A Universel Noise Réduction Framework for Denoising Digital Images

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Abstract—The trilateral filter is a nonlinear filter which performs averaging without concentrating on smoothing edges. Selection of the filter parameters is an important issue. A spatial nonlinear filter has been implemented based on local neighborhood about a pixel \( f(x, y) \) to reduce Gaussian and Impulse noise in images. Our approach is to remove universal noise automatically from synthetic images and biomedical images. The results are remarkably well in terms of quantitative measures of signal restoration as well as an image quality. We tested this procedure on synthetic as well as biomedical images. The wavelet thresholding is combined with trilateral filter to form a novel noise reduction framework, which is very efficient in reducing noise in real noisy images. Experimental results with factual data are provided.

Index Terms— Impulse noise, Gaussian noise, smoothing, Spatial component, radiometric components. Thresholding.

I. INTRODUCTION

There are various sources of noise in digital images. Dark signal nonuniformity and photo response nonuniformity type of noise is often referred to as fix pattern noise. Noise is in general space varying and channel dependent. Blue channel is more noisy channel due to the short transmittance of blue filters. Many noise reduction techniques have been developed over the years. One of the most popular methods is the median filter [2], which can suppress noise with high computational efficiency. However, since every pixel in the image is replaced by the median value in its neighborhood, the median filter often removes desirable details in the image and blurs it too. The weighted median filter [3] and the center-weighted median filter [4] were proposed as remedy to improve the median filter by giving more weight to some selected pixels in the filtering window. Although these two filters can preserve more details than the median filter, they are still implemented uniformly across the image without considering whether the current pixel is noise-free or not. Over the years, better noise removal methods with different kinds of noise detectors have been proposed, for example, switching median (SM) filter [5], multi-state median (MSM) filter [6], adaptive center weighted median (ACWM) filter [7]. Among these methods, wavelet sub bands thresholding is one of the popular approaches. In wavelet thresholding, a signal is decomposed into low frequency and high frequency sub bands. Since most of the image information is intense in a few large coefficients, the detail are processed with hard or soft thresholding operation [8]. Threshold selection is a critical task. Various threshold selection techniques have been proposed in VisuShrink [9], BayesShrink [10]. The outline of this paper is as follows. In Section II, we define the new ordered statistic. Section III describes noise removal method in detail. Section IV and V gives noise reduction frame work and the experimental results of the methods to demonstrate the performance of the new methods respectively. Finally conclusion is drawn followed by references.

II. RANK ORDER STATISTICAL METHOD FOR IMPULSE DETECTION

A. Non Linear Filter

Non linear filters based on order statistics requires that all the pixels defined in the filtering operations be ordered from their minimum gray level; to maximum gray level. Let \( f \) be the set of \( N \) pixels, the first step to order this set of pixels from their minimum to their maximum values:

\[
0 \leq f_0 \leq f_1 \leq f_2 \leq f_3 \leq \ldots \ldots \leq f_{N-1}
\]

Where  \( f_0 \) is a minimum value and  \( f_{N-1} \) is the maximum value of the pixels. In this paper, we use a standard matrix notation for images, where \( I \) is an image, \( I_{i,j} \) represents the intensity value of \( I \) at \((i, j)\) pixel location in the image domain. For the Gaussian noise, the noisy image \( I \) is related to the original image by \( I^0 \) by

\[
I_{i,j} = I^0_{i,j} \text{ with } (1 - P) \text{ probability }
\]

III. IMPLEMENTATION OF ORDER STATISTIC METHOD

The value of \( R(x) \) is very simple to introduce into existing filters. A new weighting function is incorporated into bilateral filter to implement trilateral filter. Bilateral filters are used to remove Gaussian noise. It retains the sharpness of edges. Each pixel is replaced the weighted average of the intensities in the neighborhood.
Consider $x$ be the position of the pixel, which is under consideration. The weight of $y$ with respect to $x$ is the product of spatial and radiometric components. If we consider weight of spatial component is $\omega_i$ and weight of radiometric component is $\omega_d$, where,

$$\omega_i = e^{-\frac{1}{2}\left(\frac{|y-x|}{\sigma_i^2}\right)^2}$$  \hspace{1cm} (2)

And

$$\omega_d = e^{-\frac{1}{2}\left(\frac{d_{xy}}{\sigma_d}\right)^2}$$  \hspace{1cm} (3)

$\sigma_i$ and $\sigma_d$ controls the behavior of weight. They serve as rough thresholds for identifying spatially or radiometrically close pixels.

A. Incorporation of $R(x)$ into Bilateral Filter

Let Impulsive weight $\omega_i$ at point $x$ is defined as;

$$\omega_i = e^{-\frac{1}{2}\left(\frac{R(x)}{\sigma_i}\right)^2}$$  \hspace{1cm} (4)

Approximate threshold value determine by $\sigma_i$ parameter.

For the addition of $\omega_i(x)$ function into bilateral filter, we have to determine the strength of radiometric component in the impulse noise. The impulsivity $I_v$ of $y$ w.r.t $x$ will be defined as;

$$I_v(x, y) = 1 - \left(\frac{1}{2}\left(\frac{R(x)+R(y)}{\sigma_v}\right)^2\right)$$  \hspace{1cm} (5)

The values of $I_v(x, y)$ function are in 0 and 1. The parameter $\sigma_v$ used to control the shape of the overall function. If at least one of $x$ or $y$ is impulsive and has high $R(x)$ value w.r.t $\sigma_v$, then $I_v(x, y) = 1$ and if neither pixel is impulse like then $I_v(x, y) = 0$. Thus $I_v(x, y) = 1$ is taken to reduce the impulses. The resulting weight of $y$ w.r.t central pixel $x$ is written as

$$F_w = \omega_i(x,y) * \omega_i(x,y) * \omega_i(y)^{I_v(x,y)}$$  \hspace{1cm} (6)

Where $c = 1 - I_v(x, y)$ and $c = 0$ or $1$. $c = 0$ for impulsive pixel and $c = 1$ for non impulsive pixel.

When $c = 0$, the radiometric threshold becomes very large and thus there are irrelevant radiometric differences. When $c = 1$, only radiometric weight is used to differentiate pixels, because of high impulsive threshold. In this way particular weighting function applied on each pixel.

Specifically the control parameters $\sigma_i$ and $\sigma_d$ depends on type of noise added. The values of these parameters chosen automatically according to the percentage of noise added to the image. The method applied to suppress the noise iteratively using the output of the previous iteration as the input of the next iteration. For high levels of noise (>30%) applying five to ten iterations, gives better results.

B. Parameter Selection

While doing experiments, we found that, by varying the parameter values of $\sigma_i$ and $\sigma_v$, we get different variations in the restored images and varied peak signal to noise ratio.

We have chosen $\sigma_i = 30$ and $\sigma_v = 100$ for the best results. These values work best to remove impulse and mixed noise in the digital images.

IV. IMAGE DENOISING FRAMEWORK

The proposed framework is illustrated in section II, Section III and in figure 1. A signal is decomposed into its frequency sub bands with wavelet decomposition; as the signal is reconstructed back, proposed filtering techniques is applied to the approximation sub bands. It is possible to apply wavelet thresholding to the detail sub bands, where noise components can be identified and removed efficiently. This new image denoising framework combines trilateral filtering and wavelet thresholding.

![Figure 1](image_url)

**Figure 1.** Illustration of the proposed method.

An input image is decomposed into its approximation and detail sub bands through wavelet decomposition. As the image is reconstructed back, trilateral filtering is applied to the approximation sub bands and wavelet thresholding is applied to the detail sub band. The analysis and synthesis filters form a perfect reconstruction filter bank. The illustration shows one approximation sub band and one detail sub band at each decomposition level. In the next section, we will
demonstrate that this framework produces results better than the individual applications of the wavelet thresholding or the trilateral filter.

V. EXPERIMENTAL RESULT AND DISCUSSIONS

To see the performance of the proposed framework, we have conducted some experiments. To do a quantitative comparison, we simulated noisy images by adding Gaussian noise and impulse noise. The noisy images are denoised using several algorithms and using proposed framework. The PSNR results are calculated for the quantitative measurement. Table 1. shows comparative results for digital images corrupted with impulse noise. Table 2 shows comparative results for digital images corrupted with Gaussian noise. Figure 2 to figure 7 shows visual performance of the framework.

A. PSNR comparison for Noisy Images

For each test image, four noisy images are created by adding Gaussian noise and impulse noise with 10%, 20%, 30% and 40%. PSNR results are shown in Table 1. After restoring the visual quality of images, for the performance measures, we used peak signal to noise ratio (PSNR). If \( I^0 \) is the original image and \( \hat{I} \) is the restored image and since the impulse noise is randomly generated as 0 or 255 with equal probability for all pixels,

\[
PSNR = 10 \log_{10} \left( \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} (255)^2}{\sum_{i=1}^{m} \sum_{j=1}^{n} (I - I^0)^2} \right)
\]

\( m \times n \) is the total number of pixels in an image. A larger PSNR value gives better signal restoration. We tested the implemented method by varying parameters on impulse noise levels from 10% to 40% in steps of 10%.

B. Characteristics of proposed algorithm

The main characteristics of the proposed framework are:

- Stronger removal of Gaussian and impulse noise.
- High PSNR ratio.
- High accuracy.
- Display high contrast images & denoising Biomedical as well as synthetic images.
- Easily extend to N-dimensional signal both Discrete & Continuous valued.
- Better approximate scene illumination as a sharply bounded piecewise smooth signal with locally constant gradient.
- Self adjust to image, requiring one user supplied parameter.
- Better performance for many visual applications including appearance preserving contrast reduction problems for digital photography & denoising

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<th>Methods</th>
<th>Synthetic Image 512 x 512</th>
<th>Biomedical Image 512 x 512</th>
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TABLE I

Comparative Results (PSNR in DB) for Digital Images Corrupted with Impulse Noise 10% and 20%

TABLE II

Comparative Results (PSNR in DB) for Digital Images Corrupted with Impulse Noise 30% and 40%

TABLE III

Comparative Results (PSNR in DB) for Digital Images Corrupted with Gaussian Noise 10% and 20%

TABLE IV

Comparative Results (PSNR in DB) for Digital Images Corrupted with Gaussian Noise 30% and 40%
CONCLUSION

We have done experiments on synthetic and biomedical images to reduce impulse and Gaussian noise and we obtained better results. The implemented method performs well in removing impulse and Gaussian. Many noise removal methods, such as bilateral filters, vector SD-ROM filters, median filters, RCRS filters treat impulse noise as edge pixels and hence it gives unsatisfactory results. To process impulse pixel and edge pixel differently, we used a new statistic. This statistic represents how impulsive pixel is different than the edge pixel. The weighting function removes impulsive noise without compromising the bilateral filter’s ability to remove Gaussian noise. The approach described here eliminates the coarse-grain noise in images. The wavelet thresholding eliminates some noise components better in detail sub band.

REFERENCES