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ANISOTROPIC FILTERING CONTROLLED BY IMAGE CONTENT

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ENHANCEMENT IN THE CONTEXT OF A VISUAL SYSTEM MODEL

The related problems of enhancing and restoring noisy images have received a considerable amount of attention in recent years. Restoration methods have generally been based on minimum mean-squared error operations, such as Wiener filtering or recursive filtering. The rather vague title of enhancement has been given to a wide variety of more or less ad-hoc methods, such as median filtering, which have nonetheless been found useful. In most cases, however, the aim is the same: an improvement of the subjective quality of the image.

Since Hubel and Wiesel's classic work on the visual cortex of the cat [1], [2] a wealth of evidence, both physiological and psychophysical, has been acquired on the structure and function of the visual system at retinal and primary cortical levels. Consideration of these properties led Granlund to develop the General Operator approach to image processing [3]-[6]. The fundamental premise of this theory is that natural images can be adequately described, at a local level, in terms of linear features - a "local one-dimensionality" of the perceived image. A processor based on these ideas, which implements a convolution of the image with a set of "line" and "edge" filters of various orientations, has been used successfully in texture discrimination [4].

An enhancement operation based on this model has been applied to images containing different types of noise. The results presented below demonstrate the potential of the method and support the hypothesis that the model is meaningful.

THE ENHANCEMENT OPERATION

The enhancement operation derived from the above model is a two-stage process. First, the image is convolved with a set of line and edge extraction filters of several orientations to produce a control or "bias" image. This image is complex, each point having a magnitude and direction representing the local edge or line information (Fig. 1).

Figure 1. A neighbourhood is characterized by magnitude and angle of the contribution.

In practice, the number of orientations of the filters is restricted to 4 in the range $(0, \pi)$. The magnitude, $B(x, y)$, and direction, $\theta(x, y)$, of the bias image at the point (x, y) are derived from the original image $F(x, y)$ in the following way. First, the image $F(x, y)$ is convolved with the set of 4 line and edge filters, $L_i(x, y)$ and $E_i(x, y)$ respectively, to give the magnitude in the i th direction. $B(x, y)$ and $\theta(x, y)$ are then estimated using an interpolation formula.

The design of the line and edge extraction filters was carried out using a least-square approach in the frequency domain [5]. The functions chosen have good interpolation properties, are separable, and are of smooth variation (to allow a good finite impulse response approximation).

E_i and L_i denoted edge and line filters in the i th direction. ρ and θ are fourier domain radius and angle respectively.

$$E_i(\rho, \theta) = e_i(\rho) \cdot e_i(\theta); L_i(\rho, \theta) = \ell_i(\rho) \cdot \ell_i(\theta) \quad (1), (2)$$

where

$$e_i(\rho) = \ell_i(\rho) = \exp - \left[\frac{4\ell n 2}{\ell n^2 B} \ell n^2(\rho/\rho_c) \right] \quad (3)$$

$$\ell_i(\theta) = \begin{cases} \cos^2 \left[\frac{N}{2} (\theta - \theta_i) \right] & |\theta - \theta_i| < \frac{\pi}{N}, |\theta - (\pi + \theta_i)| < \frac{\pi}{N} \\ 0 & \text{else} \end{cases} \quad (4)$$

$$e_i(\theta) = \ell_i(\theta) \text{sgn}[\cos(\theta - \theta_i)] \quad (5)$$

For realization of the filters, square windows (masks) of 15x15 pixels were used. The finite impulse response approximation to the filter functions was derived by minimization of the squared error between its transform and those of eqns (1) - (5) above. (Fig. 2).

Figure 2. Fourier domain response of a) ideal filter, b) line mask, c) edge mask. Parameters here are $B = 4$ $\rho_c = 1.11$ $\theta_i = 22.5$, $N = 2$.

Having estimated the edge magnitude and direction at each point, it is then possible to construct an anisotropic filter for the enhancement operation. This filter is the sum of two components: an isotropic low-pass smoothing function (a squared cosine) and a line extraction filter oriented in the direction given by the bias magnitude. Thus in "flat" regions of the image, the filter is isotropic, but as an edge is approached it becomes increasingly anisotropic, with a bandwidth in the direction parallel to the edge which is much lower than that perpendicular to the edge (Figs. 3 and 4).

The isotropic smoothing filter function $H(\rho, \theta)$ can be expressed:

$$H(\rho, \theta) = h(\rho) = \begin{cases} \cos^2\left(\frac{\pi \rho}{1.8}\right) & \rho < 0.9 \\ 0 & \text{else} \end{cases} \quad (6)$$

The line extraction filter $M(\rho, \theta)$ was chosen to give a reasonably flat overall response:

$$M(\rho, \theta) = m(\rho) \cdot m(\theta) \quad (7)$$

with

$$m(\theta) = \cos^2 \theta \quad |\theta| < \frac{\pi}{2}, \quad |\theta - \pi| < \frac{\pi}{2} \quad (8)$$

and

$$m(\rho) = \begin{cases} 1 - H(\rho) & \rho < 0.9 \\ \cos^2\left[\frac{\pi}{1.8}(\rho - \pi + 0.9)\right] & 0.9 \leq \rho < \pi \\ & \pi - 0.9 \leq \rho < \pi \end{cases} \quad (9)$$

Fig. 3 line extraction filter

Fig. 4 smoothing filter

The processed image, $G(x,y)$ can therefore be expressed as

$$G(x,y) = \alpha_s F(x,y) * H(x,y) + \alpha_e B(x,y) [F(x,y) * M(x,y,\theta(x,y))] \quad (10)$$

where $H(x,y)$ is the smoothing function and $M(x,y,\theta)$ is the line extraction filter. The constant α_s is chosen to maintain the mean gray level. In practice, $M(x,y,\theta)$ is obtained by interpolation of the filter responses in the 4 fixed directions.

EXPERIMENTS

A number of experiments have been undertaken to establish the feasibility of the method. Two modes of operation have been used. In the first (enhancement) mode the image was cleaned up using a bias derived from itself. The second (reconstruction) mode was used as part of a coding scheme. In this case the bias image was derived from the image before it was coded.

Once the bias image is obtained, it is possible to process the noisy image iteratively, by repetition of the operation expressed by eqn (10) (figs. 3c, 4c).

Figs. 6 and 7 are examples of results when the enhancement mode is used. The original images here are of very different types but the enhancement scheme works well in both cases. Fig. 8 is the result of a differential transform coder [7] which uses 0.35 bits/pixel to transmit this (512x512) image. A bias picture was derived from the original image (fig. 5) and its information content reduced to .22 bits/pixel by quantizing and undersampling it. Using the reconstruction mode, it was then possible to obtain a restoration of the coded image, as shown in figs. 9 and 10, at a total of .57 bits/pixel.

CONCLUSIONS

It has been shown that a successful image enhancement operator can be derived from a comparatively simple model of the visual system. The process has been shown both to remove the most visible noise from an image and to enhance exactly the features of the image (lines and edges) to which the visual system is presumed to be tuned. The results therefore provide both a demonstration of the usefulness of the method and a confirmation, albeit indirect, of the hypothesised primacy in the visual system of line and edge detection.

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Fig. 5. Original image

Fig. 6. Enhanced image 2:nd iteration

Fig. 7. a) Original fingerprint
b) 1:st iteration cleanup
c) 2:nd iteration cleanup

Fig. 8. Image coded with 0.35 bits/pixel

Fig. 9. Restoration of coded image
1:st iteration

Fig. 10. Restoration of coded image
2:nd iteration