Fuzzy Weighted Adaptive Linear Filter for Color Image Restoration Using Morphological Detectors

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Abstract — **A novel scheme for restoration of color images is presented. The proposed scheme has two phases; in the first phase it detects the pixels corrupted with impulse noise by employing the tools of mathematical morphology and the degree of noisiness is labeled by a fuzzy membership function. Subsequent phase uses a linear weighted filter that attempts to reduce noise in an efficient manner. Experimental results indicate that the proposed scheme provides a better restoration performance than many state of the art filters used for the same. The scheme is capable of preserving color and image details, while suppressing impulse noise effectively.**

Keywords- Image Restoration, Impulse Noise, Morphological Operations, Fuzzy Functions, Adaptive Linear Filter, Images in RGB and Lu*v* color space.

I. INTRODUCTION

With the wide use of color in many areas such as multimedia applications, biomedicine, internet and so on, the interest on the color perception and processing has been growing rapidly. Color, as we know is a powerful descriptor and helps us interpret and identify the objects in a picture more clearly than a gray scale image. They provide the picture with an element of closeness with the real world which obviously, isn't black and white. To add to it, there are thousands of shades our eyes can recognize thus elaborating the scope of this paper to all of these instead of restricting it to a few dozen shades of gray.

Impulse noise is characterized by discontinuities in the form of very high or very low values in a dynamic range thus giving it an overall granular kind of appearance. The standard median filter has been widely used for removing impulse noise. The problem with traditional linear or median filters and it's like [1], [4] was that they treated all the pixels even the undisturbed ones in the same manner. Though they achieve noise suppression but at the expense of considerable distortion in image features. Improvements are the adapted switching filters [5], [6] [7]. Mathematical morphology has been widely used in various image processing tasks. Morphological filters are nonlinear signal transformations that locally modify geometric features of signals. Jinsung Oh et.al [8], Deng, Z.F. et.al [9] and Z.P. Yin et.al [10] have shown the utilization of morphological filters in the perspective of impulse noise reduction from grayscale images. Jinsung Oh et.al [8] used a ranked directional morphological operator, Deng, Z.F. et.al [9] used opening closing sequence filter and Z.P. Yin et.al [10] used conditional morphological operators. The morphological operators used in these filters differ from each other by the structuring elements they use or the sequence of operation they perform. The experiments have shown that the morphological filters are able to clean impulse noise effectively, but then the biases that are introduced by the operators tend to lose image details. Some of the two phased schemes utilize fuzzy techniques for noise detection. Like Wenbin Luo [11] used a histogram based fuzzy noise detection technique. Then the fuzzy membership values are used in a modified median filter that filters out the noise. The filters we discussed so far are used for impulse noise reduction from gray scale images. Deng, Z.F et.al [12] used Median Controlled Adaptive Recursive Weighted Median Filter for restoring color image corrupted by impulse noise.

In this paper, a new class of filter for color image processing is developed. The Morphological Operations in RGB color space are introduced, which are an extension of mathematical morphology from gray-scale images to color images. One of the key features of fuzzy logic is its ability to deal with the typical uncertainty, which characterizes any physical system. Indeed, fuzziness affects many aspects of image processing such as input signal can be noisy and incomplete. In the proposed scheme a fuzzy membership function is used that gives each pixel a fuzzy flag indicating how much a pixel looks like an impulse. These fuzzy flags are used as weights corresponding to the pixel in a modified adaptive linear filter. The experimental results have been compared with various other filters indicating the efficiency of the proposed technique. The measures such as Peak Signal to Noise ratio (PSNR) and Normalized Color Difference (NCD) are used to prove the noise reducing and detail preserving capability of the proposed scheme.

II. PROPOSED SCHEME

The proposed method uses a sequence of morphological operations for noise classification. A 5X5 flat structuring element of value one has been used for morphological noise detection. The flat structure of it reduces the complexity of the overall technique. After the sequence of morphological operations, a fuzzy membership function as shown in figure (1), is used to find how much noisy a pixel is. Then these membership values corresponding to any pixel is used as the weight in the filter. Generally in the fixed small window size filters, the amount of noise density filtered will be very less, for filtering high density noise the window size of the filter may

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increase. This may lead to blurring in the output images. In order to overcome this, here we use an adaptive weighted linear filter that restores the color image effectively.

A. Morphological Noise Detection

A color pixel at (x, y) in a given domain of color image can be described by a color vector (R(x, y), G(x, y), B(x, y)) in RGB color space, where $(x, y) \in Z^2$. In order to process the color image, it is first decomposed into its three component images. Now each component image is treated as a separate intensity image. All the operations are performed on these component images independently. Noise detection employing a sequence of morphological operations is performed in two stages.

B. Stage-I of Noise Detection

This involves the application of basic morphological operations such as Dilation and Erosion on the image function f(x, y) that is the value of the component (R, G or B) under consideration at position (x, y). Considering, b(x, y) as the structuring element, Dilation $(f \oplus b)$ and Erosion $(f \Theta b)$ operations can be represented by equation (1) and (2) respectively.

$$(f \oplus b)(x, y) = \max\{ f(x-s, y-t) * b_n(s,t) | (x-s), (y-t) \in D_f ; (s,t) \in D_b \} \quad (1)$$

$$(f \Theta b)(x, y) = \min\{ f(x+s, y+t) * b_n(s,t) | (x+s), (y+t) \in D_f ; (s,t) \in D_b \} \quad (2)$$

, where Df and Db denote the domain of the image f and the domain of the structuring element b, respectively. As shown, the above operations find out the minimum and maximum color component pixels in their neighborhood. Now as the salt and pepper impulse noise itself implies significant discontinuities in their neighborhood, they can be detected comparing the results of dilated or eroded image with the original one. If the values after dilation or erosion turn out to be the same as before, the pixel is classified as the noisy one with the noise flag set. Else it is considered a noise free pixel. Using this concept a binary array B(x, y) containing the noise flags can be derived as explained in equation (3).

$$B(x, y) = \begin{cases} 1 & f(x, y) = (f \oplus b)(x, y) \quad or \quad f(x, y) = (f \Theta b)(x, y) \\ 0 & otherwise \end{cases} \quad (3)$$

However, there are some issues with this. Sometimes the edge pixels or other such sharp discontinuity areas which otherwise form a part of the image itself are also misclassified as being noisy pixels. Therefore, a second stage of noise classification is also employed.

C. Stage-II of Noise Detection

Based on the basic operations of Erosion and Dilation, Opening $(f \circ b)$ and Closing $(f \bullet b)$ operations are defined as given in equation (4) and (5) respectively.

$$(f \circ b)(x, y) = ((f \Theta b) \oplus b)(x, y) \quad (4)$$

$$(f \bullet b)(x, y) = ((f \oplus b) \Theta b)(x, y) \quad (5)$$

Combining the opening-closing operators, the local characteristic at position (x, y) is determined as in equation (6).

$$D(x, y) = \left| \frac{(f \circ b)(x, y) + (f \bullet b)(x, y)}{2} - f(x, y) \right| \quad (6)$$

Whilst the local characteristic value D for a pixel is more, it shows that it differs from its neighbourhood significantly. Suppose, the pixel under consideration is an edge pixel, then the connecting edge pixels in its neighborhood also have the similar characteristics. Using these concepts, the pixel with higher local characteristic value is suspected to be an impulse noise. To decide, how much noisy a pixel is we make use of a fuzzy membership function. The binary array B(x, y) containing the noise flags, is then revised to contain the fuzzy flags that indicate the degree of noisiness.

D. Computation of Fuzzy Weights

A fuzzy system is characterized by fuzzy variables which are members of a fuzzy set. A fuzzy set based on the concept of partial membership is a generalization of a classical set. Let F be a fuzzy set defined on the universe of discourse U. The fuzzy set is described by the membership $\mu_{F(u)}$ that maps U to the real interval [0, 1]. A membership of value 0 signifies the fact that the element $u \in U$ does not belong to the set F, a membership of value 1 signifies that the element $u \in U$ belongs to the set F with full certainty. Whereas, a membership of any real value from 0 to 1 represents the element u to be a partial member of the set F.

In the proposed scheme, a fuzzy membership function as graphically shown in figure [2] is employed. The universe of discourse is the local characteristic values D as computed using the equation (6). For any value $d \in D$ the fuzzy membership value is computed as,

$$\mu_d = \begin{cases} 0 & if \quad d \le d_{\min} \\ \dfrac{\mathrm{d} - \mathrm{d}_{\min}}{\mathrm{d}_{\max} - d_{\min}} & if \quad d > d_{\min} \quad or \quad d < d_{\max} \\ 1 & if \quad d \ge d_{\max} \end{cases} \quad (7)$$

, where $d_{\min}$ and $d_{\max}$ are two preset parameters. Massive experiments indicate that for most of the cases, images can be

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restored with high quality with the proposed algorithm when $d_{\min} = 15$ and $d_{\max} = 25$. For all noise-free pixels, μ_d is set to zero.

As discussed earlier, these noise detection techniques defined in two stages are to be applied on the three color components of the image independently. The sequence of above described operations is used to realize accurate noise detection. Once the noise is detected we move to the next phase, where the noise will be eliminated by applying an adaptive weighted linear filter.

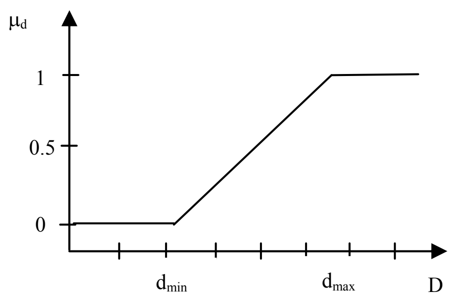

Figure 1: A Continuous Fuzzy Membership Function

E. Noise Elimination

Adapted switching filters improve the efficiency by freeing the filter from the constraints imposed by a fixed window size. Adaptive switching filters have the capability to alter the window size according to the presence of noise affected pixels within the filter window. The adaptive mean filter used in the scheme, determines the filtering window size for every detected noise pixel based on the number of its neighboring noise-free pixels. For each detected noise pixel (x, y), the filtering window with the size of (2Lf+1)*(2Lf+1) centered about it is used. Starting with Lf=1, the filtering window is iteratively extended outwards by one pixel in its four sides until the number of noise-free pixels within this window is at least one. The output of the adaptive mean filter applied at position (x, y) is obtained by:

$$\mathrm{h}(x, y) = \mu_d * m^{\alpha}(x, y) + (1 - \mu_d) f(x, y) \tag{8}$$

, where mα(x, y) is the alpha-trimmed mean value calculated as:

$$\mathrm{m}^{\alpha}(\mathrm{x}, \mathrm{y}) = \frac{1}{\mathrm{p(x, y)} - 2\lfloor \alpha \mathrm{p(x, y)} \rfloor} \sum_{k=\lfloor \alpha \mathrm{p(x,y)} \rfloor + 1}^{p(x,y) - \lfloor \alpha \mathrm{p(x,y)} \rfloor} F(k) \tag{9}$$

, where p(x, y) is the number of noise pixels within the filtering window, α is the trimming parameter (0<α<0.5) and F (k) denoted the kth data item in increasing order samples of noise free pixels. After each component of the color image in RGB space have been processed by means of the above mentioned techniques, they are concatenated into one, rendering a single restored color image.

III. Experimental Results

The proposed method has been simulated using MATLAB7. For the experimentation a 5X5 flat structuring element is chosen, while $d_{\min} = 15$ and $d_{\max} = 25$, and α has been considered to be 0.3. A number of color images have been corrupted by impulse noise with the noise density varying from 0.1 to 0.9 and the proposed scheme has been applied for the restoration. The results have been compared with some of the recent filters [1], [2], [3], [4], [12] used for impulse noise reduction from color images. The measure used for comparison is the Peak Signal to Noise Ratio (PSNR), computed as

$$PSNR = 10 \log_{10}\left(\frac{255^2}{MSE}\right) \tag{10}$$

$$where, MSE = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} \left\| o'_{i,j} - o_{i,j} \right\|}{MN} \tag{11}$$

M and N denote the image dimensions. $o'_{i,j}$ and $o_{i,j}$ show the original and restored image pixels located at (i,j) respectively. Since RGB is not a perceptually uniform space in the sense that differences between colors in this space do not correspond to color differences perceived by humans, the restoration errors are often analyzed using the perceptually uniform color spaces. In this work, the CIE LUV color space is used and the normalized color difference (NCD) defined as:

$$\Delta E = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(L^*_{oi} - L^*_{xi})^2 + (u^*_{oi} - u^*_{xi})^2 + (v^*_{oi} - v^*_{xi})^2} \tag{12}$$

$$NCD = \frac{N\Delta E}{\sum\sqrt{(L^*_{oi})^2 + (u^*_{oi})^2 + (v^*_{oi})^2}} \tag{13}$$

where L* represents lightness values and u*,v* chrominance values corresponding to original oi and restored xi samples expressed in the CIE LUV color space. Various filters as mentioned earlier are applied on Lena.jpg and Zelda.jpg. Figure (3) and (5) shows the comparison of these filters with the proposed scheme based on PSNR value. It is straightforward to see from the figures that the proposed method provides significantly higher PSNR values than other compared filters. Subjective evaluation done in figures (2), (4), (6) and (7) further states the noise reduction capability of the scheme in different types of color images. Normalized Color Differences (NCDs) computed for different images are shown in figure (8). Lower NCD values show better preservation. The scheme is able to preserve color attributes significantly even for the images with high variations.

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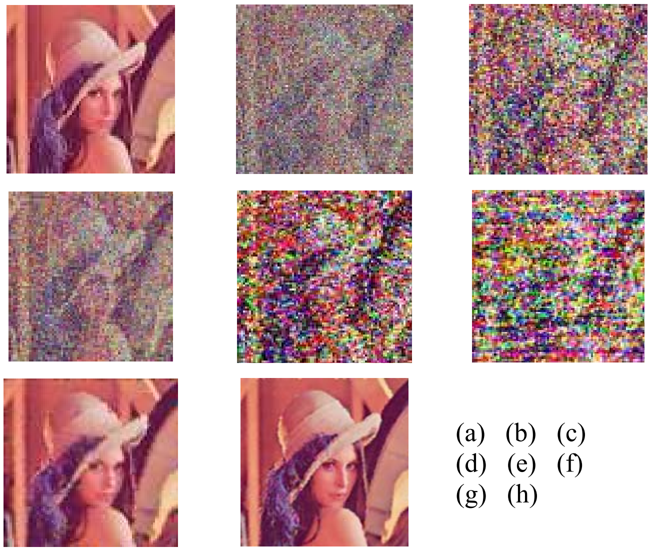

Figure 2: (a) Original Lena 256 X256 image (b) Noisy image (density 80%) (c) SMF output (d) WMF output (e) RWM output (f) MC LIN's output (g) ARWMF output (h) proposed method's output

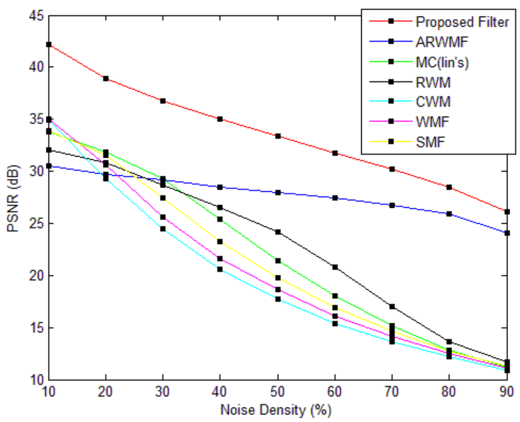

Figure 3: Image Restoration Performance in terms of PSNR when applied on 256X256 Lena image

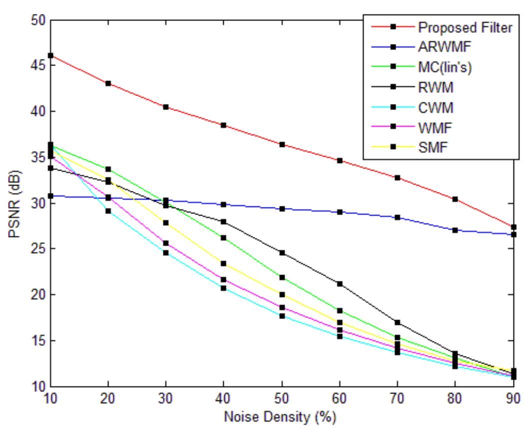

Figure 4: Image Restoration Performance in terms of PSNR when applied on 256X256 Zelda image

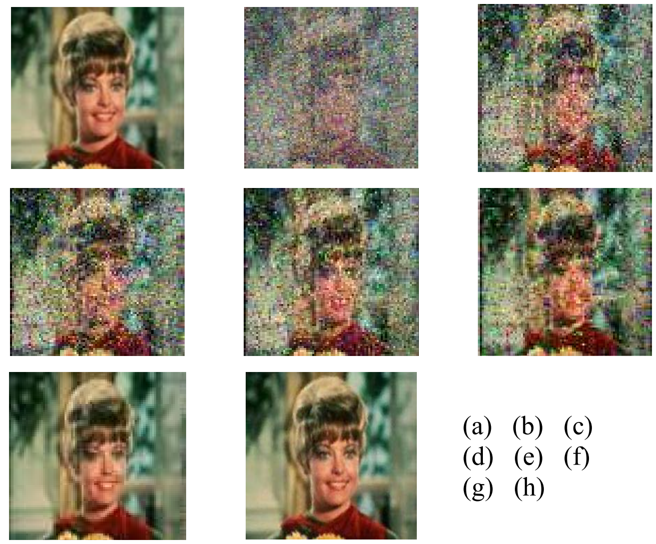

Figure 5: (a) Original Zelda 256 X256 image (b) Noisy image (density 60%) (c) SMF output (d) WMF output (e) RWM output (f) MC LIN's output (g) ARWMF output (h) proposed method's output

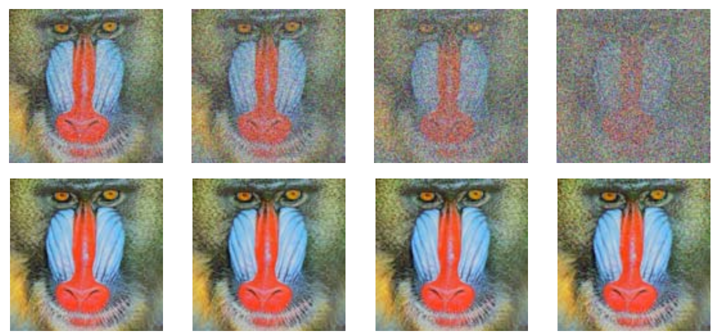

Figure 6: (a) 512X512 Baboon Noisy image (density 20%) (b) Noisy image (density 40%) (c) Noisy image (density 60%) (d) Noisy image (density 80%) (e), (f), (g) & (h) shows the corresponding restored images by the proposed method

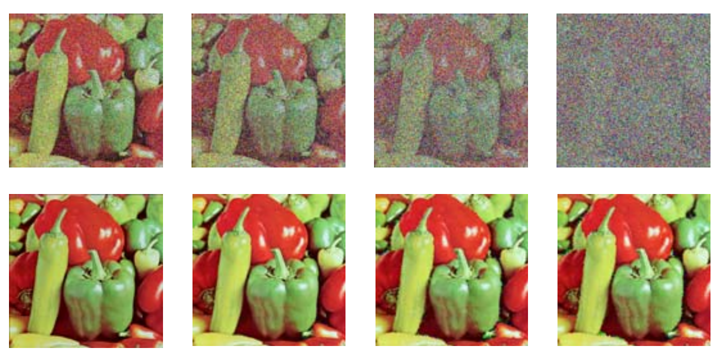

Figure 7 : (a) 512X512 Pepper Noisy image (density 30%) (b) Noisy image (density 50%) (c) Noisy image (density 70%) (d) Noisy image (density 90%) (e), (f), (g) & (h) shows the corresponding restored images by the proposed method

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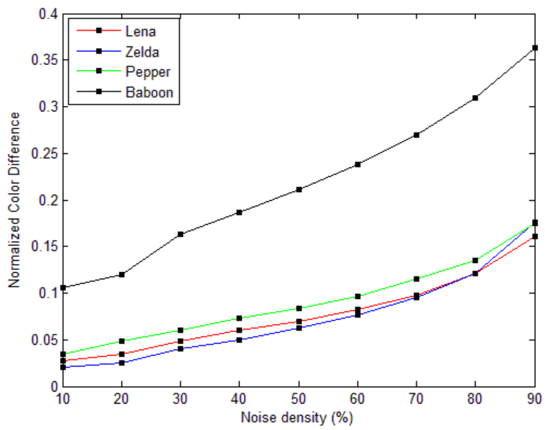

Figure 8 : Image Restoration Performance in terms of NCD

IV. CONCLUSIONS

Morphological operators are nonlinear operators, which have been utilized in the proposed technique effectively to detect the set of corrupted pixels in the color images. Fuzzy logic is capable of dealing with the typical uncertainty that characterizes any physical system. As fuzziness affects the processing of a noisy and incomplete signal, a fuzzy membership function is used that gives each pixel a fuzzy flag indicating how much a pixel looks like an impulse. Then an adaptive weighted linear filter is used to eliminate noise from each of the red, green and blue components of the noisy pixels of the color image. The experimental results reveal that the proposed method not only has outstanding noise detection and image restoration feat but also has excellent strength in combating a wide variation of noise densities from color images.

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