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Denoising color images using enhanced fuzzy two-step filters

[1]P.Pardhasaradhi, [2]P.Seetharamaiah and [3]T.Nagarjuna

[1,3]Department of CSE, Bapatla Engineering College, Bapatla, Andhra Pradesh, India.
[2]Department of CS&SE, Andhra University, Visakhapatnam, Andhra Pradesh, India.

Abstract
Enhancement and reducing the noise in a color image is a critical issue in the digital image processing field. This paper presents an Enhanced fuzzy filter for the reduction of Gaussian noise for digital color images. This approach is composed of two sub-filters, where the first fuzzy sub-filter computes the fuzzy distances between the color components of the central pixel and its neighborhood using Gaussian combination membership function, and the goal of the second sub-filter is to correct the pixels where the color components differences are corrupted so much that they appear as outliers in comparison to their environment. The performance of the new approach is compared with conventional filters, both visually and quantitatively using PSNR values.

Keywords: Additive noise, color images, fuzzy filter, noise reduction, Gaussian.

INTRODUCTION

The fundamental problem of image and signal processing is to effectively reduce noise from a digital color image while keeping its features intact (e.g., edges, color component distances, etc.). Three main types of noise exist: impulse noise, additive noise, and multiplicative noise. Impulse noise is usually characterized by some portion of image pixels that are corrupted, leaving the remaining pixels unchanged. Examples of impulse noise are fixed-valued impulse noise and randomly valued impulse noise. We talk about additive noise when a value from a certain distribution is added to each image pixel, for example, a Gaussian distribution. Multiplicative noise is generally more difficult to remove from images than additive noise because the intensity of the noise varies with the signal intensity (e.g., speckle noise). Fuzzy set theory and fuzzy logic [1] offer us powerful tools to represent and process human knowledge represented as fuzzy if-then rules. Fuzzy image processing [2] has three main stages: 1) image fuzzification, 2) modification of membership values, and 3) image defuzzification. The fuzzification and defuzzification steps are due to the fact that we do not yet possess fuzzy hardware. Therefore, the coding of image data (fuzzification) and decoding of the results (defuzzification) are steps that make it possible to process images with fuzzy techniques. The main power of fuzzy image processing lies in the second step (modification of membership values). After the image data is transformed from input plane to the membership plane (fuzzification), appropriate fuzzy techniques modify the membership values. This can be a fuzzy clustering, a fuzzy rule-based approach, a fuzzy integration approach, etc. Several fuzzy filters for noise reduction have already been developed, e.g., the iterative fuzzy control based filters from [3], [4], the GOA filter and so on. Most of these state-of-the-art methods are mainly developed for the reduction of fattailed noise like impulse noise. These fuzzy filters are able to outperform rank-order techniques (such as the median based filters). Nevertheless, most of the current fuzzy techniques do not produce convincing results for additive noise, which is illustrated in [5] and [6]. Another shortcoming of the current methods is that most of these filters are especially developed for gray scale images. It is, of course, possible to extend these filters to color images by applying them on each color component separately, independent of the other components. However, this introduces many artifacts, especially on edge or texture elements. Therefore, this paper presents a new and simple fuzzy technique for filtering color images corrupted with narrow-tailed and medium narrow-tailed noise (e.g., Gaussian noise) without introducing these artifacts.

This approach usually involves formulating a criterion of goodness that will yield an optimal estimate of the desired result. By contrast, enhancement techniques basically are heuristic procedures designed to manipulate an image in order to take advantage of the psychophysical aspects of human visual system. For example, histogram equalization is considered an enhancement technique because it is primarily on the pleasing aspects it might present to the viewer, whereas removal of image blur by applying a deblurring function is considered a restoration technique. If H is a linear, position-invariant process, then the degraded image is given in the spatial domain by

$$g(x, y) = h(x, y) * f(x, y) + \square(x, y)$$

where $h(x, y)$ is the spatial representation of the degradation function and the symbol "*" indicates convolution [2]. During image transmission, noise which is usually independent of the image signal occurs.

Noise may be additive, where noise and image signal g is independent.

$$f(x, y) = g(x, y) + v(x, y)$$

where $f(x, y)$ is the noisy image signal, $g(x, y)$ is the original image

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*Corresponding Author

P.Pardhasaradhi,
Department of CSE, Bapatla Engineering College, Bapatla, Andhra Pradesh, India.

Email: pardhu.pathella@gmail.com

signal and v(x, y) is the noise signal which is independent of g [3]. The additive noise image v models an undesirable, unpredictable corruption of g. The process v is called a two dimensional random process or a random field. The goal of restoration is to recover an image h that resembles g as closely as possible by reducing v.

CONVENTIONAL NOISE REMOVAL TECHNIQUES

Noise reduction is the process of removing noise from a signal. Noise reduction techniques are conceptually very similar regardless of the signal being processed, however a priori knowledge of the characteristics of an expected signal can mean the implementations of these techniques vary greatly depending on the type of signal. Although linear image enhancement tools are often adequate in many applications, significant advantages in image enhancement can be attained if non-linear techniques are applied [3]. Non-linear methods effectively preserve edges and details of images, whereas methods using linear operators tend to blur and distort them. Additionally, non-linear image enhancement tools are less susceptible to noise.

One method to remove noise is to use linear filters by convolving the original image with a mask. The Gaussian mask comprises elements determined by a Gaussian function. It gives the image a blurred appearance if the standard deviation of the mask is high, and has the effect of smearing out the value of a single pixel over an area of the image. Averaging sets each pixel to the average value of itself and its nearby neighbors. Averaging tends to blur an image, because pixel intensity values which are significantly higher or lower than the surrounding neighborhood would smear across the area. Conservative smoothing is another noise reduction technique that is explicitly designed to remove *noise spikes* (*e.g.* salt and pepper noise) and is, therefore, less effective at removing *additive noise* (*e.g.* Gaussian noise) from an image.

Additive noise is generally more difficult to remove from images than impulse noise because a value from a certain distribution is added to each image pixel, for example, a Gaussian distribution. A huge amount of wavelet based methods are available to achieve a good noise reduction (for the additive noise type), while preserving the significant image details.. The wavelet denoising procedure usually consists of shrinking the wavelet coefficients, that is, the coefficients that contain primarily noise should be reduced to negligible values, while the ones containing a significant noise-free component should be reduced less. A common shrinkage approach is the application of simple thresholding nonlinearities to the empirical wavelet coefficients [5], [6]. Shrinkage estimators can also result from a Bayesian approach, in which a prior distribution of the noise-free data (e.g., Laplacian , generalized Gaussian [12]) is integrated in the denoising scheme.

Fuzzy set theory and fuzzy logic offer us powerful tools to represent and process human knowledge represented as fuzzy if-then rules. Several fuzzy filters for noise reduction have already been developed, e.g., the iterative fuzzy control based filters from [8], the GOA filter [9], [10], and so on. Most of these state-of-the-art methods are mainly developed for the reduction of fat-tailed noise like impulse noise. Nevertheless, most of the current fuzzy techniques do not produce convincing results for additive noise . Another shortcoming of the current methods is that most of these filters are especially developed for gray scale images. It is, of course, possible to extend these filters to color images by applying them on each color component separately, independent of the other components. However, this introduces many artifacts, especially on edge or texture elements.

A new fuzzy method proposed by Stefan Schulte, Valérie De Witte, and Etienne E. Kerre, is a simple fuzzy technique [11] for filtering color images corrupted with narrow-tailed and medium narrow-tailed noise (e.g., Gaussian noise) without introducing the above mentioned artifacts. Their method outperforms the conventional filter as well as other fuzzy noise filters. In this paper, we are presenting a modified version of the fuzzy approach proposed by Stefan Schulte, et.al, [11], which uses a Gaussian combination membership function to yield a better result, compared to the conventional filters as well as the recently developed advanced fuzzy filters.

ENHANCED FUZZY METHOD

In the proposed method, RGB space is used as the basic color space. Colors in RGB space are represented by a 3-D vector with first element being red, the second being green and third being blue, respectively. These three primary color components are quantized in the range 0 to 2m-1, where m=8. A color image C can be represented by a 2-D array of vectors where (i, j) defines a position in C called pixel and Ci,j,1, Ci,j,2, and Ci,j,3, denotes the red, green and blue components, respectively.

Sub-Filter I

The general idea in this method is to take into account the fine details of the image such as edges and color component distances, which will be preserved by the filter. The goal of the first filter is to distinguish between local variations due to image structures such as edges. The goal is accomplished by using Euclidean distances between color components instead of differences between the components as done in most of the existing filters. The proposed method uses 2-D distances instead of 3-D distances (distance between three color components red, green and blue), that is, the distance between red-green (RG) and red-blue (RB) of the neighborhood centered at (i, j) is used to filter the red component. Similarly, the distance between RG and green-blue (GB) is used to filter the green component and the distance between RB and GB is used to filter the blue component, respectively. The method uses three fuzzy rules to calculate the weights for the Takagi-Sugeno fuzzy model.

The current image pixel at position (i, j) is processed using a window size of (2K+1)×(2K+1) to obtain the modified color components. From experimental study, we found that the suitable value for K is 3 for high noise and 1 for low noise. To each of the pixels in the window certain weights are then assigned namely Wk,l, where k, l _ {-1, 0, 1}. Wi+k,j+l,1 , Wi+k,j+l,2 , and Wi+k,j+l,3 denotes the weights for the red, green and blue component at position (i + k, j + l), respectively. These weights are assigned according to the following three fuzzy rules. The fuzzy rule for the red component using RG and RB couple can be represented as follows:

IF DISTANCE(RG, NEIGHBOR(RG)) is SMALL AND DISTANCE(RB, NEIGHBOR(RB)) is SMALL THEN the weight Wk,l,1 is LARGE.

Similarly, fuzzy rules for the green component (using RG and GB couple) and the blue component (using RB and GB couple) can be computed. In the above fuzzy rules DISTANCE represents the Euclidean distance.

DISTANCE (RG, NEIGH(RG)) = [(Ci+k,j+l,1 - Ci,j,1)2 + (Ci+k,j+l,2 - Ci,j,2)2]$^{1/2}$

In the proposed approach, the membership function SMALL has been modified which incorporates a two-sided composite of two different Gaussian curves. The Gaussian function depends on two parameters σ and c as given by

$$f(x;\sigma,c) = e^{\frac{-(x-c)^2}{2\sigma^2}}$$

The membership function *gauss2mf* (supported by MATLAB) is a combination of two of these two parameters. The first function, specified by _1 and c1, determines the shape of the leftmost curve. The second function specified by _2 and c2 determines the shape of the right-most curve. Whenever c1 < c2, the gauss2mf function reaches a maximum value of 1. Otherwise, the maximum value is less than one. The membership function SMALL is then defined as

$\mu_S(x)$ = gauss2mf(x, [σ_x, Cx, σ_x, 0])

where σ_x is the standard deviation of the distance measure and Cx is the mean of the distance measure, respectively.

The fuzzy intersection operator, known as triangular norms (T-norms), used in this paper is the algebraic product T-norms. For example, the antecedent of Fuzzy rule 1 is:

μ_{SMALL}(DIST(RG, NEIGH(RG))) . μ_{SMALL}(DIST(RB, NEIGH(RB)))

The above obtained value, called the activation degree of the fuzzy rule 1, is used to obtain the corresponding weight. So the weights Wi+k,j+l,1 for the red component is given by.

$W_{i+k,j+l,1}$ = μ_{SMALL}(DIST(RG, NEIGH(RG))) . μ_{SMALL}(DIST(RB, NEIGH(RB)))

Similarly, Wi+k,j+l,2 and Wi+k,j+l,3 can be computed representing the weights for the green and blue component, respectively. Then the output of the Fuzzy Sub-filter I, denoted as FS1, for the red component is given by:

$$FS1(i,j,1) = \frac{\sum_{k=-K}^{+K}\sum_{l=-K}^{+K} w(i+k,j+l,1)\cdot N(i+k,j+l,1)}{\sum_{k=-K}^{+K}\sum_{l=-K}^{+K} w(i+k,j+l,1)}$$

Similarly, FS1i,j,2 and FS1i,j,3 can also be computed which represents green and blue components of the Fuzzy sub-filter I output image respectively.

Sub-Filter II

The second sub-filter is used as a complementary filter to the first one. The goal of this sub-filter is to improve the first method by reducing the noise in the color components differences without destroying the fine details of the image. In this step, the local differences in the red, green and blue environment are calculated separately. These differences are then combined to calculate the local estimation of the central pixel. In this step also, a window of size (2L+1) × (2L+1) is used centered at (i, j) to filter the current image pixel at that position. From experimental study, we found that the suitable value for L is 2 for high noise and 1 for low noise. The local differences for each element of the window for the three color components are calculated as follows:

DRk,l = FS1i+k,j+l,1 – FS1i,j,1 , DGk,l = FS1i+k,j+l,2 – FS1i,j,2 , DBk,l = FS1i+k,j+l,3 – FS1i,j,3 , where k, l _ {-1, 0, +1}.

The output of the Fuzzy sub-filter 2, denoted as FS2, for the red component is then given by

$$FS2(i,j,1) = \frac{\sum_{k=-L}^{+L}\sum_{l=-L}^{+L}(F(i+k,j+l,1)-\varepsilon(k,l))}{(2L+1)^2}$$

Similarly, FS2i,j,2 and FS2i,j,3 can also be computed which represents green and blue components of the output image respectively.

RESULTS AND DISCUSSION

As a measure of objective similarity between a filtered image and the original one, we use the peak signal-to-noise ratio (PSNR) in decibels (dB).

PSNR(*img*, *org*) = 10 log10(S2/MSE(*img*, *org*))

This similarity measure is based on another measure, namely the mean-square error (MSE).

$$MSE(img, org) = \frac{\sum_{c=1}^{3}\sum_{i=1}^{N}\sum_{j=1}^{M}[org(i,j,c) - img(i,j,c)]^2}{3.N.M}$$

where *org* is the original color image, *img* is the filtered color image of size *N.M*, and *S* is the maximum possible intensity value (with *m*-bit integer values, *S* will be 2m-1). The standard color images used in this paper are House image. The restored images using conventional filters and the proposed fuzzy method along with their corresponding PSNR values are shown in figures 1. From experimental results, it has been found that our proposed method receives the best numerical and visual performance for low levels and higher levels of additive noise, by appropriately selecting window size for the two fuzzy sub-filters.

Fig 1. (a) Original House image (256×256) (b) Noisy image (Gaussian noise, σ = 20) (c) After applying Mean filter (3×3 window) (d) After applying Median filter (3×3 window) (e) After applying Fuzzy filter of [11] (f) After applying Enhanced Fuzzy filter .

The proposed method performs relatively well for the three test-images in comparison to conventional filters. The main advantage of this filter is that noise is suppressed very well while fine details and edges do not lose much sharpness. Additionally the visual results illustrate that the proposed method restores the original color components differences much better than other methods. This method can also use as an additional filter for some wavelet-based methods.

CONCLUSION

A fuzzy filter for restoring color images corrupted with additive noise is proposed in this paper. The proposed filter is efficient and produces better restoration of color images compared to other filters. Numerical measures such as PSNR and visual observation have shown convincing results. Further work can be focused on the construction of other fuzzy filtering methods for color images to suppress multiplicative noise such as speckle noise.

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