Non linear smoothing method based on the just -noticeable Contrast

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Abstract

The present paper provides a new smoothing method, based on psychophysical phenomena, in which the optimum smoothing parameters are automatically chosen. The method is a nonlinear one and it has some similarities with well-known morphological filters.

Theory of our approach

Weber and Fechner's law is, without a doubt, the simplest and most well known law for Just Noticeable Contrast measurement. In their experiments they showed that the Just Noticeable Contrast, $\frac{\Delta B}{B} = C_w$ is nearly constant for a wide range of luminance. Much work has shown that Weber and Fechner's law can be applied only for relatively high luminance in a homogeneous background [1]. However, Holladay showed that a non-uniform background could be treated as an equivalent uniform one with a given mean luminance called the adaptation luminance [1]. Taking into account these results Moon and Spencer modeled the Just-Noticeable Contrast C_{min} for a given experimental setup (see fig.(1)) by the equation :

$$C_{min} = \begin{cases} \frac{C_W}{B_c}\left(A + B_A^{1/2}\right)^2 & \text{if } B_A \geq B_c \\ \frac{C_W}{B_c}\left(A + \left[\frac{B^2}{B_A}\right]^{1/2}\right)^2 & \text{if } B_A < B_c \end{cases} \quad (1)$$

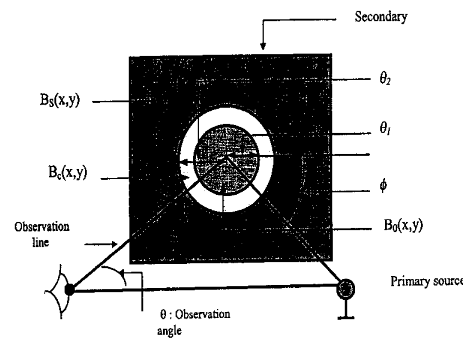

Figure 1: Contrast Threshold for an Object on Background

where C_w is the Weber's constant, and A=0.8 [2,3]. B_s is the surround luminance, B_c is the near background luminance and B_A is the adaptation luminance. For a constant surround B_S different from B_c and for the geometry of fig (1), according to [1,3] one has:

$$B_A = 0.923 B_c + 0.077 B_S \quad (2)$$

For surround luminance B_s different from background luminance B_c, the Just-Noticeable Contrast varies according to the parabolic curves in fig.(2) [4]. Each curve represents one determined surround intensity B_s. In complex scenes, we cannot speak of a uniform background, since the images are composed of several regions with different intensities. It is, however, reasonable to consider that the average gray-level of the image approximates relatively well the surround intensity. To perform a noise filtering, we first define an observation window centered on the current pixel (see fig.(3)).

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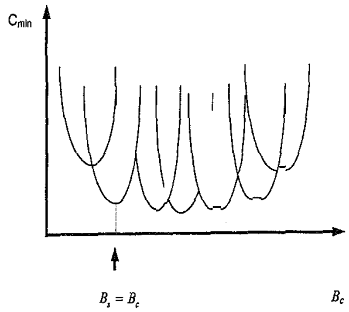

Figure 2 : Contrast Sensitivity (from Moon and Spencer experiments)
B_c is the average luminance of a crown around the object, and B_S is global luminance of the overall background

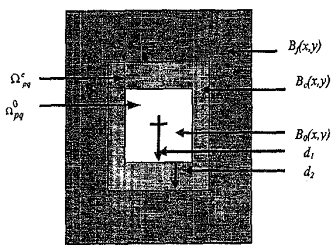

Figure 3 : Visual window.
$B_o(x,y)$, $B_c(x,y)$ and $B_s(x,y)$ are respectively the luminance of the object, of the crown and of the overall background.

Then, the contrast C(x,y) of the considered pixel is compared to the perceived minimum contrast, as defined by Equation (3). To calculate the contrast of the considered pixel, we use the following equation:

$$C(x,y) = \frac{\Delta B(x,y)}{B_c(x,y)} \quad (3).$$

where B_c (x, y) is the average luminance of the crown around the considered pixel, and ΔB (x, y) is the average spatial gradient determined along several directions. Such spatial gradients are obtained through the application of a series of directional Gabor filters [5]. Let us call $G^k(x,y)$ the impulse response of such a filter in the θ_k direction as defined in [5] , and $F^k(x,y)$ the response associated with this filter. Then one gets:

$$F^k(x,y) = B(x,y) * G^k(x,y) \quad (4)$$

and $$\Delta B(x,y) = \frac{1}{N}\sum_k F^k(x,y). \quad (5)$$

It is worth remarking here that the use of Gabor filter is justified by the fact that we are concerned with human visual system mechanisms and any other simple directional gradient operator with large mask could be used to save computation time. B_C (x, y) is given by:

$$B_c(x,y) = \frac{\sum_{(p,q)\in\Omega^1_{xy}} B(x-p,y-q)\,\varphi_{xy}(p,q)}{\sum_{(p,q)\in\Omega^1_{xy}} \varphi_{xy}(p,q)} \quad (6)$$

with: $\varphi_{xy}(p,q) = \left[(x-p)^2 + (y-q)^2\right]^{\frac{1}{2}}$ and

$\Omega^1_{xy} = \{(p,q) / d_1 < d((x,y),(p,q)) \} \le d_1 + d_2$

where the distances d_1 and d_2 are such that $d_1=2d_2$ as done in [6] and in accordance with the experimental data reported in [1, 3]. The algorithm then works as follows: If the contrast C (x, y) is greater than or equal to C_{min}, which is determined by equation (3), then its level remains unchanged. If instead, C (x,y) is smaller than C_{min}, then a new high luminance value B_{new}, defined by expression (8), is assigned to the considered pixel . The consequence of this treatment is that an area with a small gradient is homogenized, while an area with large luminance variations remains unaffected. The result of the operation is twofold: the contours are preserved, and the noise is smoothed out as in the nonlinear anisotropic diffusion filtering method of Perona and Malik [7]. Note that the proposed nonlinear transformation has some similarities with the one used in mathematical morphology, for a dilation [8]. To summarize, the proposed operation assigns a luminance, D (x,y), given by :

$$D(x,y) = \begin{cases} B(x,y) & C(x,y) \ge C_{min} \\ B_{new} & C(x,y) < C_{min} \end{cases}, \quad (7)$$

where $$B_{new} = \max(B_c, B_0) \quad (8),$$

$$B_0(x,y) = \frac{\sum_{(p,q)\in\Omega^0_{xy}} B(x-p,y-q)\,\varphi_{xy}(p,q)}{\sum_{(p,q)\in\Omega^0_{xy}} \varphi_{xy}(p,q)} \quad (9)$$

The set of pixels within the center zone is:

$$\Omega_{xy}^{0} = \{(p,q) / d\{(x,y),(p,q)\} \leq d_1 .$$

An alternative choice for B_{new} (x,y) uses the "min" operator instead of the "max", but runs the risk of losing details with low luminance during the operation. A multitude of nonlinear filtering methods have been proposed. An extensive comparative study of these methods with ours would be prohibitively long. Nevertheless, we provide a quantitative comparison of our algorithm with three related methods, the box-car, median and center-weighted median filters. This comparison is based on two quantitative and objective measures: the normalized mean square error (NMSE) and the normalized absolute mean error (NAME).

Results

To demonstrate the robustness of our algorithm, we first added gaussian noise on each original image, and then we applied the method to the noisy version of the image. Results after filtering are shown in Fig. (4) and Fig. (5). The method was tested on several images with equivalent results. Only two of these images have been retained for the illustration herein. For each case of the figure, we present the original image (a), the noisy image (b), and results obtained after filtering with median filter (c), after smoothing with a box-car filter (d), after filtering with the center-weighted median filter (e), and finally, the results using our method (f). Qualitatively, it can be observed that our method filters out the noise without affecting the thin details (Fig. 4f and 5f). The median and box-car filters tend to blur fine details (Fig. 4 (c, d) and 5 (c, d)). Finally, the center-weighted median filter (Fig. (4e and 5e)) gives similar results to ours, except for the lower luminance. The quantitative comparisons of tables (1) and (2) point out a slight advantage of our method to restore the source image over the center-weighted filter and over other filters. It is shown through these results that, taking the definition of Just Noticeable Contrast, as given by Holladay's principle, is better adapted to real images, and that one can achieve a satisfying low-pass filtering while preserving the location of the edges. Quantitative assessment of image restoration was based on two different measures. Both indicate better performance for our algorithm as compared to the median filter, box-car filter, and to the center-weighted median filter.

The average filter reduces noise whatever its origin, but blurs the image and results, in some cases, in a contrast inversion. The median filter generally produces dilation or erosion of contours. It is known that the median filter is well adapted to the case of the impulse noise but only moderately efficient for the gaussian noise. The usefulness of the contrast concept for image restoration purposes is demonstrated in this paper. Its superiority is confirmed by the facts that the proposed method is simple, less time consuming than, for instance, the center-weighted median filter. Its success in smoothing out gaussian noise is noticeable. Finally, our method offers a good compromise between noise reduction and contrast enhancement.

Error	*Median filter (7x7)*	*Average filter (7x7)*	*Center-weighted median filter (7x7). W=7*	*Our method (7x7)*
NMSE	*1.14*	*1.21*	*0.75*	*0.63*
NAME	*30.32*	*33.58*	*27.50*	*25.05*

Table 1: Error for the Lena image.
The lower values indicate the better results.

Error	*Median filter (7x7)*	*Average filter (7x7)*	*Center-weighted median filter (7x7).W=13*	*Our method (7x7)*
NMSE	*1.27*	*1.25*	*0.61*	*0.582*
NAME	*47.16*	*47.05*	*32.15*	*30.57*

Table (2): Error for the Mandrill image.

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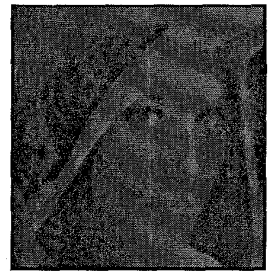
a

b



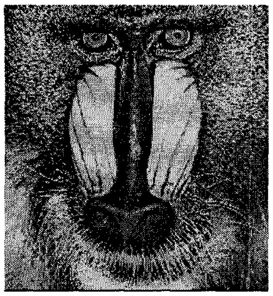
c

d

e

f

Figure (4): The Lena portrait
(a) Original image. (b): Noisy image (Gaussian noise with σ^2=169),
(c): Median filter (size 7x7). (d): Average filter (size 7x7) and (e): Center-weighted median filter (7x7, W=7). (f): Our method (C_w=10%) (window size 7x7).



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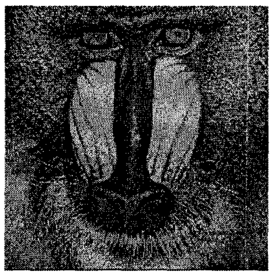

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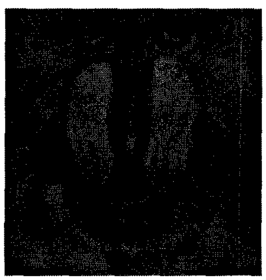

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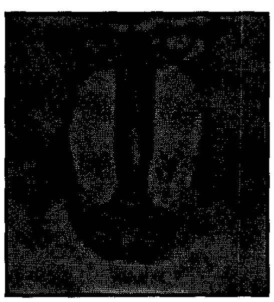

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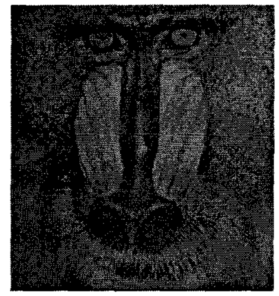

e

f

Figure 5: A Mandrill photograph
(a): Original image . (b): Noisy image (Gaussian noise with σ^2=169),
(c): Median filter (size 7x7).
(d): Average filter (size 7x7) . (e): Center-weighted filter (size 7x7, W=13).
(f): Our method (with C_w=8 %).