# An Image Enhancement Technique Combining Sharpening and Noise Reduction

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***Abstract*—A new approach to contrast enhancement of image data is presented. The proposed method is based on a multiple-output system that adopts fuzzy models in order to prevent the noise increase during the sharpening of the image details. Key features of the proposed technique are better performance than available methods in the enhancement of images corrupted by Gaussian noise and no complicated tuning of fuzzy set parameters. In fact, the overall nonlinear behavior of the enhancement system is very easily controlled by one parameter only.**

***Index Terms*—Fuzzy neural networks, image enhancement, image processing, nonlinear filters.**

## I. Introduction

IMPROVING the quality of sensor data is a key issue in image-based instrumentation. Indeed, preprocessing techniques can play a very relevant role in increasing the accuracy of subsequent tasks such as parameter estimation and object recognition. In this respect, contrast enhancement is often necessary in order to highlight important features embedded in the image data. The enhancement of noisy data, however, is a very critical process because the sharpening operation can significantly increase the noise. Different techniques have been proposed in the literature. They generally adopt the unsharp masking approach [1]. In the well-known linear unsharp masking method, a fraction of the high-pass filtered version of the input image is added to the original data in order to obtain an enhanced image [2]. The adoption of the high-pass filter, however, makes this simple method very sensitive to noise and often unsuitable for real applications. More effective techniques use a nonlinear filter instead of the high-pass linear operator in order to achieve a tradeoff between noise attenuation and edge enhancement. In this respect, a very interesting class of nonlinear methods is represented by polynomial unsharp masking techniques, such as the Teager-based operator [3] and the powerful cubic unsharp masking method [4]. In a different class of nonlinear approaches, a weighted median replaces the high-pass linear filter [5]. In this framework, a very effective technique based on the permutation weighted median has recently been introduced [6].

In this paper, a new nonlinear method for the enhancement of noisy data is presented. The proposed approach consists in a multiple-output processing system that adopts fuzzy networks in order to combine contrast enhancement and noise reduction. Indeed, the fuzzy paradigm is well suited to address conflicting tasks such as detail sharpening and noise smoothing. In addition, the multiple-output structure increases the overall performance of the fuzzy processing because the operation can repeatedly be applied to the image data. The method significantly improves our previous technique [7] from both points of view of simplicity and effectiveness. The nonlinear behavior of the overall system is easily controlled by one parameter only. Results of computer simulations show that the proposed method outperforms state-of-the-art nonlinear operators in the literature.

This paper is organized as follows. Section II explains the basic operations of fuzzy networks; Section III describes their application in a multiple-output architecture; Section IV discusses the experimental results; Section V focuses on some implementation aspects; and, finally, Section VI reports conclusions.

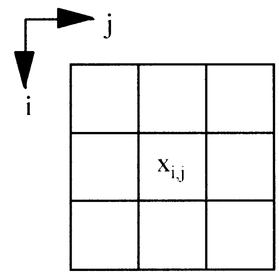


Fig. 1. 3 × 3 neighborhood.

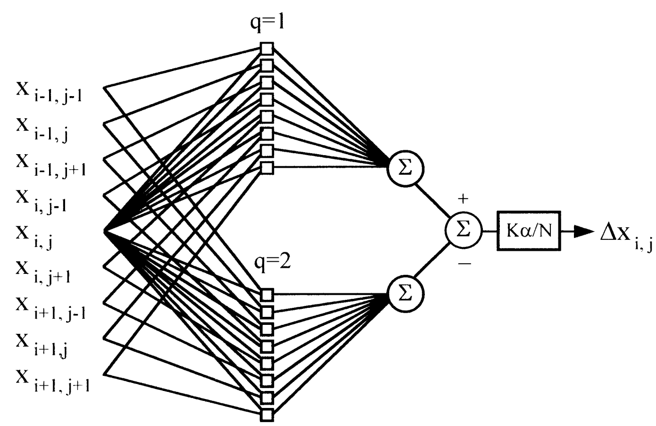


Fig. 2. Basic structure of a fuzzy network.

## II. Theoretical Background

Fuzzy networks have been shown to be very effective for image processing applications such as noise removal [8]. For the sake of clarity, the basic operation of a fuzzy network is explained in details. Let us consider a digitized image having $L$ gray levels. Let $x_{i,j}$ be the pixel luminance at location $[i, j]$, $(0 \leq x_{i,j} \leq L-1)$, as represented in Fig. 1.

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The structure of a simple fuzzy network operating on a $3 \times 3$ window is represented in Fig. 2. The network is composed of two symmetrical sub-networks. Square blocks in the first hidden layer denote fuzzy set-based operations. Typically, the network output is an estimate of the noise amplitude. This estimate is computed by considering (fuzzy) relations between the central pixel and its neighbors. For the sake of simplicity, let $A$ denote the set of $N = 8$ neighboring pixels. Thus, according to the graph in Fig. 2, the output is yielded by the following relationship:

$$\Delta x_{i,j} = \frac{K\alpha}{N}\left[\sum_{x_{m,n}\in A}\mu_{R_1}(x_{i,j}, x_{m,n}, \alpha) - \sum_{x_{m,n}\in A}\mu_{R_2}(x_{i,j}, x_{m,n}, \alpha)\right] \quad (1)$$

where $K = 1$ and $R_q$ $(q = 1, 2)$ represents the class of fuzzy relations described by the parameterized membership function [8]

$$\mu_{R_q}(u, v, \alpha) = \begin{cases} \mathrm{MAX}\left\{\left(1 - \frac{|u - v - \alpha|}{2\alpha}\right), 0\right\} & q = 1 \\ \mathrm{MAX}\left\{\left(1 - \frac{|u - v + \alpha|}{2\alpha}\right), 0\right\} & q = 2. \end{cases} \quad (2)$$

It should be observed that, by varying the value of $\alpha\,(0 < \alpha \le L - 1)$, different nonlinear behaviors can be obtained. For example, let us focus on fuzzy relation $R_1$. When $\alpha$ is large, the fuzzy relation represents "$u$ is much larger than $v$." Conversely, when $\alpha$ is small, the fuzzy relation becomes "$u$ is close to $v$." The (possibly) noise-free value $y_{i,j}$ of the pixel luminance at location $[i, j]$ is then obtained by subtracting the noise estimate $\Delta x_{i,j}$ from the original pixel luminance $x_{i,j}$

$$y_{i,j} = x_{i,j} - \Delta x_{i,j}. \quad (3)$$

The processing defined by (1)–(3) performs data smoothing and is typically applied to a noisy input image. Large values of $\alpha$ increase the noise cancellation at the price of a possible increase of the detail blur. The optimal choice depends on the amount of noise corruption and is typically a tradeoff between noise removal and detail preservation.

Now, let us consider a noise-free image. A sharpening effect can easily be implemented by using the same fuzzy network operations defined by (1) and (2). In this case, we choose $\alpha = L - 1$, $K = 2$ and we add the corresponding network output $\Delta x'_{i,j}$ to the original pixel luminance $x_{i,j}$

$$y_{i,j} = x_{i,j} \oplus \Delta x'_{i,j} \quad (4)$$

where symbol $\oplus$ denotes the bounded sum: $a \oplus b = \min\{a + b, L - 1\}$. In fact, we can think of the sharpening effect as the opposite of the smoothing action. Notice that the bounded sum is formally required in order to limit the output value as follows: $y_{i,j} \le L - 1$. The parameter settings are based on a heuristic approach. An application example is depicted in Fig. 3. The result represented in Fig. 3(b) highlights, in particular, the correct localization of edges and the absence of oscillations.

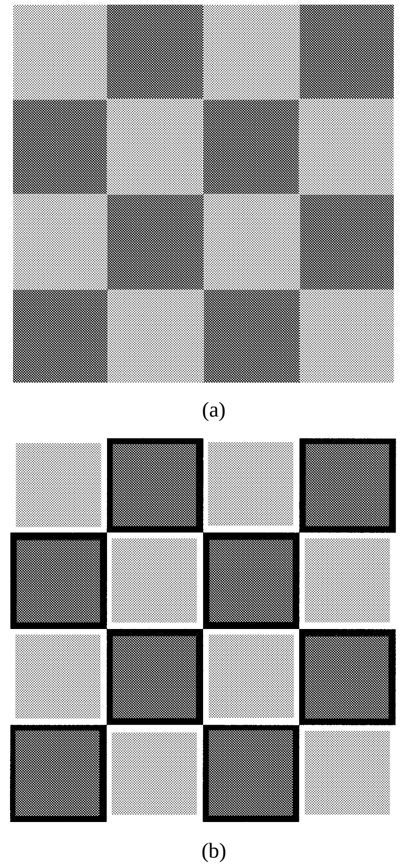

Fig. 3. (a) Detail (magnified ×4) of a test image; (b) result of the fuzzy sharpening.

If the input image is noisy, we can combine a sharpening and a smoothing network in the same processing system. The former aims at increasing the luminance difference between the central pixel and its neighborhood, while the latter aims at reducing the noise increase

$$y_{i,j} = x_{i,j} \oplus (\Delta x'_{i,j} - \Delta x_{i,j}). \quad (5)$$

An appropriate choice of $\alpha$ in the smoothing network permits us to remove noise in the uniform regions of the image, where the effect is more annoying from the point of view of the human perception.

## III. Combining Fuzzy Networks

More fuzzy networks can be adopted in the same structure in order to increase the enhancement effect. The proposed multiple-output system includes three fuzzy networks and deals with a $4 \times 4$ neighborhood, as shown in Figs. 4–6. Each processing step involves two different operations dealing with an appropriate choice of pixel patterns. The first operation performs smoothing only. This operation evaluates the output $y_{i,j}$ by processing the luminances in the pixel pattern A (Fig. 5). This processing is performed by fuzzy network 1

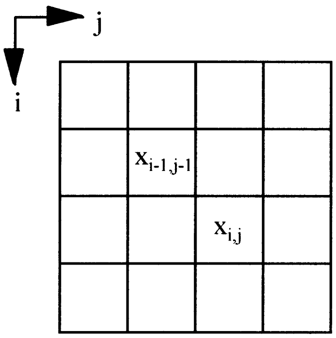


Fig. 4. 4 × 4 window.

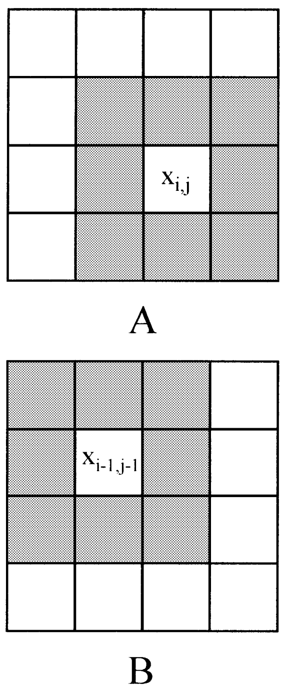


Fig. 5. Different pixel patterns for the multiple-output processing.

(Fig. 6). According to the mechanism described in the previous section, the output $y_{i,\,j}$ is given by the following relationship:

$$y_{i,\,j} = x_{i,\,j} - \Delta x_{i,\,j}^{(A)} \tag{6}$$

$$\Delta x_{i,\,j}^{(A)} = \frac{\alpha}{N}\left[\sum_{x_{m,\,n}\in A}\mu_{R_1}(x_{i,\,j},\, x_{m,\,n},\, \alpha) - \sum_{x_{m,\,n}\in A}\mu_{R_2}(x_{i,\,j},\, x_{m,\,n},\, \alpha)\right]. \tag{7}$$

The processing is recursive, i.e., the new value $y_{i,\,j}$ is immediately assigned to $x_{i,\,j}$ and re-used for further processing.

The second operation is performed by fuzzy networks 2 and 3. It evaluates the output $y_{i-1,\,j-1}$ by processing the luminances in the pixel pattern B (see Fig. 5). It should be observed that these luminances represent the results of the first operation because the processing is recursive and the window scans the image from left to right and from top to bottom. Since the second operation acts on prefiltered data, the effectiveness of the image enhancement process increases. The output $y_{i-1,\,j-1}$ is evaluated by the following relations:

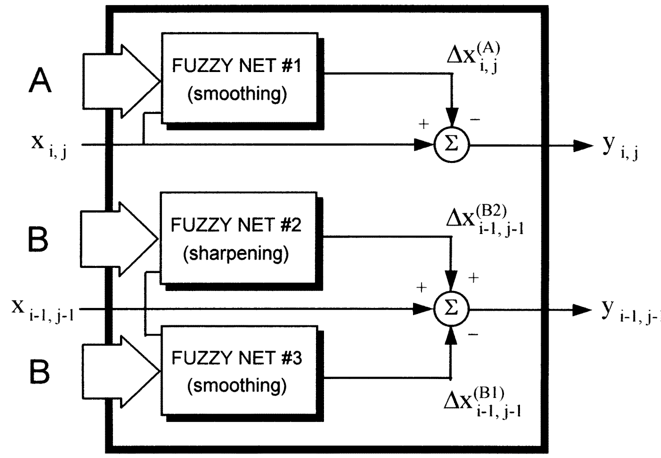


Fig. 6. Block diagram of the multiple-output system.

$$y_{i-1,\,j-1} = x_{i-1,\,j-1} \oplus \left(\Delta x_{i-1,\,j-1}^{(B2)} - \Delta x_{i-1,\,j-1}^{(B1)}\right) \tag{8}$$

$$\Delta x_{i-1,\,j-1}^{(B1)} = \frac{\alpha}{N}\left[\sum_{x_{m,\,n}\in B}\mu_{R_1}(x_{i-1,\,j-1},\, x_{m,\,n},\, \alpha) - \sum_{x_{m,\,n}\in B}\mu_{R_2}(x_{i-1,\,j-1},\, x_{m,\,n},\, \alpha)\right] \tag{9}$$

$$\Delta x_{i-1,\,j-1}^{(B2)} = \frac{2(L-1)}{N}\left[\sum_{x_{m,\,n}\in B}\mu_{R_1}(x_{i-1,\,j-1},\, x_{m,\,n},\, L-1) - \sum_{x_{m,\,n}\in B}\mu_{R_2}(x_{i-1,\,j-1}, x_{m,\,n}, L-1)\right]. \tag{10}$$

It is worth pointing out that the nonlinear behavior of the overall system is easily controlled by the value of parameter $\alpha$ only $(0 < \alpha \le L-1)$. In fact, according to (10), the strength of the sharpening action is assigned. On the contrary, the effectiveness of the smoothing effect depends on $\alpha$ [see relations (8) and (9)]. A large value increases the noise removal. A small value decreases this effect.

## IV. Experimental Results

The performances of the proposed method and other techniques are analyzed by considering a 256 × 256 slice of the well-known 512 × 512 "Lena" picture ($L = 256$) corrupted by Gaussian noise with $\sigma^2 = 50$ [Fig. 7(a)]. The result of the application of the linear unsharp masking operator is depicted in Fig. 7(b) [1], [2]. A limited enhancement of the image details is obtained at the price of a very annoying increase of the noise corruption. The results yielded by nonlinear unsharp masking techniques using the Teager operator [3] and the weighted median [5] are shown in Fig. 7(c) and (d), respectively. It is apparent that such techniques are better than the linear method. However, their sensitivity to noise is clearly perceivable. The cubic unsharp masking operator is much more powerful [4]. The corresponding result is shown in Fig. 8(a). Basically,

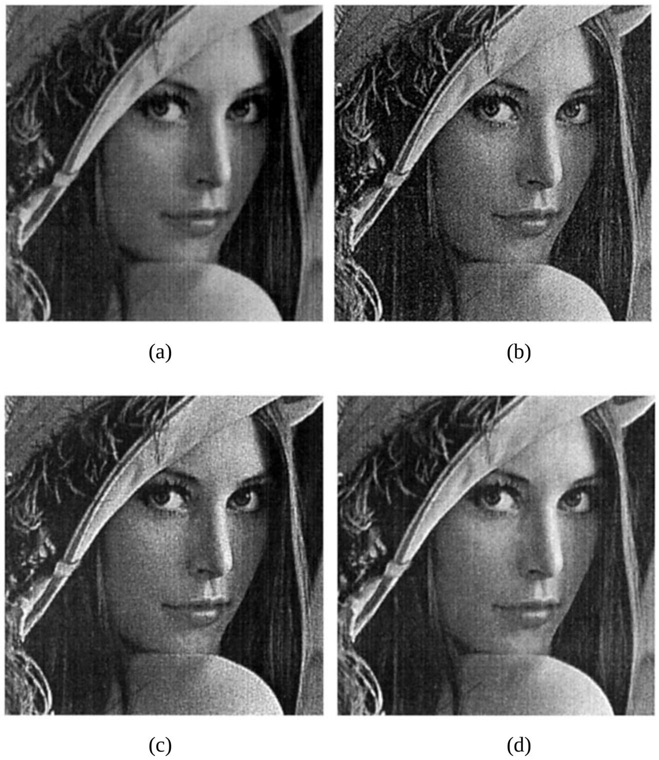


Fig. 7. (a) Noisy image, (b) result yielded by the linear unsharp masking technique, (c) result yielded by the Teager-based unsharp masking operator, and (d) result yielded by the weighted median unsharp masking method.

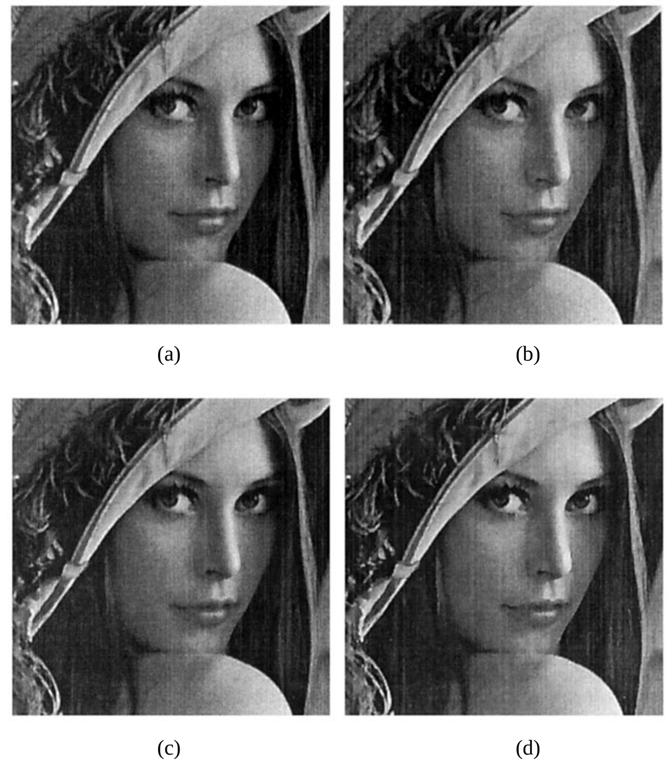


Fig. 8. (a) Result yielded by the cubic unsharp masking operator, (b) result yielded by the permutation weighted median unsharp masking technique, (c) result yielded by our previous operator, and (d) result yielded by the proposed method.

the processed image remains as noisy as the input data. A similar result can be obtained by using the recent technique based on the permutation weighted median [6] [Fig. 8(b)]. We can observe that no relevant noise amplification has been generated during the enhancement process. The result yielded by our previous technique is depicted in Fig. 8(c). No noise increase is perceivable. Finally, the result of the application of the proposed method is reported in Fig. 8(d) ($\alpha = 18$). The significant improvement is apparent. The image looks almost noiseless, and the details are sharply reproduced. The better performance of the proposed approach can be highlighted by evaluating the mean square error (MSE) of the processed data with respect to the original uncorrupted image. Since these enhancement techniques tend to sharpen the image details, the MSE evaluation has been performed by excluding the detailed areas of the image. For this purpose, we have generated a map of the uniform regions by using the Sobel operator [9] and a simple thresholding technique. The MSE values related to the uniform regions of the image are reported in Table I. It can be observed that, unlike other techniques, the proposed method can significantly reduce the noise during the sharpening of the image details. A possible extension of the method to the enhancement of images degraded by compression artifacts is the subject of a present investigation.

## V. Implementation Aspects

The development of fast algorithms is very important in image-based instrumentation. An efficient implementation of the method can be obtained by rewriting relations (6) and (8) as follows

$$y_{i,j} = x_{i,j} - \frac{1}{N} \sum_{x_{m,n} \in A} f(x_{i,j}, x_{m,n}, \alpha) \tag{11}$$

$$y_{i-1,j-1} = x_{i-1,j-1} \oplus \frac{1}{N} \sum_{x_{m,n} \in B} g(x_{i-1,j-1}, x_{m,n}, \alpha) \tag{12}$$

where

$$f(x_{i,j}, x_{m,n}, \alpha) = \alpha(\mu_{R_1}(x_{i,j}, x_{m,n}, \alpha) - \mu_{R_2}(x_{i,j}, x_{m,n}, \alpha)) \tag{13}$$

$$f_1(x_{i-1,j-1}, x_{m,n}) = 2(L-1)(\mu_{R_1}(x_{i-1,j-1}, x_{m,n}, L-1) - \mu_{R_2}(x_{i-1,j-1}, x_{m,n}, L-1)) \tag{14}$$

$$f_2(x_{i-1,j-1}, x_{m,n}, \alpha) = \alpha(\mu_{R_1}(x_{i-1,j-1}, x_{m,n}, \alpha) - \mu_{R_2}(x_{i-1,j-1}, x_{m,n}, \alpha)) \tag{15}$$

$$g(x_{i-1,j-1}, x_{m,n}, \alpha) = f_1(x_{i-1,j-1}, x_{m,n}) - f_2(x_{i-1,j-1}, x_{m,n}, \alpha). \tag{16}$$

Thus, we can significantly reduce the computational burden by using look-up tables (LUTs) for implementing $f$ and $g$. The fast algorithm is written in C language and requires 43 ms to process a $256 \times 256$ image on a 1000 MHz Athlon-based PC. For a comparison, we considered the nonfuzzy methods listed in Table I, and we measured the corresponding processing

TABLE I
LIST OF MSE VALUES

| | |
|---|---|
| **Noisy data** | **49.5** |
| **Linear unsharp masking** | **1034.8** |
| **Teager-based unsharp masking** | **239.5** |
| **Weighted median unsharp masking** | **139.1** |
| **Permutation w. median unsharp masking** | **50.6** |
| **Cubic unsharp masking** | **50.6** |
| **Our previous method** | **49.0** |
| **Proposed method** | **30.4** |

times. We obtained the following results: 11 ms (linear unsharp masking and Teager-based unsharp masking), 13 ms (cubic unsharp masking), 27 ms (weighted median unsharp masking), and 121 ms (permutation weighted median unsharp masking). Even if our algorithm is not as fast as some other operators, it does not represent the slowest technique. Due to the adoption of LUTs, the execution time of our method lies in the range of values yielded by established methods in the field. It should be observed that the proposed approach is based on a two-output system that is specifically designed to exploit much more information than conventional nonlinear techniques. The time that is necessary to process such information is the price to be paid for obtaining a superior performance.

## VI. CONCLUSION

A new method for contrast enhancement of noisy images has been presented. The method is based on a multiple-output system whose behavior can gradually range from detail sharpening to noise smoothing due to the adoption of fuzzy models. In this respect, fuzzy networks offer some important advantages. Fuzzy networks can effectively model conflicting tasks such as noise removal and edge highlighting. Combining fuzzy networks in the same processing architecture is also very easy. The proposed enhancement system includes three networks operating on different subsets of input data. Nevertheless, no complicated tuning of fuzzy set parameters is necessary because the overall nonlinear behavior is very easily controlled by one parameter only. Results of computer simulations have shown that the proposed method outperforms state-of-the-art techniques in the enhancement of noisy image data. An efficient implementation of the method has also been presented. The extension of the method to the processing of multichannel image data is the subject of a present research work.

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