Directional Adaptive Multilevel Median Filter for Salt-and-Pepper Noise Reduction

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ABSTRACT
This paper presents a novel two-stage adaptive noise reduction scheme for images corrupted by salt and pepper noise. The first stage identifies the impulse noise in the image by classifying the pixels into two classes- the 'noise-free pixels' and the 'noise corrupted pixels', based on the intensity values of the pixels. The second stage aims to reduce the impulse noise from the image by processing the 'noise corrupted pixels' while the 'noise-free pixels' are kept intact. This stage consists of two steps. In the first step, the denoised value of each 'noise corrupted pixel' is calculated using adaptive multilevel median filter. The second step enhances the image quality by applying directional filtering to the denoised image of the first step. Extensive computer simulations indicate that this technique provides significant improvement over many other existing techniques in terms of PSNR.

Keywords
Image restoration, impulse noise, adaptive median filter, noise detection, denoising, directional filtering

1. INTRODUCTION
Images are often corrupted by impulse noise, also known as salt and pepper noise. This is primarily due to malfunctioning of pixels in camera sensors, faulty memory locations in hardware, or transmission of the image in a noisy channel. It is well known that linear filtering techniques fail when the noise is non-additive and are not effective in removing impulse noise. This has promoted research in the use of nonlinear signal processing techniques to remove impulse noise while preserving image details. Among them, the median filter and its modifications are used widely because of their effective noise suppression capability. However, most of the median filters (MF) are implemented uniformly across the image and thus tend to modify both *noise corrupted pixels* and *noise-free pixels*. Consequently, the median filtering operation for removal of impulse noise often leads to images with blurred and distorted features. Ideally, the filtering should be applied only to corrupted pixels while leaving uncorrupted pixels intact. Applying median filter unconditionally across the entire image as practiced in the conventional schemes [1]-[7] would inevitably alter the intensities and affect the signal details of uncorrupted pixels. Therefore, discrimination between uncorrupted pixels and the corrupted pixels prior to applying nonlinear filtering has become highly desirable. Consequently, many authors have introduced the switching concept [8]–[17] wherein an impulse detector is used to determine whether a pixel should be modified or not. The switching median filters have been found to be more effective than the uniformly applied methods.

Many recent denoising techniques[18]-[22] have been proposed that use a fixed-size local window for processing, and performing image denoising simply and efficiently using adaptive median filters. In [18], a new impulse detector (NID) for switching median filer has been proposed. NID uses the minimum absolute value of four convolutions which is obtained by using one-dimensional Laplacian operators to detect noisy pixels. The differential rank impulse detector (DRID), presented in [19], implements the impulse detector based on a comparison of signal samples within a narrow rank window by both rank and absolute value. An alpha-trimmed mean-based method (ATMBM) has been presented in [20]. It uses the alpha-trimmed mean in impulse detection and replaces the noisy pixel value by a linear combination of its original value and the median of its local window. In [21], a decision-based algorithm (DBA) has been presented to remove the corrupted pixel by the median or by its neighboring pixel value according to the proposed decisions. In [22], a simple fuzzy impulse detector (SFID) has been proposed to remove the impulse noise. A noise adaptive fuzzy switching median filter [NAFSM] has been proposed in [23] which employs fuzzy reasoning [24] to handle uncertainty present in the extracted local information. In [25], a simple adaptive median filter has been proposed which expands the size of its filtering window according to the local noise density. In [26], directional filtering has been used to preserve the details and edges of the restored image.

The performance of the variety of adaptive median filters presented in the literature quoted above is good at lower noise density levels, due to the fact that there are fewer corrupted pixels that are replaced by the median values. At higher noise densities, the number of replacements of corrupted pixel increases considerably. Thus, increasing window size will provide better noise removal performance. However, the corrupted pixel values and replaced median pixel values are less correlated. As a consequence, the edges are smeared significantly. The main drawback of decision- based or switching median filter is that defining a robust decision measure is difficult because the decision is usually based on a predefined threshold value. An additional drawback is that the noisy pixels are replaced by some median value in their vicinity without taking into account local features such as possible presence of edges. Hence, details and edges are not recovered satisfactorily, especially when the noise level is high. To overcome the above drawbacks Chan and Nikolova have proposed a two-phase algorithm called Median-type Noise Detectors and Detail-Preserving Regularization (MNDDR) [27]. In the first phase of this algorithm, an adaptive median filter (AMF) is used to classify corrupted and uncorrupted pixels; in the second phase, specialized regularization method is applied to the noisy pixels to preserve the edges and noise suppression. The main drawback of this method is that the processing time is very high because it uses a very large window size of 39x39 in both phases to obtain the optimum output. To overcome this problem, a new algorithm is proposed in this paper.

The proposed algorithm is a hybrid inspired by the simple adaptive median filter and directional filtering. In the first stage, the pixels are divided into two classes- the *noise-free pixels* and the *noise corrupted pixels,* based on the intensity values of the pixels. The second stage aims to eliminate the impulse noise from the image. An important outcome of this segregation is that only the *noise corrupted pixels* are processed, while the *noise-free pixels* are kept intact. This stage consists of two steps. In the first step, the median of each pixel is calculated using adaptive multilevel median filter with progressively increasing size of the filter window. The second step enhances the image quality by applying directional filtering to the restored image obtained in the first step.

Extensive computer simulations indicate that this technique provides significant improvement over many other existing techniques [18]-[22],[27] in terms of both quantitative (PSNR) and qualitative measures.

The rest of the paper is organized as follows. In Section 2, the proposed algorithm is introduced. The implementation results and comparison are provided in Section 3. The conclusions are provided in Section 4..

2. PROPOSED METHODOLOGY

The proposed filter is a double stage filter- a hybrid of an adaptive median filter and a directional filter. The methodology can hence be divided into two stages, the noise detection and the noise cancellation.

Stage 1. Noise detection

The purpose of this stage is to identify the *noise corrupted pixel.* It is assumed that the two intensities that present the impulse noise are the maximum and the minimum values of the image's dynamic range (i.e. 0 and *L*-1) where L is the maximum possible number of intensity levels. Thus, in this stage, at each pixel location (*i, j*), the mask α is marked by using the following equation:

$$\alpha(i, j) = \begin{cases} 1 & : \ f(i,j) = L-1 \\ 1 & : \ f(i,j) = 0 \\ 0 & : \ otherwise \end{cases} \tag{1}$$

where the value 1 presents the *noise corrupted pixel* and the value 0 represents the *noise-free pixel.*

After classifying the pixels using (1), the total number of the *noise corrupted pixel, K* is calculated and is given by (2).

$$K = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \alpha(i,j) \tag{2}$$

Using the value of *K*, the impulse noise level η that corrupts the image can be roughly estimated. The value of η is the ratio of the *noise corrupted pixels* to the total number of pixels contained in the image, as defined in the following equation:

$$\eta = K / (MN) \tag{3}$$

The value of η lies in between 0 and 1 (i.e. $0 < \eta < 1$) with both the extremes representing trivial cases. This value and the noise mask α will be used in the following stage for noise removal.

Stage 2: Noise Cancellation*:*

There are two steps to this stage:

a) *Filtering step*

In the first step, the input image *X* is filtered to produce the filtered image *Y*. Similar to many switching median filter methods, the output image is defined as:

$$Y(i,j)=[1-\alpha(i,j)]X(i,j)+\alpha(i,j)M(i,j) \tag{4}$$

where α is the noise mask, defined by (1) in Stage 1, where *M* is the median value obtained from an adaptive method. The determination of *M* is discussed later. As $\alpha(i, j)$ only can take value of either 0 or 1, as defined by (1) the output value $Y(i,j)$ is either equal to $X(i,j)$ or $M(i,j)$. Thus, the calculation of $M(i,j)$ is only done when $X(x,y)$ is a *noise corrupted pixel* (i.e. $\alpha(i,j) = 1$). For the *noise-free pixel* (i.e. $\alpha(i,j) = 0$), the value of $X(i,j)$ is copied directly as the value of $Y(i,j)$. This significantly speeds up the process, because all pixels need not be filtered. Thus, alternatively, $Y(i, j)$ can be re-written as:

$$Y(i,j) = \begin{cases} X(i,j) \ : & \alpha(i,j) = 0 \\ M(i,j): & otherwise \end{cases} \tag{5}$$

The adaptive methodology is used to determine $m(x,y)$. This means that the size of the filter used at every pixel location is changed according to the local information. To determine $M(i,j)$, only *noise corrupted pixels* marked with 1 will be replaced by an estimated correction term. The proposed technique uses a square filtering window with odd (2s+1) x (2s+1) dimensions, given as[23]

$$W_{2s+1}(i,j) = \{X(i+m, j+n)\} \tag{6}$$

where $m,n \in (-s,\ldots,0,\ldots,s)$

Then, the number of *noise-free pixels*, in the filtering window is counted using (7)

$$G_{2s+1}(i,j) = \sum_{m,n \in (-s,\ldots,0,\ldots,s)} \alpha(i+m, j+n) \tag{7}$$

If the current filtering window W_{2s+1}does not have a minimum number of one *noise-free pixel* (i.e., $G_{2s+1}(i, j) < 1$), then the filtering window will be expanded by one pixel at each of its four sides (i.e., s ← s+1). This procedure is repeated until the criterion of is met. For each detected *noise corrupted pixel*, the size of the filtering window is initialized to 3x3, i.e.,s =1. These *noise-free pixels* will all be used as candidates for selecting the median pixel, M(i ,j), given by

$$M(i,j) = \text{median}\{ X(i+m, j+n) \} \ \text{ with } \alpha(i+m, j+n) = 1 \tag{8}$$

This criterion of choosing only *noise-free pixels* is imposed to avoid selecting a *noise corrupted pixel* as the median pixel. Since the detection of *noise corrupted pixel* is based on the salt-and-pepper noise intensities, 0 and 255, *noise-free pixels* may be falsely identified as *noise corrupted pixel* at image uniform regions having same intensities as 0 or 255. Consequently, the filtering window will be expanded continuously and the selected median pixel may be inappropriate to be used as a correction term. Considering this possibility, the search for *noise-free pixels* is halted when the filtering window has reached a size of 7x7 (or s=3) although no *noise-free pixel* is detected, i.e., $G_7(i, j) = 0$. In this case, the median will be computed by using the first four pixels in the 3x3 filtering window defined by

$$W_3(i,j) = \{X(i+m, j+n)\} \ \text{ where } m, n \in (-1,..,0,...,1) \tag{9}$$

Hence, the median can now be determined as

$$M(i,j) = \text{median}\{ Y(i-1,j-1), Y(i,j-1), Y(i-1,j+1), Y(i-1,j)\} \tag{10}$$

where s = 3 and $G_7(i, j) = 0$

b) Image enhancement

In order to preserve the details and edges of the restored image, *Y(i,j)*, directional filtering is applied. The role of impulse noise ratio η now comes into the picture. The directional filtering is applied only if noise ratio η is greater or equal to a threshold T. A reasonable threshold T can be determined using computer simulation. For the image 'Lena', it has been found to be 0.8.

A pixel Y_k in the image is partitioned into (Z_1, Z_2, Z_3, Z_4), as shown in figure 1 [26] where {Y_1, Y_2, Y_4} belongs to Z_1, which are in the upper left portion of the mask. The processed value of Z_1 is calculated as follows:

$$d_1 = | Y,- Y_2| \quad d_2 = | Y,- Y_2| \quad d_3 = | Y,- Y_2| \tag{11}$$

$$Z_1 = \begin{cases} avg(Y_1, Y_2) & if\ d_1 = \min(d_1, d_2, d_3) \\ avg(Y_1, Y_4) & if\ d_1 = \min(d_1, d_2, d_3) \\ avg(Y_2, Y_4) & if\ d_1 = \min(d_1, d_2, d_3) \end{cases} \tag{12}$$

Z_2, Z_3 and Z_4 with {Y_2, Y_3, Y_6}, {Y_4, Y_7, Y_8} and {Y_6, Y_8, Y_9} will also be calculated in this manner.

$$Y_K = \text{mean}(Z_1, Z_2, Z_3, Z_4) \tag{13}$$

The final restored image *Y*(*i*, *j*) is hence obtained by processing each pixel using equation (13).

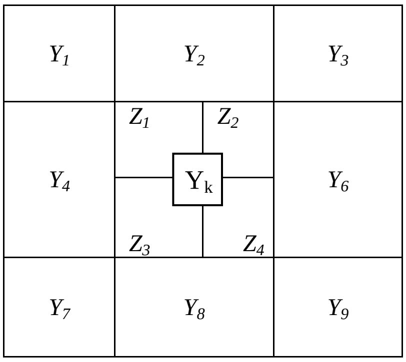

Fig. 1 Directional filtering window

3. EXPERIMENTAL RESULTS

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

$$\text{PSNR} = 10log_{10}\frac{(2^b-1)^2}{\frac{1}{MxN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(X(i,j)-Y(i,j))^2} \tag{14}$$

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 the quality of an image is the subject of visual pleasure, visual inspection is also carried out on the filtered images as to judge the effectiveness of the filters in removing impulse noise.

In this framework, it is assumed that an image corrupted with P% of salt-and-pepper noise is made up of 0.5P % of salt noise and 0.5P% of pepper noise [23]. A wide range of noise ratios varying from 1%, 10% to 90% with increments of 10% have been tested for and the results tabulated as shown below.

Table 1. Comparison of Restoration Results in PSNR(dB) for Image ''LENA''

	10%	20%	30%	40%	50%	60%	70%	80%	90%
NID[18]	37.46	34.03	31.00	28.72	26.42	23.98	21.95	18.72	13.18
DRID [19]	39.11	36.22	33.92	32.15	29.94	27.53	24.07	17.84	11.33
SFID[20]	41.66	37.55	33.97	30.50	26.46	22.61	18.43	14.53	10.38
ATMBM[21]	41.56	37.42	34.47	31.10	27.03	23.21	19.09	15.21	11.16
DBA [22]	41.67	37.49	35.40	34.04	32.31	30.47	28.34	26.10	23.72
NAFSM [23]	42.14	38.47	35.86	33.93	32.02	32.57	28.97	27.14	24.53
MNDDR[27]	42.5	38.5	36.2	35.01	32.7	32.1	29.9	28.52	26.46
PROPOSED ALGORITHM	43.64	39.74	37.36	35.23	33.52	32.67	30.47	28.63	26.89

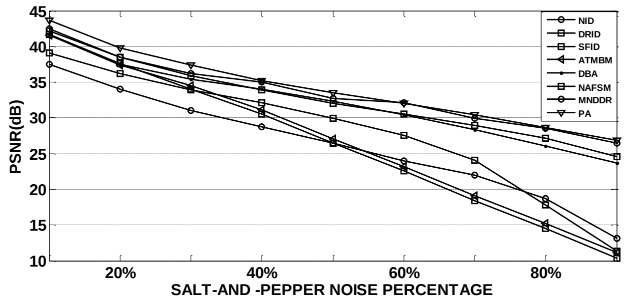

Fig. 2 Comparison of restoration results in PSNR versus salt-and-pepper noise percentage for image 'Lena' obtained by various methods

Table I lists the restoration results in PSNR (db) of various approaches for 512x512 grayscale image 'Lena' corrupted by fixed-valued impulse noise with various noise ratios. These include MF, NID, DRID, SFID, ATMBM, DBA, NAFSM and MNDDR. Fig. 2 graphically depicts the comparison of efficacy of restoration in terms of PSNR (dB) for the proposed method and the six existing methods for the image 'Lena' corrupted with varying degrees of noise percentage.

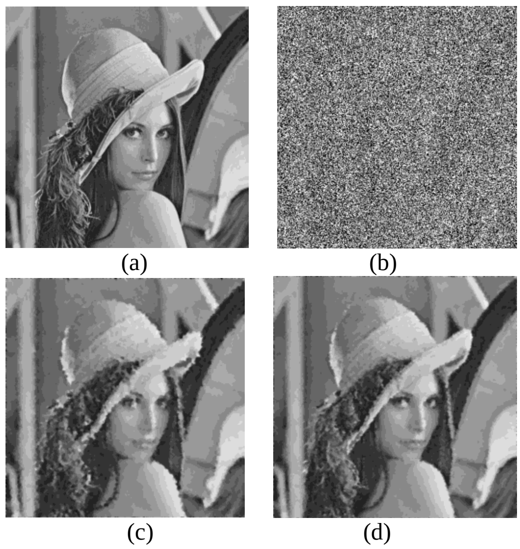

Fig. 3 Restoration results of proposed method in restoring corrupted image 'Lena' (a) Original noise-free image (b) Corrupted image with 90% impulse noise (c) Restored image with NAFSM (d) Restored image with proposed algorithm

It can be seen that the proposed algorithm performs significantly better than other methods at all salt-and-pepper noise percentages. This can be seen both at the quantitative and qualitative levels. The visual observation of fig.3 clearly shows the marked difference between the PSNR obtained by the NAFSM method and the proposed algorithm (PA) at 90% noise.

4. CONCLUSION

A novel directional adaptive multilevel median filter for removing salt-and-pepper noise has been proposed in this paper which can reduce the impulse noise efficiently while preserving the edges very well. The simulation results demonstrate that the proposed approach performs better than other existing techniques in terms of both quantitative evaluation and visual quality.

In the authors' opinion, future research should focus on reducing the processing time when the image is corrupted with high-density of salt-and –pepper noise.

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