Gaussian Noise Reduction using Adaptive Window Median Filter

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ABSTRACT
This paper proposes an adaptive window median filter (AWMDF) for Gaussian noise reduction. This is a spatial method where an *n* x *n* filtering window is applied around each noisy pixel. However, to make this possible for the boundary pixels, the image has to be padded on all sides by some padding method. The symmetrical padding method has been adopted here. Odd sized window is preferred as it provides better results for median estimation. Depending upon the noise levels, the method chooses desired window sizes. For low noise levels, the 3x3 filtering window is preferred, for medium noise levels, the 5x5 filtering window is preferred while for high noise levels, the 7x7 filtering window is preferred. Higher sized windows viz. 9x9, 11x11, etc. do not provide any advantage at any noise levels. The advantage of this filter is its simplicity and ease of application and provides reasonable qualitative and quantitative results**.**

Keywords
Gaussian noise, median filter, spatial method

1. INTRODUCTION
Denoising has become an essential step in image analysis. Indeed, due to sensor imperfections, transmission channel defects, as well as physical constraints, noise weakens the quality of almost every acquired image. Three main types of noise exist in the form of impulse noise, additive noise and multiplicative noise [1, 2]. 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. Additive noise is one where 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. speckles noise. The main goal of any image denoising algorithm is to reduce the noise level, while preserving the image features such as edges, textures, etc.

Linear processing techniques are very important tools that are used extensively in digital signal image processing. Their mathematical simplicity and the existence of a unifying linear systems theory make their design and implementation easy. Moreover, linear processing techniques offer satisfactory performance for a variety of applications. However, many digital image processing problems cannot be efficiently solved by using linear techniques. Linear filters[2], which were originally used in image filtering applications, cannot cope with the nonlinearities of the image formation model and cannot take into account the nonlinearities of human vision. Furthermore, human vision is very sensitive to high-frequency information. Image edges and image details (e.g. corners and lines) have high frequency content and carry very important information for visual perception. Filters having good edge and image detail preservation properties are highly suitable for digital image filtering. Most of the classical linear digital image filters have low-pass characteristics [3].They tend to blur edges and to destroy lines, edges, and other fine image details. These reasons have led researchers to the use of nonlinear filtering techniques. A multiplicity of nonlinear digital image processing techniques has appeared in the literature. The following classes of nonlinear digital image signal processing techniques can be identified at present: 1) order statistic filters **2)** homomorphic filters, **3)** polynomial filters, 4) mathematical morphology, 4) neural networks, and **5)** nonlinear image restoration. The median filter is one of the most prominent orders statistic filters[4-7]. This paper proposes an adaptive window median filter for Gaussian noise removal where the size of the window chosen depends upon the level of noise.

The rest of the paper is organized as follows. The proposed methodology is introduced in Section II. The experimental results and comparison table are presented in Section III. The conclusions are provided in Section IV.

2. PROPOSED METHODOLOGY
The proposed technique is a spatial method of reducing Gaussian noise. An $n \times n$ filtering window is applied around each noisy pixel. However, to make this possible for the boundary pixels, the image has to be padded on all sides by some padding method. The symmetrical padding method has been adopted here. Odd sized window is preferred as it provides better results for median estimation. For a 3x3 filtering window, median is found from the nine neighboring pixels using eq.1.

$$M(i,j) = \text{median}[(X(i-1,j-1), X(i-1,j), X(i-1,j+1), X(i,j-1), X(i,j), X(i,j+1), X(i+1,j-1), X(i+1,j), X(i+1,j+1)] \quad (1)$$

A similar procedure follows for the 5×5, 7×7 and 9×9 window. The process for reducing Gaussian noise using this filter is as follows:

Stage 1: Determination of level of noise in the image introduced by the image processing equipment by using a benchmark image.

Stage 2: Selection of the window size i.e. 3x3, 5x5, 7x7 or 9x9, according to the level of noise in the image.

Stage 3: Determination of the median of the neighborhood of each pixel of the image using appropriate size of adaptive filtering window to obtain the denoised image.

Stage 4: Application of the above step for different noise levels.

3. SIMULATIONS RESULTS AND DISCUSSIONS

This section compares the proposed algorithm with other existing techniques based on their simulation results. Peak signal-to-noise ratio (PSNR) is used to access the restoration results which measures how close the restored image is to the original image. The PSNR (dB) is defined as

$$\text{PSNR}= 10log_{10} \frac{(2^b-1)^2}{\frac{1}{MxN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(X(i,j)-Y(i,j))^2} \quad (2)$$

where b refers to a b-bit image, M x N is the size of the image, *X(i,j)* refers to the original image and *Y(i,j)* refers to the denoised image. Since image is subjected to the human eyes, visual inspection is also carried out on the filtered images to judge the effectiveness of the filters in removing impulse noise. A wide range of noise levels varying from σ = 5 to 50 in steps of 5 have been tested for comparison of results.

Table 1 lists the restoration result in PSNR (dB) of the proposed median method for 512 × 512 grayscale image 'Lena' corrupted by Gaussian noise of various noise levels. It can be seen that at low noise levels (σ = 5 to 15), the 3 × 3 filtering window provides best results in comparison to higher window sizes. At medium noise levels (σ = 20 to 30), the 5 × 5 filtering window provides the best results while for high noise levels, the 7 × 7 filtering window provides the best results. These results were generalized for a wide variety of images and the following conclusion has been drawn:

a) If the noise level is low, the 3 × 3 filtering window should be used,
b) If the noise level is medium, the 5 × 5 filtering window should be used and,
c) If the noise level is high, the 7 × 7 filtering window should be used.

Fig. 1 to 3 show the visual output of restoration results obtained from the proposed method for σ= 15, 30 and 50 using each of the window sizes.

Table 1
Comparison of restoration results of Median filter with varying window size in PSNR (dB) for image 'Lena'

Noise (σ)→ / Filtering technique↓	5	10	15	20	25	30	35	40	45	50
INPUT PSNR	34.13	28.13	24.61	22.12	20.20	18.70	17.41	16.36	15.42	14.60
VISUSHRINK[8]	34.3	28.2	24.6	22.1	20.67	18.7	17.34	16.4	15.73	14.6
SURESHRINK[9]	25.1	25.1	25.1	25.1	25.1	25.0	24.9	24.8	24.7	24.6
AWMDF (3×3)	**34.88**	**32.58**	**30.44**	28.58	27.01	25.67	24.52	23.49	22.53	21.65
AWMDF (5×5)	31.42	30.75	29.96	**29.21**	**28.34**	**27.55**	26.77	26.15	25.42	24.68
AWMDF (7×7)	29.26	29.00	28.61	28.18	27.75	27.30	**26.87**	**26.41**	**25.96**	**25.55**
AWMDF (9×9)	27.9	27.76	27.52	27.20	26.89	26.64	26.29	26.06	25.74	25.38

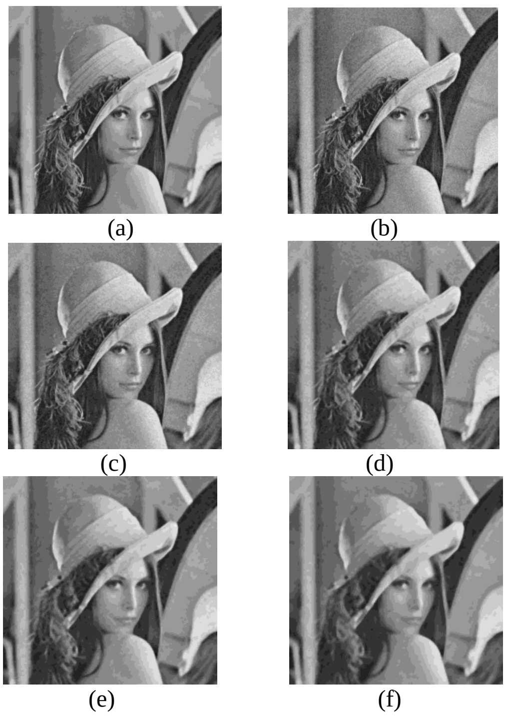

Figure 1. Restoration results (a) Noise-free image 'Lena' (b) Image corrupted image with Gaussian noise with σ =15 (c) Result using 3×3 AWMDF (d) 5×5 AWMDF (e) 7×7 AWMDF (f) 9×9 AWMDF

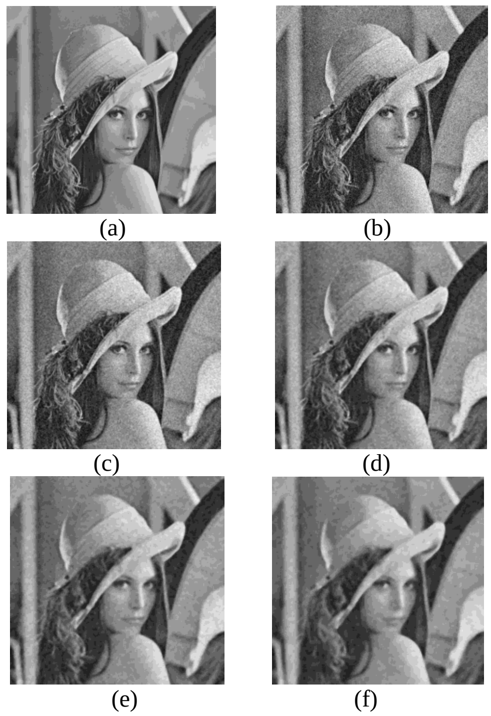

Figure 2. Restoration results (a) Noise-free image 'Lena' (b) Image corrupted image with Gaussian noise with σ =30 (c) Result using 3×3 AWMDF (d) 5×5 AWMDF (e) 7×7 AWMDF (f) 9×9 AWMDF

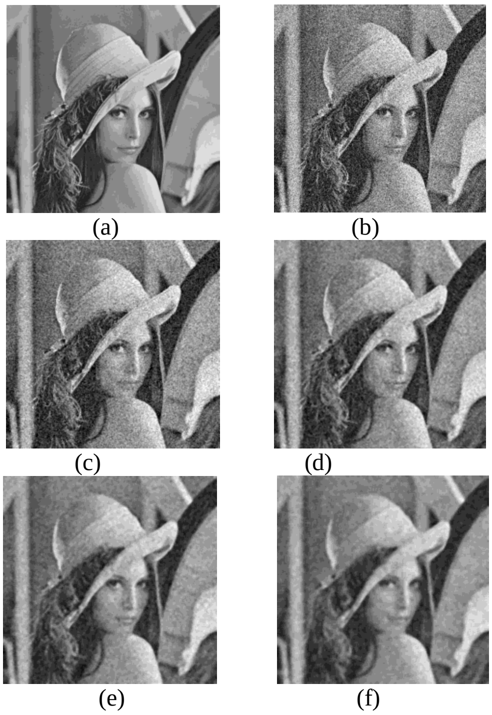

Figure 3. Restoration results (a) Noise-free image 'Lena' (b) Image corrupted image with Gaussian noise with σ =50 (c) Result using 3×3 AWMDF (d) 5×5 AWMDF (e) 7×7 AWMDF (f) 9×9 AWMDF

It can be seen that the proposed algorithm performs satisfactorily at various Gaussian noise levels. This can be seen both at the quantitative and qualitative level.

4. CONCLUSION

A median filter with adaptive window has been proposed in this paper that can reduce the Gaussian noise and also preserve the edges to some extent. The advantage of this filter is its simplicity. Depending upon the noise levels, the method chooses desired window sizes. As discussed, for low noise levels, the 3×3 filtering window is preferred, for medium noise levels, the 5×5 filtering window is preferred while for high noise levels, the 7×7 filtering window is preferred. Higher sized windows viz. 9×9, 11×11, etc. do not provide any advantage at any noise levels.

It is suggested that future research should focus on reducing the processing time when the image is corrupted with various levels of Gaussian noise.

5. REFERENCES

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