A New Image Smoothing Method Based on a Simple Model of Spatial Processing in the Early Stages of Human Vision

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***Abstract*—The difficulty of preserving edges is central to the problem of smoothing images. The main problem is that of distinguishing between meaningful contours and noise, so that the image can be smoothed without loss of details. Substantial efforts have been devoted to solving this difficult problem, and a plethora of filtering methods have been proposed in the literature. Non-linear filters have proved to be more efficient than their linear counterparts. Here, a new nonlinear filter for noise smoothing is introduced. This filter is based on the psychophysical phenomenon of human visual contrast sensitivity. Results on real images are presented to demonstrate the validity of our approach compared to other known filtering methods.**

***Index Terms*—Holladay principal, just-noticeable contrast, nonlinear filters, Weber-Fechner law.**

I. Introduction

THE most critical problem encountered in noise filtering is discriminating the meaningful salient features of the image from the noise. In spite of the great efforts devoted to solving this problem, more investigations are still needed. Noise filtering generally involves making some mathematical assumptions about the noise. Many studies assume an additive white Gaussian noise, although, for a few situations, where the noise is signal dependent, methods based on statistical signal analysis are used [1], [2]. Here we will assume an image degraded by an additive white Gaussian noise, although this assumption is not necessary to the proposed approach. Additive white Gaussian noise can be reduced by a low-pass filtering. However, this filtering also affects contours and details of objects, which correspond to high spatial frequencies. Finding a good trade off between noise reduction and preservation of details is an active area of research.

Two different families of filtering have been classically used to address this problem.

1) Linear filters: They have simple mathematical formulations. Indeed, there is a clearly defined theory for designing a linear filter with a given deterministic frequency response. The well known linear filters are, for example, the Gaussian filter, the box-car filter and the binomial filter [3].
2) Nonlinear filters: They are often more difficult to analyze in terms of frequency response. However, for some of these filters it is possible to associate a pseudo-impulse response, and therefore, to state a transfer function [4]. Much work has been devoted to analyzing the behavior of nonlinear filters, in order to better synthesize them [5]–[8]. One class of nonlinear filters under study is the morphological filters, which employ a mathematical formulation similar to that of linear system theory [9]. Another appealing class of nonlinear filters are those based on partial differential equations [10], and specifically the nonlinear anisotropic diffusion equation [11]. In spite of these efforts, there is still no good theory for designing a nonlinear filter having a particular deterministic frequency response. The purpose of this paper is to propose a new approach to designing a nonlinear filter based on some properties of the human visual system.

II. Basic Notions

The perception of contrast in a natural image depends on several parameters, such as the size of the observed object, the luminance of the background, the visual angle (angle between line of sight and the light source) and the spatial frequency of the observed pattern [12], [13]. Taking all of these parameters into account using a single contrast analysis method is a rather difficult task. Thus, we will limit this study to the effect of background luminance on contrast perception. Specifically, we will deal with the just-noticeable contrast (JNC) phenomenon referred to in the Weber-Fechner experiments [14]. The traditional Weber-Fechner definition of contrast is useful for a uniform target embedded in a uniform background, but breaks down when either the target or the background, or both, is structured (nonuniform) [15]. Moon and Spencer have studied nonuniform surrounds and have derived a modified analytic expression for luminance using Holliday's principle [16]. The basic idea of this principle is that a nonuniform luminance distribution can be replaced by an equivalent uniform distribution called an adapted luminance. Unlike the Weber–Fechner JNC, which is constant over a wide range of background luminance [14], [17], the JNC defined in Moon and Spencer's experiment [18], [19] varies according to a family of curves as shown in Fig. 1, where we consider a central object and a surrounding image background. B_c

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is the average luminance of the background, and B_f is the global average luminance of the entire image (see also Fig. 2).

III. MOON-SPENCER'S JNC AND ITS ADAPTATION TO DIGITAL IMAGES

In this section, we will first highlight some drawbacks of the Weber–Fechner rule when applied to actual scenes. The contrast definition of Moon and Spencer will then be introduced and adapted for digital image. We will also introduce some ideas derived from studies of primate cortical mechanisms [20]–[22]. The idea of using the JNC for low level vision has appeared in some previous works, but in a simplified and unrealistic form [23]–[25]. Our approach was inspired by that of Kundu and Pal [23], in which an edge thresholding method based on Weber-Fechner's law was proposed. In this method [23], a small neighborhood around each pixel, i.e. a 3×3 pixel region, is considered. The region consists of the central pixel (m, n) with an assigned gray level g_{mn}, and a surround consisting of the eight neighboring with a mean gray-level $\bar{g}_{mn} = 1/8 \sum_{k=-1}^{1} \sum_{l=-1, k,l\neq 0}^{1} g_{m-k,n-1}$. A pixel is identified as a contour point if its local contrast

$$C_{mn} = |g_{mn} - \bar{g}_{mn}|/\bar{g}_{mn} \quad (1)$$

is greater than $C_{\min}$, the JNC. Note that for this method, the contrast of a point of noise could exceed the Weber-Fechner constant $C_{\min}$, and thus discriminating noise points from contour points is difficult. Furthermore, four parameters must be tuned for best selection of contour points. Thus, although Kundu and Pal's idea is appealing, it does not perform well when actually applied to images. Indeed, in a complex visual scene, the background is not uniform. It is composed of many regions of different luminance and spatial frequencies. In such cases, a local band-limited contrast would be relevant for an efficient image analysis as shown by Peli [26], [27]. To improve Kundu and Pal's method, we use the definition of contrast proposed by Moon and Spencer, and adapt it for use on digital images. We will therefore perform a local analysis of the image contrast as done in [26], [27]. Let us recall Moon and Spencer's results as reported in [12], [19]. It was found that both the immediate surround luminance $B_c(x, y)$ and the global luminance $B_f(x, y)$ (see Fig. 3) should be taken into account in the computation of the contrast. Another relevant quantity introduced in Moon and Spencer's model is the adaptation luminance $B_a(x, y)$. This is a corrected luminance value related to both B_c and B_f. It is based on the way in which apparent background luminance is treated by the visual systems of human psychophysical subjects [12], [16], and was not employed by Weber–Fechner. In Moon and Spencer's formulation [16], it is given by

$$B_a = 0.923 B_c + \frac{k}{\pi} \int_{\phi_1}^{\phi_2} \int_{\theta_1}^{\theta_2} \frac{B_f(\theta, \phi)}{\theta^2} \sin\theta \cos\theta \, d\theta \, d\phi \quad (2)$$

where θ is the visual angle, ϕ is the angle between the primary light source and the center of the object (see Fig. 2), and k is a constant determined experimentally (see [12], [16]). The geometry in Fig. 3 represents a simplification of the model. Using

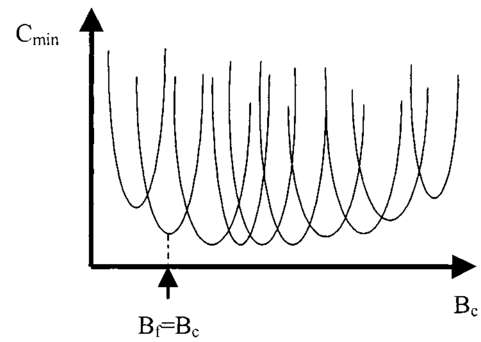

Fig. 1. Contrast sensitivity curves (from Moon and Spencer experiments). B_c is the average luminance of the surround around the object and B_f is the global luminance of the overall background.

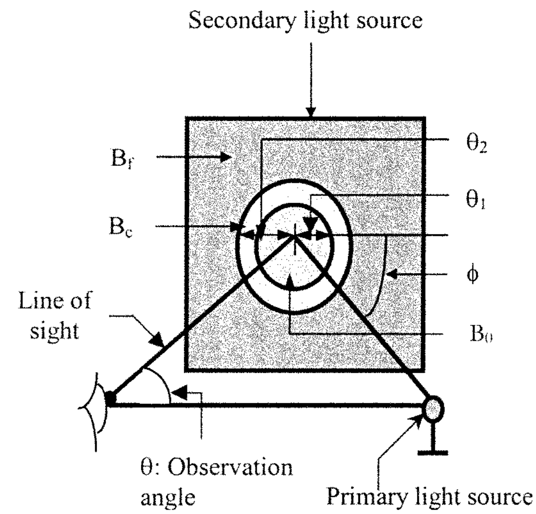

Fig. 2. Simplified observation field of Moon and Spencer's model (from Kretz [19]).

this geometry, setting $\theta_1 = 0.5°$ and $\theta_2 = 0.75°$ (determined experimentally [12]), and integrating, we get

$$B_a = 0.923 B_c + 0.077 B_f. \quad (3)$$

Using Holladay's principle and other previous results, Moon and Spencer proposed a new definition of JNC $(C_{\min})$ based on the concept of adaptation luminance [12]. They considered two different formulations. Three decades later, Kretz [19] expressed $C_{\min}$ as a function of the adaptation luminance $B_a(x, y)$ and the surround luminance $B_c(x, y)$, as follows:

$$C_{\min} = \begin{cases} \frac{C_w}{B_c}\left(A + \sqrt{B_a}\right)^2, & \text{if } B_a \geq B_c \\ \frac{C_w}{B_c}\left(A + \sqrt{\frac{B_c^2}{B_a}}\right)^2, & \text{if } B_a < B_c. \end{cases} \quad (4)$$

In this expression, A is an experimentally measured constant equal to 0.8 and C_w is the Weber-Fechner constant. To illustrate the relationship between the size of the object and that of the near background, we suppose that the observer is placed at a distance R from the center O of the object (in Fig. 3(b) A' is the position of the observer's eye). The extent of the object, and of the surrounding region in the digital square image, are specified by B and C, respectively. Distance d_1 is the extent of the object

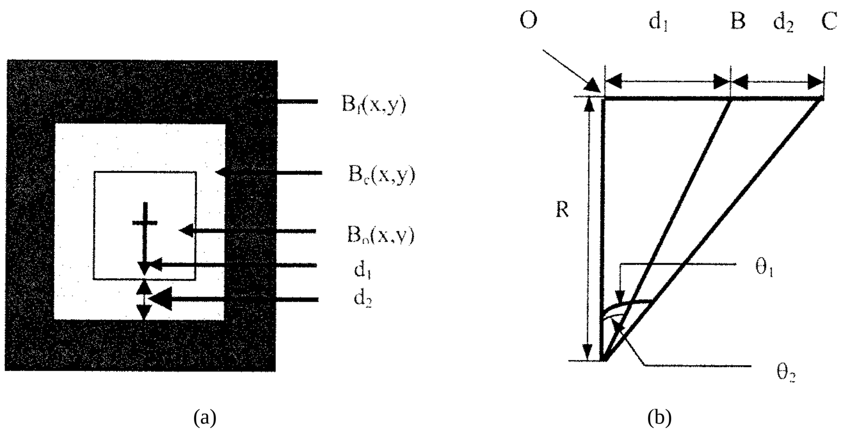

Fig. 3. Geometric representation of the foveal image. (a) Representation of the foveale image of Moon and Spencer's model on a square discrete lattice and (b) schematic view of the eye (in A') looking to the image block.

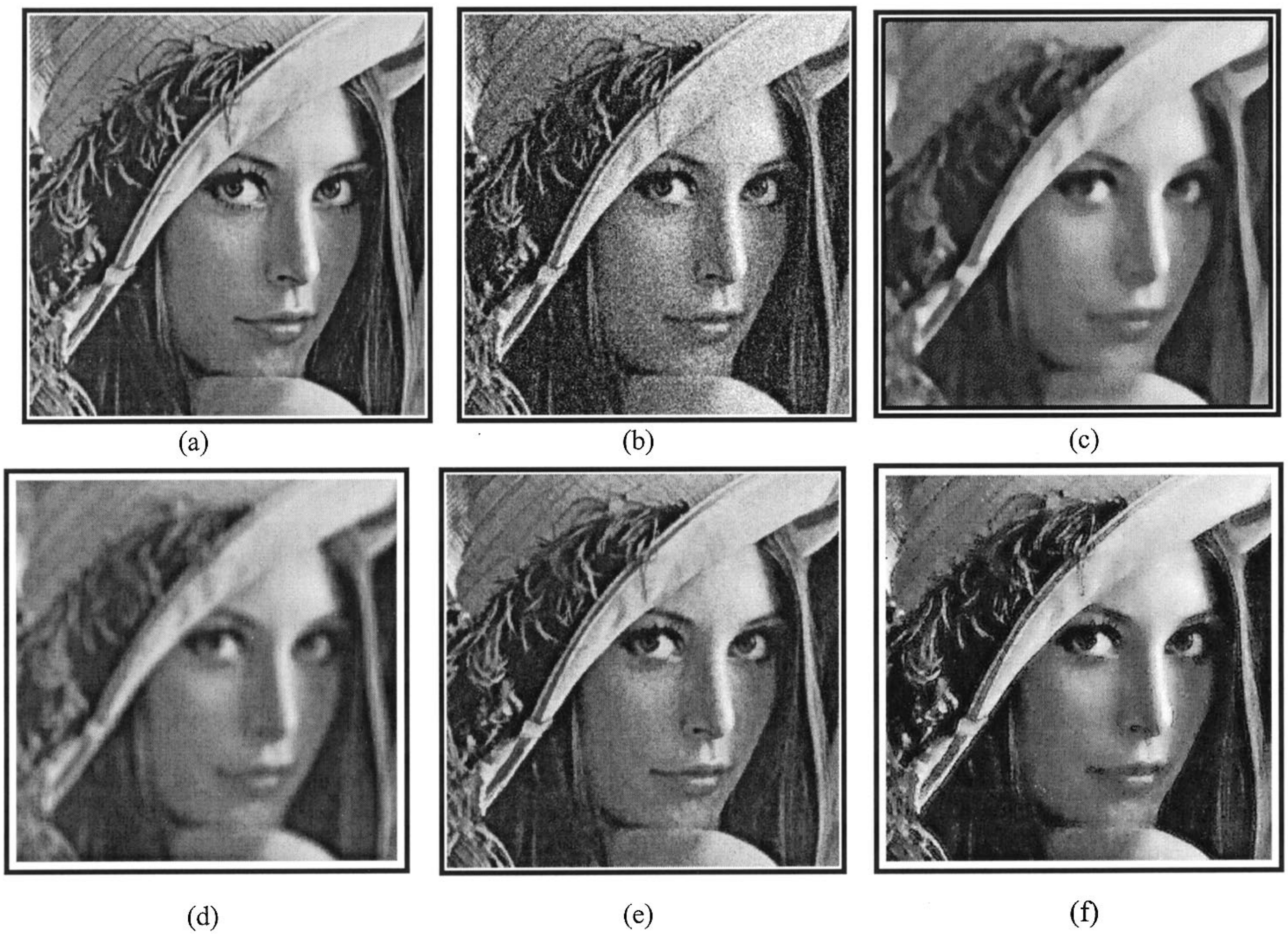

Fig. 4. Lena image—(the window size of the considered filters is 7×7). (a) Original, (b) noisy (Gaussian noise $\sigma^2 = 169$), (c) median, (d) boxcar, (e) CWM, and (f) our method ($\beta = 10\%$).

and d_2 is the thickness of the surrounding region. Using the geometry of Fig. 3(b), we can derive

$$\frac{\tan\theta_1}{\tan\theta_2} = \frac{d_1}{d_1 + d_2}. \tag{5}$$

Using $\theta_1 = 0.5°$ and $\theta_2 = 0.75°$, we obtain $d_2 \cong 0.5 \cdot d_1$. This relationship allows us to choose the size of the sliding window that we will use to analyze the image. For the given values of θ_1 and θ_2 an appropriate window size of 7×7 pixels is indicated. This corresponds to a central region of 5×5 pixels, and a surround thickness of one pixel.

IV. Details of Our Method

In our proposed method, the local contrast $C(x, y)$ of each pixel, considered as the center of an analysis window, is com-

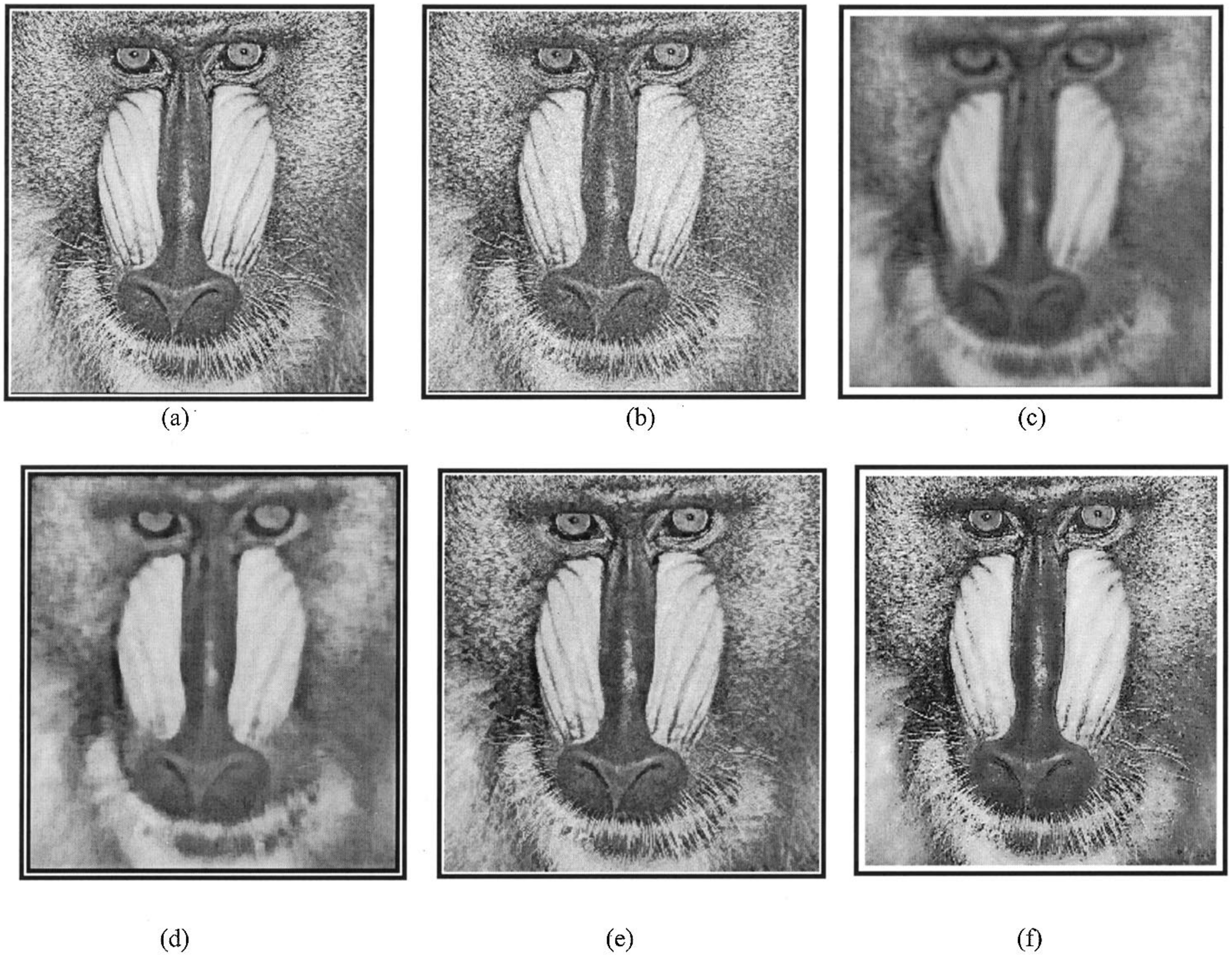

Fig. 5. (a) Original image, (b) noisy image (Gaussian noise $\sigma^2 = 169$), (c) median (7×7), (d) boxcar (7×7), (e) CWM $(7 \times 7, W = 13)$, and (f) our method $(\beta = 10\%)$.

TABLE I
NMSE AND MAE RESULTS FOR LENA IMAGE

Error	Median	Box car	CWM	Our method
NMSE	1.14	1.21	0.75	0.63
MAE	30.32	33.58	27.50	25.05

TABLE II
NMSE AND MAE RESULTS FOR MANDRILL IMAGE

Error	Median	Box car	CWM	Our method
NMSE	1.27	1.25	0.61	0.582
MAE	47.16	47.05	32.15	30.57

puted and compared with the JNC as defined in (4). As in Kundu and Pal's method [23]

$$C_w = \beta \cdot C_{\max} \tag{6}$$

where $C_{\max}$ is the maximum contrast, and β is a parameter, ranging from 0.02 to 0.1. The parameter β controls the amount of smoothing effect. According to (4), a large β value yields a high JNC and consequently the amount of image smoothing is very large. A low β value yields a low JNC and therefore the smoothing effect is not impressive. The parameter β is comparable to the scale parameter of the LOG (Laplacian of Gaussian) filter [28] controlling the edge scale. The contrast is given by the following equation:

$$C(x, y) = \frac{\Delta B(x, y)}{B_c(x, y)} \tag{7}$$

where $B_c(x, y)$ is the average luminance of the region around the considered pixel, and $\Delta B(x, y)$ is the average response of a bank of bandpass Gabor filters applied to the original signal. Here the classical definition of contrast is improved by the use of Gabor filters to decompose the image into components of different spatial frequency and direction. This new definition is similar to that introduced by Peli [26] in order to take into account human frequency contrast sensitivity near threshold. Peli used an isotropic Gaussian envelope. Here, we use an anisotropic Gabor filter based on the physiological properties of visual cortical simple cells [28]–[31]. These filters are optimal for localizing a stimulus in space and spatial frequency [29], [30]. Moreover, it has been shown that this transform achieves an efficient decomposition of the image into meaningful bandpass oriented components [30]–[32]. Let us call $G^k(x,y)$ the impulse response of such filter in the θ_k direction as defined in [30], [31], and $F^k(x,y)$ the response associated with this filter. Then, for each k index, a bandpass filtered signal is obtained via the relation

$$F^k(x,y) = B(x,y) * G^k(x,y) \tag{8}$$

where $B(x,y)$ is the original signal and $*$ the convolution operator. In this study we use for $G^k(x,y)$ the expression proposed by Burgi and Pun in [33]

$$\begin{aligned} G^k(x,y) =& \psi \\ &\exp -\left(\frac{(x\cos\theta_k + y\sin\theta_k)^2}{2\sigma_1^2} + \frac{(-x\sin\theta_k + y\cos\theta_k)^2}{2\sigma_2^2}\right) \\ &\cdot \cos 2\pi\nu(x\cos\theta_k + y\sin\theta_k) \end{aligned} \tag{9}$$

where ψ is a factor of normalization, σ_1 and σ_2, which define the size of the filter, are such that $\sigma_2/\sigma_1 = 1.88$, as reported in [33], [34] (for receptive fields of simple cells of primary visual cortex), and ν is the spatial frequency of the lobes. In our case, θ varies, but σ_1 and σ_2 are fixed. Notice that only the even-symmetric component of the known Gabor filter is used. Indeed, Malik and Perona provided some arguments for using even-symmetric filters only [35]. Moreover, it was demonstrated in many studies [33], [35]–[37] that even-symmetric oriented Gabor filters are sufficient for capturing the essential bandpass components of the signal and offers a useful representation of images.

Once the bandpass components of the signal are captured, the average local bandpass signal along N orientations is computed, as reported in [38], using

$$\Delta B(x,y) = \frac{1}{N}\sum_k F^k(x,y). \tag{10}$$

Here, for the sake of simplicity, we did not introduce competitive mechanisms (where strong responses are selected) as done in [33], [38]. This simple summation model is of limited value, as are many models based on mammalian vision in which the channel's responses are linearly combined [38]–[40]. Here, the average orientation bandwidth of the receptive field of a cortical simple cell is assumed to be about 45°, as in [40]–[42]. Thus, only the four orientations of 0°, 45°, 90°, and 135° are used (i.e. $N = 4$).

The proposed local contrast, as defined by (7), is obtained by dividing ΔB by the average luminance $B_c(x,y)$ of the surround computed in the window analysis according to the relation

$$B_c(x,y) = \frac{\sum_{(i,j)\in\Omega_{xy}^1} B(i,j)\cdot\varphi_{xy}(i,j)}{\sum_{(i,j)\in\Omega_{xy}^1}\varphi_{xy}(i,j)} \tag{11}$$

where $\varphi_{xy}(i,j) = [(i-x)^2 + (j-y)^2]^{-1/2}$ and $\Omega_{xy}^1 = \{(i,j)/d_1 < d\{(x,y),(i,j)\} \le d_1 + d_2\}$, and $d\{(x,y),(i,j)\}$ is the Euclidean distance associated with the two points. Notice that the weighting function $\varphi_{xy}(i,j)$ gives more weight to the nearest neighboring pixels and less to more distant ones. Once these quantities computed, the gray-level of the current pixel (i.e. the one in the center of the analysis window) is transformed into $B_{\text{out}}(x,y)$ according to the following rule:

$$B_{\text{out}}(x,y) = \begin{cases} B(x,y) & C(x,y) \ge C_{\min} \\ B_{\text{new}} & C(x,y) < C_{\min} \end{cases} \tag{12}$$

where $B_{\text{new}} = \max(B_c, B_0)$, with $B_0(x,y)$ given by

$$B_0(x,y) = \frac{\sum_{(i,j)\in\Omega_{xy}^0} B(i,j)\cdot\varphi_{xy}(i,j)}{\sum_{(i,j)\in\Omega_{xy}^0}\varphi_{xy}(i,j)} \tag{13}$$

with $\varphi_{xy}(i,j) = ((x-i)^2 + (y-j)^2)^{-1/2}$ and $\Omega_{xy}^0 = \{(i,j)/d\{(x,y),(i,j)\} \le d_1\}$.

An alternative method for computing $B_{\text{new}}(x,y)$ might use the "min" operator instead of the "max" one, or any linear combination of $B_0(x,y)$ and $B_c(x,y)$. Unlike Kundu and Pal's method a point of noise would be eliminated using our JNC rule, since only average values are used in the computation of local contrast. Our nonlinear transformation is based on the earlier work of Weber and Fechner and of Holladay, which proposed that an object is visible only if its contrast is greater than or equal to the perceived JNC ($C_{\min.}$). By our method, a noisy area with small gradient values is smoothed, while an area with large luminance variations remains unaffected. Well contrasted regions are preserved, and noise is smoothed out.

V. Results and Discussion

Several studies have shown that nonlinear filtering is suitable for the reduction of noise (either impulsion or Gaussian noise). A multitude of nonlinear filtering methods have been proposed and an extensive comparative study of these methods with ours is impractical. 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 mean absolute error (MAE), respectively given by

$$\text{NMSE} = \frac{\sum_{x=1}^{M_1}\sum_{y=1}^{M_c}[f_0(x,y) - f_r(x,y)]^2}{\sum_{x=1}^{M_1}\sum_{y=1}^{M_c}[f_b(x,y) - f_0(x,y)]^2} \tag{15}$$

and

$$\text{MAE} = \frac{1}{M_1\cdot M_c}\cdot\sum_{x=1}^{M_1}\sum_{y=1}^{M_c}|f_r(x,y) - f_0(x,y)| \tag{16}$$

where $f_o(x,y)$, $f_b(x,y)$ and $f_r(x,y)$ represent the original image, the noisy image and the filtered one respectively, and where $M_1\cdot M_c$ is the total number of pixels along the lines and columns.

To demonstrate the robustness of our algorithm, the tested images are degraded by an additive white Gaussian noise with zero mean and a variance $\sigma^2 = 169$. Results after filtering are shown in Fig. 4 and Fig. 5. The method was tested on various types of images with equivalent results. Only two of these images are shown. For each figure, we present (a) the original image, (b) the noisy image, (c) the image after filtering with the median filter, (d) the image after smoothing with a box-car filter, (e) the image after filtering with the Center-Weighted Median filter [4],

[7], and (f) the image after applying our method. Qualitatively, it can be observed that our method filters out the noise without affecting the details [Fig. 4(f) and 5(f)]. The median and boxcar filters, on the other hand, tend to blur fine details [Fig. 4(d), (e) and 5(d), (e)]. Finally, the CWM filter [Fig. 4(f) and 5(f)] gives similar results to ours, except for a lower luminance level. All filters in the simulation operate on 7×7 window samples and a weight of 13 is used for the CWM filter. Note that since our parameter is related to local contrast, proper filter adjustment can be automatically achieved. This is not the case for CWM, where a proper adjustment of the central weight cannot be achieved without prior knowledge of the signal and the noise as discussed in [4].

The quantitative comparison summarized in Tables I and II demonstrates a slight advantage of our method over the center-weighted filter and the other filters, in smoothing out additive white noise Gaussian. Our results show that using a local band-limited contrast based on Moon and Spencer's definition of JNC is more suitable for natural images, and can achieve satisfactory low pass filtering, while preserving image details. Noise filtering was quantitatively assessed using two different methods. Both indicate that our algorithm performs better than the median filter, box-car filter, and slightly outperforms the center-weighted median filter. The average filter reduces noise regardless of its origin, but blurs the image and results, in some cases, in a contrast inversion [11]. The median filter generally produces dilation or erosion of contours [11], [2], such as corners. It is well known that the median filter is well suited for the case of impulse noise but is only moderately effective in the case of Gaussian noise. Our results clearly demonstrate the usefulness of a psychophysically based contrast concept for noise filtering purposes.

In this paper, we showed that algorithms derived from the study of the mammalian visual system can form the basis for an effective nonlinear filter treatment for the removal of image noise. Our results clearly demonstrate the usefulness of Moon and Spencer's contrast definition for this purpose. We do not claim that our proposed method is the optimal solution to the problem of image smoothing. Our intent was to demonstrate the usefulness of biologically inspired methods for image processing. To fully realize these benefits, much further research is needed. In future work, we will attempt to optimize the computational cost of the method. The influence of β on the results also warrants further investigation. We will also derive an adaptive smoothing treatment where β is locally adjusted according to an analysis of the window (i.e. it is a texture, or whether it is a homogeneous region or an edge region). This study is an attempt to introduce principles derived from early processing in the mammalian visual system into image processing but should not itself be viewed as a model of early biological vision.

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