An Improved Median Filter For Mixed Noise Removal From Gray Scale Images

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***Abstract*— Reducing noises from images is a very wide research area in the domain of image processing. An efficient noise removal technique based on median filter to restore gray scale images corrupted by mixed noise, by preserving image details has been presented in this paper. This filtering method consists of two steps: the noisy pel detection and the mixed noise filtering. Noises addressed in this method are mixed impulse noise and Gaussian noise. The technique reduces mixed noises significantly without reducing on edge sharpness. Experimental results show that the proposed method outperforms the classic median and mean filtering algorithms, along with stabilizing the tradeoff between noise removal and image detail protection. So, this technique find relevance in various image processing systems including digital television, medical image processing systems, digital camera, surveillance systems etc.**

Keywords- impulse noise; mixed noise; gaussian noise

I. INTRODUCTION

Digital images get corrupted by different types of noises like impulse noise, Gaussian noise, mixed noise etc. Impulse noise presents itself as sparsely occurring white and black pixels in an image. The statistical noise whose probability density function is same as that of the normal distribution is known as Gaussian noise. Here the noise amplitudes can take only those values which are Gaussian-distributed. An image can contain more than one type of noise. Mixed noise refers to a combination of different types of noises.

At the time of capturing by camera sensors or during transmission in the channel, noises get added in the image. An important image processing operation in image and video is image denoising. Various algorithms are already available to reduce impulse noise which preserves image details also. Median filter is one among them, which has effective noise control capability. But, most of the median filters usually modify both noisy and noise-free pixels since they are implemented evenly across the image. The common scenario is that when impulse noise is removed effectively, it is always accompanied by distortion and loss of fine details. When it comes to mixed noise, the task is more challenging.

A technique to detect the presence of impulse noise switching median filters was presented. It was developed using single dimensional Laplacian operators based on the minimum absolute value of four convolutions [3]. Results obtained from simulations reveals that the proposed filter outperforms existing switching median filters with reduces computational complexity.

A decision-based, signal adaptive median filtering algorithm for removing salt-and-pepper noise has been introduced [4]. The algorithm achieved high noise detection rate and SNR measures without smudging edges in the image. Noise detection is carried out in two passes: noisy pixels are first selected using the homogeneity level, a refining process follows to eliminate false detections. Experimental results shows that this technique perform well, in terms of noise inhibition and detail preservation ability.

To remove impulse noise from densely corrupted images, a two-pass rank order filter has been proposed and the functioning of this filter is adaptive in nature [5]. The results obtained using order statistic filters in high noise situations were found to be very poor. Experiments showed that if the filter is applied twice, better results are obtained. This technique is called two-pass filtering. Results were further improved by incorporating an adaptivity concept to the two-pass filter.

An improved mixed impulse and Gaussian noise removal technique based on noisy pixel detection and fuzzy filtering is proposed in this paper. Better noise removal ability is exhibited by this method than complex detectors, and the method requires no previous training. When the proposed method is applied, it is found that mixed noise is removed from the heavily noise corrupted image very effectively. On the other hand it can easily be verified that the details are preserved consistently during the process of filtering. The results obtained out of the proposed method are found to be outperforming most of the existing filtering techniques.

Section II details the solution strategy which describes how a pixel is tested for noisiness and how those pixels are modified. In section III, the performance analysis is carried out, and is compared with that of mean and median filters in terms of Peak Signal to Noise Ratio (PSNR) values.

II..MATERIALS AND METHODS

Noises considered are mixed noise which consist of impulse and Gaussian noise. An image pixel may be corrupted to a positive impulse or a negative impulse. To an image corrupted by impulse noise, Gaussian noise is added for testing purpose.

The proposed algorithm consists of two steps: 1) The noisy pixel detection and 2) Mixed noise cancellation using a modified median filter. Each pixel is tested to discover whether it is noisy or not, so that only the noisy pixels need to undergo the filtering process. In the mixed noise cancellation step, each pixel is undergoes the filtering process based on the noisiness of each pixel. The steps of the algorithm are elaborated in the following sections.

A. Noisy Pixel Detection

Let f represent the, noisy image [7] of size m x n , and let f_{ij} be the pel value at location (i, j). So, f ={f_{ij} :1<= i<=m,1<= j<= n. Let W_{ij} represent the 3x3 window centered at f_{ij}.

To test whether f_{ij} is a noisy pixel, the proposed algorithm performs the following steps.

Step 1: Calculate the maximum value M_{ij} of $| f_{ij} - s_{ij} |$ for all s_{ij} € W_{ij} and $s_{ij} \neq f_{ij}$. The value of M_{ij} provides an effective way to detect noises.

Step 2: To find out the density of noise associated with the pixel f_{ij} a fuzzy flag with the following membership function given in Eqn. (1) is used [7]:

$$flag_{ij} = \begin{cases} 0 & M_{ij} <= T_1 \\ \dfrac{M_{ij} - T_1}{T_2 - T_1} & T_1 <= M_{ij} <= T_2 \\ 1 & M_{ij} >= T_2 \end{cases} \qquad (1)$$

T_1 and T_2 are two pre-defined parameters. Experiments in [7] indicate that restoration is optimal when $10 \leq T_1 \leq 20$ and $22 \leq T_2 \leq 32$ .T1 is fixed as 15 and T_2 as 25 for conducting experiments [7]. For all noise-free pixels, $flag_{ij}$ is set to zero.

B. Mixed Noise Cancellation

The term $flag_{ij}$ is computed for all f_{ij}, which is the pixel under consideration. Then f_{ij} is replaced by a value obtained from the linear combination of its actual value, fij and its median $median_{ij}$ of W_{ij}. [7].

$$y_{ij} = (1 - flag_{ij}) \text{ x } f_{ij} + flag_{ij} \text{ x } median_{ij} \qquad (2)$$

y_{ij} represents the new value of f_{ij} . If the pixel is noise-free, ($flag_{ij}$ =0) , y_{ij} remains as it is,(i.e., $y_{ij} = f_{ij}$) . If a pixel is deeply corrupted by noise, where $flag_{ij}$ = 1, y_{ij} takes the value of its median, $median_{ij}$. As far as the remaining pixels are concerned ($0 < flag_{ij} < 1$), the restored pixel value y_{ij} is replaced by a value by computing the linear combination of f_{ij} and $median_{ij}$ as in Eqn. (2). Algorithm 1 gives the detailed algorithm for the proposed method.

Algorithm 1: Proposed Filtering Algorithm

1. Read the input image f of size m x n
2. For each pixel f_{ij} [1<=i<=m; 1<=j<=n], W_{ij} being a 3 x 3 window centered at (i,j), perform the following steps

   Step 1: Calculate the maximum value of the difference M_{ij} of $| f_{ij} - S_{ij} |$ for all S_{ij} € W_{ij} and $S_{ij} \neq f_{ij}$

   Step 2: Membership function $flag_{ij}$ is calculated as

$$flag_{ij} = \begin{cases} 0 & M_{ij} <= T_1 \\ \dfrac{M_{ij} - T_1}{T_2 - T_1} & T_1 <= M_{ij} <= T_2 \\ 1 & M_{ij} >= T_2 \end{cases}$$

Step 3: Restored value of f_{ij} is y_{ij} ,calculated as $y_{ij} = (1 - flag_{ij}) \times f_{ij} + flag_{ij} \times median_{ij}$

3. Stop.

III. RESULTS AND DISCUSSION

To assess the performance of the proposed filtering technique, experimental results with images having different features from the Berkeley Segmentation Dataset and Face Detection Data Set and Benchmark (FDDB) dataset are used as shown in Figure 1.

(a)Original Image from Berkeley Segmentation Dataset (BSD)

Figure 1. Sample images from standard BSD and FDDB datasets

In Table I and table II, the performance of the proposed method is compared with that of mean and median filters, in terms of Peak Signal to Noise Ratio (PSNR). A number of test images from Berkeley Segmentation Dataset and FDDB database are used for this comparison and the density of noise added was also varied. Salt and pepper noise and Gaussian noise with varying density were added to the tested image one by one to obtain a noisy input. The results of experiments are listed in Table 1 and Table 2, along with the result of mean and median filtering removal algorithm. From Table 1 and 2, it can be inferred that the results generated by using proposed algorithm outperforms the results of mean and median filter.

Figure 2 and Figure 3 shows images after adding mixed noise and images after applying the proposed filter. Datasets used are Berkeley Segmentation Dataset and FDDB dataset.

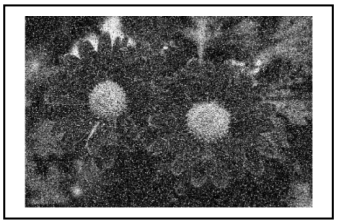
TABLE I. COMPARISON OF PSNR VALUES FOR FLOWER IMAGE FROM BERKELEY SEGMENTATION DATASET FOR GAUSSIAN NOISE ENERGY SIGMA=30, WITH VARYING IMPULSE NOISE ENERGY

Impulse Noise (%)	**PSNR (db)**		
	Mean Filter	***Median Filter***	***Proposed filter***
10	42.5308	42.3417	46.0003
20	38.2776	39.8859	43.8666
30	35.1625	37.1656	40.4716
40	32.6054	33.9844	38.4705
50	29.9666	30.4861	35.1806
60	27.8237	27.1917	33.9708
70	26.1166	24.0617	30.9237
80	24.1660	21.1606	27.0851
90	22.7396	18.5605	24.5283

TABLE II. COMPARISON OF PSNR VALUES FOR IMAGE FROM FDDB DATASET FOR GAUSSIAN NOISE ENERGY SIGMA=20, WITH VARYING IMPULSE NOISE ENERGY

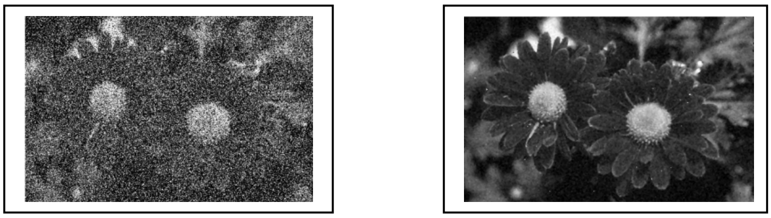
Impulse Noise (%)	**PSNR (db)**		
	Mean Filter	***Median Filter***	***Proposed filter***
10	41.4984	41.6695	44.5142
20	37.8211	39.6371	42.8546
30	34.6832	36.7209	40.5115
40	32.0667	33.5666	37.7642
50	29.6769	30.1083	34.5948
60	27.5887	26.8886	31.5823
70	25.7337	23.8195	28.6823
80	24.2463	21.1672	26.0468
90	22.6383	18.4455	23.4257

Figure 4 shows the performance evaluation of the proposed filter along with mean and median filters for comparison. From fig. 3, it is clear that the proposed filter outperforms the other two filters. Since each pixel in the entire image is tested to check whether it is noisy or noise free, and only the noisy pixel is replaced with the filtered value, the fine structures and sharp intensity edges are preserved. The algorithm tested on bench mark dataset showed that the proposed method gives better restoration in terms of peak-to-noise-ratio (PSNR) when compared with the other two techniques. The proposed filtering framework has a simple computational structure and greatly outperforms the mean and median filters on both PSNR values and perceptual image quality.



(a)

(b)



(c) (d)

Figure 2. Images from Berkeley Segmentation Dataset.

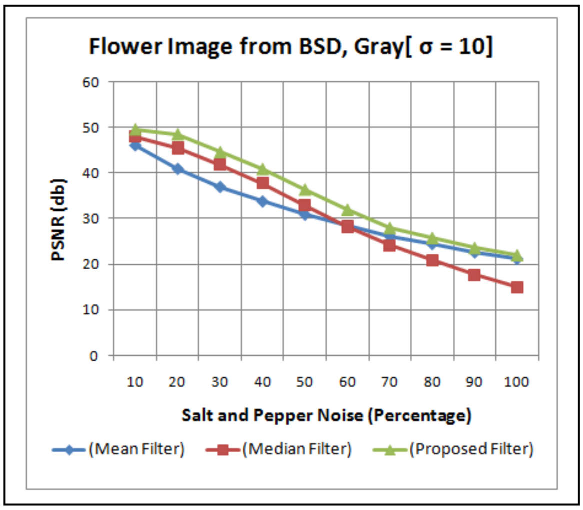
(a)σ=10, impulse noise energy =10 % (b) Filtered
(c) σ=20, impulse noise energy = 20 % (d) Filtered

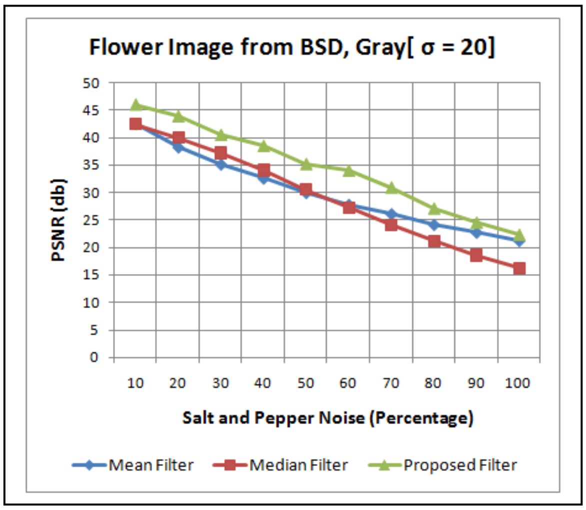
(a) (b)

(c) (d)

Figure 3. Images from FDDB Dataset.

(a)σ=10, impulse noise energy =10 % (b) Filtered
(c) σ=20, impulse noise energy = 20 % (d) Filtered





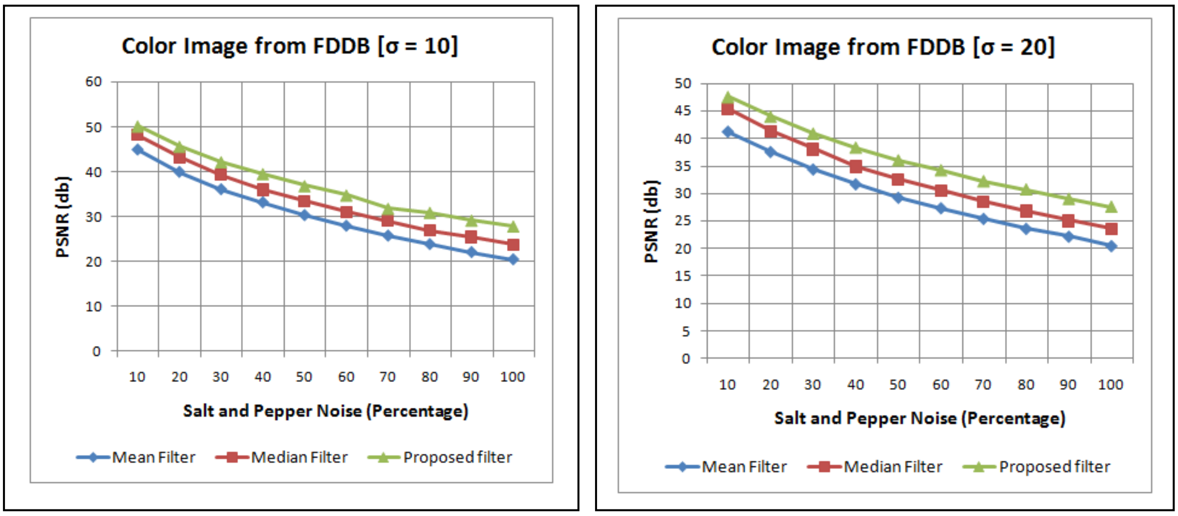


Figure 4. PSNR values for the image from Berkeley Segmentation Dataset and FDDB dataset, corrupted by various energies of mixed noise.

CONCLUSION

A novel and efficient noise filtering technique have been proposed to reduce mixed Gaussian and impulse noise. Extensive computer simulations have proved that this method reduce mixed noise significantly, while preserving image details and providing competitive results.

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