, etc. [14] proposed a diffusion neural network model that performs the Gaussian operation efficiently by the diffusion process. They applied this model to the DOG(difference of Gaussians) operation to detect the intensity changes in an image.

In this paper we propose a neural network extracting the edge of the selected orientation and the selected spatial frequency in an image. The proposed neural network is composed of a diffusion network which convolves the input images with a Gaussian function, and a spatial difference network that subtracts the neighboring diffused cell from the diffused one. The diffusion network has excitatory connections to the nearest neighboring cells for diffusion. The spatial difference network has specially designed connections suitable to detect the contours of a specific orientation. Simulation results show that the proposed neural network can extract the edges of selected orientation efficiently by applying the neural network to real image.

## 2 Hierarchical Spatial Filters with Orientation Selectivity

In a number of diverse areas, such as simulation of visual physiology, modeling early human vision, image processing and understanding, there is a need for providing a rapid means which segregate an image into a set of images with modest bandwidths in both spatial frequency and orientation. The proposed neural network architecture selectively responsive to both orientation and spatial frequency of image features was

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composed of diffusion network and spatial difference network.

### 2.1 Diffusion Network

This diffusion process can be realized by a simple network shown in Fig. 1. In this network each neuron cell has a self-decay loop with the decay rate of 1-4$\alpha$, connections of weight $\alpha$ to the four neighboring cells, an external input path, and an output path. We note here that the connection weights are fixed-valued throughout a diffusion process. The response of this neural network is described as the following discrete equation,

$$V(i,j,n+1) = \alpha V(i+1,j,n) + \alpha V(i-1,j,n) + \alpha V(i,j+1,n) + \alpha V(i,j-1,n) + (1-4\alpha)V(i,j,n) + I(i,j,n) \quad (1)$$

where $V(i,j,n)$ and $I(i,j,n)$ stand for the state value and the input excitation of the neuron in position $(i,j)$ at the $n$th diffusion step, respectively. Equation (1) is based on the diffusion equation [15]. The diffusivity $\alpha$ in Eq. (1) corresponds to the connection weight in the model shown in Fig. 1. The solution of Eq. (1) or the diffusion equation with an impulse input and no boundary condition is given by a Gaussian function with the variance of

$$\sigma^2 = 2\alpha n. \quad (2)$$

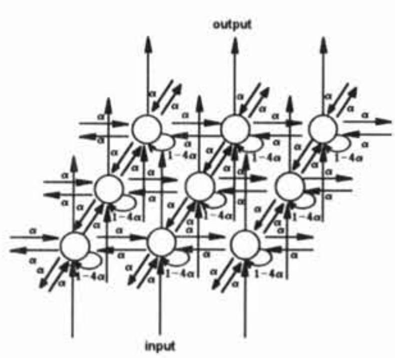


Fig. 1. Diffusion network.

Equation (2) shows that the variance of the Gaussian is changeable by the number of diffusion steps $n$ with a fixed connection weight $\alpha$. The fixed-valued connection weights make the hardware implementation very easy. And this neural network can be applied to the Gaussian signal processing.

### 2.2 Orientation Selective Neural Network

An orientation selective neural network is shown in Fig. 2 [16]. The first stage is diffusion network selective to a spatial frequency. The second stage, called the spatial difference network, performs the difference operation for the nearest neighboring diffused cells. The first-order difference response is acquired by the one-time difference operation in the spatial difference network. And also the 2nd-order difference result is produced by the repetition of the difference operations. Thus, high-order difference responses can be computed from the iterated difference operation. Finally, the difference results of the selected orientation are created by the connection of spatial difference network to the selected orientation. This difference operations can be used for detecting local image characteristics such as edges, lines, corners, and textures.

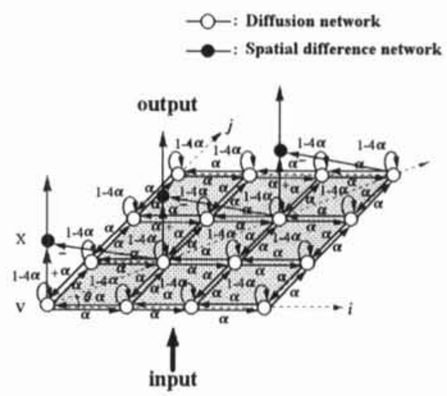


Fig. 2. An orientation selective neural network.

The difference responses of cells oriented at angle of 0° are created as follows:

$$X_1(i,j) = V(i,j) - V(i+1,j) \quad (3a)$$
$$X_{k+1}(i,j) = X_k(i,j) - X_k(i+1,j),\ k>0 \quad (3b)$$

where $X_k$ is the difference results obtained at the spatial difference network and $k$ is the difference iteration. The connection structure performing the difference operation for the neighboring cells in the eight directions is shown in Fig. 3. Figure 3 represents the connection scheme for difference operations for neuron cells oriented at angles of 0°, 26.6°, 45°, 63.5°, 90°, 116.5°, 135°, and 153.4°. The orientation bandwidth of the proposed neural network is about 22.5°. Thus, the proposed neural network has orientation selectivity to extract the edges of the eight different directions for the whole space, and the detected edges are perpendicular to the direction of the connected cells.

The proposed neural networks can be characterized by spatial frequency and orientation bandwidth. It has been found that spatial frequency bandwidths are almost proportional to the center frequency by repeated diffusion process in the diffusion network. Also orientation selectivity on the selected spatial frequency

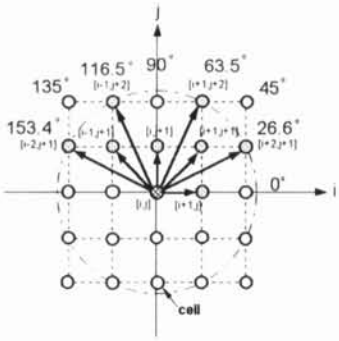


Fig. 3. Connection scheme of neuron cells to detect edge orientation.

can be obtained by operations of the spatial difference network. We shall find the frequency characteristics of the impulse response at each diffusion process. Responses to the selected orientation are obtained by the directional difference operations on the specific spatial frequency bandwidth selected by the steps of the sequential diffusion process. This is illustrated in Fig. 4. Figure 4 describes the results obtained by the 2nd-order difference operations on the cells corresponding to two different orientations of 45° and 90°. Each response can be characterized by an orientation, defined by several parallel elongated excitatory and inhibitory regions, and by the spatial frequency, corresponding to the inverse of the distance between bright bars. And their Fourier spectra are represented in Fig. 4(c) and (d), where the origin is at the center of each figure. As shown in Fig. 4, the spectrum of each channel has the shape of ellipse. When we continue the diffusion process, the spatial frequency bandwidth becomes narrower.

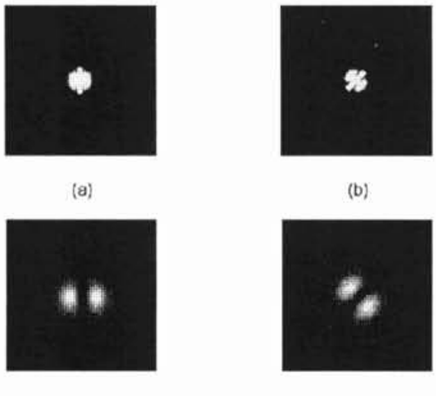


Fig. 4. (a) and (b): Impulse responses, (c) and (d): amplitude spectrum for orientation selective neural network ($n$=12, $k$=2).

## 3 Experimental Results

We implemented an orientation selective neural network to detect the edges of the selected orientation in images. Figure 5 shows the simulation results obtained from the use of the proposed neural network with the image of circle. Figure 5(a) is a synthesized image with 256×256 pixels, Fig. 5(b)-(i) shows the obtained edges of the selected orientation. And Fig. 5(j) is the combined result of Fig. 5(b)-(i).

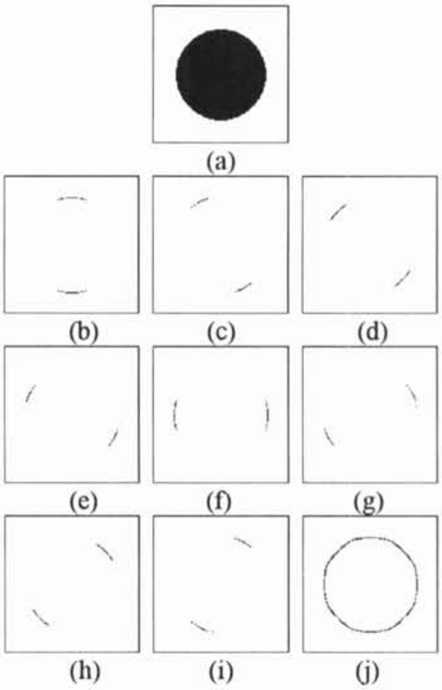


Fig. 5. Results of the orientation selective neural network for the image of circle ($n$=12, $k$=2): (a) A circle image, (b) 0°, (c) 26.6°, (d) 45°, (e) 63.5° ,(f) 90°, (g) 116.5°, (h) 135°, (i) 153.4°, and (j) the combined edges of (b)-(i).

As another example, the simulation results of the Statue image are shown in Fig. 6. Figure 6(a) shows the Statue image of 256×256 pixels with 8-bit gray level. Fig. 6(b)-(e) show the simulation results obtained by the neural network. We noticed that the neural network can efficiently extract the direction selective edges of the selected spatial frequency.

## 4 Conclusion

we have proposed a neural network that extracts efficiently the direction selective edge information of the specific spatial frequency by the diffusion process. The neural network has been tested with a circle image

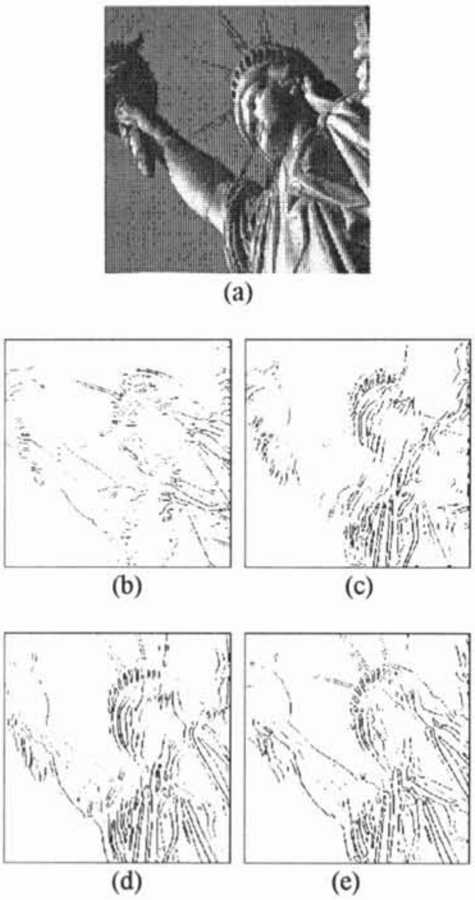


Fig. 6. The edges detected by the orientation selective neural network for Statue image ($n$=12, $k$=2): (a) Original image, (b) 0°, (c) 45°, (d) 90°, and (e) 135°.

and the Statue one. The simulations showed good results. The fixed-weighted connections make it easy to implement the neural network in hardware. The neural network can be applied to image analysis, feature extraction, and texture segmentation.

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