An Improved Switching Median Filter
Based on Local Outlier Factor

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Abstract— In this paper an improved switching median filter based on local outlier factor for the restoration of gray scale and color images that are highly corrupted by impulse noise is proposed. In first stage the proposed algorithm detects noisy pixels by local outlier factor incorporating with Boundary Discriminative Noise Detection (LOFBDND). Since this detection stage using LOF detects edge as noise and miss detect some noisy pixels which will result in high miss detection and false alarm rate so before going into filtering stage, next step will take out edge information. Then the directional weighted median filter is applied to remove the detected noise by replacing each noisy with the weighted mean of its neighbors in the filtering window of 5×5, while taking four different directions in that window. The proposed algorithm shows better results than Switching Median Filter Based on Local Outlier Factor and also directed towards edge preservation. Experimental results show improvements both individually and quantitatively (in terms of peak signal to noise ratio, mean absolute error, miss detection rate and false alarm rate).

Keywords— Impulse noise, local outlier factor, switching median filter, directional weighted median filter.

INTRODUCTION

Digital images are often contaminated by impulse noise due to a number of non-idealities caused by malfunctioning of camera's sensor cells, transmission errors, faulty memory locations or timing errors in analog to digital conversion in the imaging process. Salt and pepper noise is a kind of impulse noise that usually corrupts images by replacing some of the pixels of the original image with new pixels having luminance values near or equal to the minimum or maximum of the allowable dynamic luminance range. Since the performances of sub-sequent image processing tasks are dependent on the success of image noise removal operation, it is important to remove impulse noise from image in most of the applications. Linear filtering techniques [1] are not effective in removing impulse noise, because it distorts the useful information in the image and fails to preserve image details and texture while removing the noise, therefore non-linear filtering techniques are widely used in the restoration process.

Median filters are usually implemented uniformly across the images causing both noise and noise-free pixels to be modified and some desirable and important details to be removed. Additionally, the filter is effective only for low noise densities and exhibits blurring if the window size is large and leads to insufficient noise removal if the window size is small [2]. The edge details of the original image will not be preserved by MF when the noise level is over 50%. To overcome this problem, "Switching Median Filtering" [3] has been proposed for enhancing the filtering effect and preserving the details. In switching median filter there are two phases: noise detection and filtering noisy image. Noise detection is done using a priori threshold value to decide if pixel is corrupted or not and accordingly median filter is to be applied or not. By doing this, the filtering step will not modify those uncorrupted pixels. Various new switching filters with an impulse detector are proposed to enhance the effect of median filter.

The improved switching median (ISM) filter [4] has impulse detector based on four one-dimensional Laplacian operators and to separate them from edges. Directional weighted median filter (DWM) filter [5] is another filter with good detail features preserving ability in which impulse detector is based on the differences between the current pixel and its neighbors aligned with four main directions and then uses weighted median filter to restore image. In boundary discriminative noise detection (BDND) [6] algorithm the local histogram is used to determine the decision boundaries between noise-free and noisy pixels. Adaptive Switching Median (ASWM) [7] with high noise detection ability for random-valued impulse noise uses a threshold calculated locally from image pixels intensity values in a sliding window. But with noise density above 60%, the precision of noise detection decreases.

Local Outlier Factor (LOF) is an outlier detection strategy in data mining [8]. This approach uses local outlier factor to indicate outlier-ness degree of object i.e. how much outlying an object is. Since gray level value of corrupted pixel is different from noise-free pixels. LOF is used to quantify this distinction. In the first stage, LOF coupled with Boundary Discriminative Noise Detection is given [9]. Then in next stage directional weighted median filter is adopted to filter noisy pixels. This approach considers edge pixels as noise and miss-detect some noisy pixels because local outlier factor of edge pixels are different. So miss-detection rate and false alarm rate is high and edges are not preserved. The proposed algorithm will remove this problem and further enhance image.

The rest of the paper is structured as follows: A brief Literature Survey is presented in Section II. Section III describes the proposed algorithm. Section IV presents the simulation results and a comparative performance of algorithm for various images. Section V draws the conclusion of the proposed work.

LITERATURE SURVEY

Impulse Noise in Image

Impulse noise corruption is often found in digital images. Impulse noise is independent and uncorrelated to the image pixels and is distributed over the image in random manner. Hence comparing with Gaussian noise, for an image corrupted with impulse noise, only certain percentage of image pixel is contaminated and the rest of pixels will be noise-free. Intensity of damaged pixel is significantly different when compared to intensity of the pixels in neighborhood. Impulse noise is further classified as salt and pepper noise and random valued noise.

In salt and pepper noise the noisy pixel takes either maximum gray level-255 or minimum gray level-0 and it looks like white and black spots on the images, thus they are called as salt and pepper noise.

$$Y_{i,\,j\,=} \begin{cases} 0 \text{ or } 255 \text{ with probability p} \\ \\ x_{i,j} \text{ with probabilty } 1-p \end{cases}$$

Here $Y_{i,\,j}$ represents the corrupted image pixel, p is the noise probability of impulse noise and $X_{i,\,j}$ is the uncorrupted image pixel.

In case of random valued impulse noise, noise can take any gray level value within the interval [0,255]. In this case noise is randomly distributed over the entire image and probability of occurrence of any gray level value as noise will be same. We can mathematically represent random valued impulse noise as below.

$$Y_{i,\,j\,=} \begin{cases} n_{i,j} \text{ with probability p} \\ \\ x_{i,j} \text{ with probabilty } 1-p \end{cases}$$

Where $n_{i,j}$ is the gray level value of the noisy pixel.

Linear Filters

Filtering is a neighborhood operation, in which the value of any given pixel in the output image is determined by applying some algorithm to the values of the pixels in the neighborhood of the corresponding input pixel [1]. A pixel's neighborhood is some set of pixels, defined by their locations relative to that pixel. Mathematically, a filter may be defined as a function which maps an image x into image y:

$$F(x) = y$$

The filter is said to be linear when the function F satisfies both the superposition and proportionality principles. Linear filtering is filtering in which the value of an output pixel is a linear combination of the values of the pixels in the input pixel's neighborhood. For example, an algorithm that computes a weighted average of the neighborhood pixels is one type of linear filtering operation. Two dimensional and m-dimensional linear filtering are also performed with the extension of one-dimensioal linear filtering techniques to two or more dimensions. If the filter evaluates the output image only with the input image, the filter is called non-recursive. On the other hand, if the evaluation process requires input image samples together with output image samples, it is called recursive filter.

Non-Linear Filters

Median Filters

Median Filters [1] are very efficient in impulse noise removal at low density levels. The median filter follows the moving window approach for filtering. A 3×3, 5×5 or 7 ×7 kernel of pixels is taken and scanned over pixel matrix of the entire image. In median filtering, first sorting of the entire pixel values from the surrounding neighborhood is done into numerical order and median value is calculated. Then the centre pixel of kernel is replaced by this median value. The median value should be written into a separate array or buffer so that the results are not corrupted as the process is continued.

Max-Min Filter

Min and Max filter works on ranked set of pixels. Contrary to median filter which replaces the reference pixel with the median value, the Min filter replaces it with the lowest value instead. Mathematically, it can be defined as:

$$F(x,y) = \min \{g(r,c), (r,c) \in W\}$$

Similarly, the max filter replaces the reference pixel with the highest value within the window, i.e.

$$F(x,y) = \max \{g(r,c), (r,c) \in W\}$$

The min filter is useful for reduction of salt noise, whereas max filter can help remove pepper noise.

'α' Trimmed Mean Filter

This filter uses another combination of order statistics and averaging [1]. In this case an average of pixels values closest to median filter excluding the D lowest and D highest values in an ordered set is taken. For D=0, the filter behaves like a regular arithmetic mean filter; for D= (mn-1)/2 it is equivalent to median filter. It is used in cases where image is corrupted by more than one type of noise.
Mathematically

$$\hat{f}(x,y) = \frac{1}{mn - d} \sum_{(s,t) \in S} g_r (s,t)$$

The disadvantage is that, when the image is corrupted by SPN more than 50% the algorithm fails because of trimming even uncorrupted pixels and blurring of the edges takes place and hence fine details are lost [10].

Unsymmetric Trimmed Median Filter

An Unsymmetric Trimmed Median Filter (UTMF) was proposed in order to overcome problems with ATMF. In UTMF, the elements in selected 3×3 window are arranged in increasing or decreasing order. Then it removes the pixel values 0's and 255's in the image (i.e. the pixel values causing SPN) are removed from the image. Then the median value of the remaining pixels is corrupted. The noisy pixel is replaced with this median value. It is called trimmed median filter because the pixel values 0's and 255's are trimmed from the selected window.

Switching Median Filters

In the earlier decades, median-based filters have gained much attention because of they are simple for implementation. Nevertheless, because the median filters are implemented in a uniform manner across the image, they modify both noise pixels and uncorrupted good pixels. To avoid the distortion of good pixels, a new scheme is introduced which consists of two stages: firstly impulse detection algorithm is applied before filtering and then in next stage detection outcomes are used to control whether a pixel should be modified or not while applying filter. This approach is called Switching Median Filtering. Fig. 1 shows a general framework for this kind of filtering which proved to be more effective than previous methods that are uniformly applied when the noisy pixels are sparsely distributed in the image.
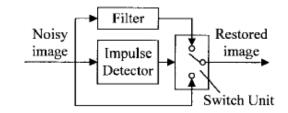

Fig.1 A general framework of switching based image filters

An Efficient Switching Median Filter Based on Local Outlier Factor

Wei Wang and Peizhong Lu [9] proposed a new technique of image filtering using the switching median filter which is based on Local Outlier Factor where the LOF of each pixel is computed. In detection phase noisy pixels are identified by local outlier factor incorporating with boundary discriminative noise detection (LOFBDND). Then in filtering phase, it uses directional weighted median filter to eliminate the detected impulses by replacing each noisy pixel with the weighted mean of its neighbors in the filtering window.

Local Outlier Factor

Local Outlier Factor is used for identifying density-based local outliers [8]. The local outlier factor is computed on the basis of local density, where locality can be found by k-nearest neighbors, whose distance is used to calculate the density. By comparison of the local density of an object and the local densities of its neighbors, one can identify areas of similar densities, and also points that have a substantially lower density than their neighbors which are considered as outliers. The local density is computed by the distance at which a point can be reached from its neighbors.

k-distance(A): the distance of the object A to the k-nearest neighbour.
$N_k(A)$: set of k-nearest neighbours

$$\text{reachability-distance}_k (A, B) = \max\{k\text{-distance}(B), d(A,B)\}$$

The local reachability density of an object A is:

$$\text{Lrd(A)} = 1 \Big/ \left(\frac{\sum B \in N_K(A) \text{reachability} - \text{distance}_k (A,B)}{|N_K (A)|} \right)$$

Now, the local reachability densities are then compared with those of the neighbors using

$$\text{LOF}_k (A) = \frac{\sum_{B \in N_K (A)} \frac{\text{lrd(B)}}{\text{lrd(A)}}}{|N_K (A)|}$$

which is the average local reachability density of the neighbors divided by the object's own local reachability density. If the value is 1 then it indicates that the object is comparable to its neighbors (and not an outlier). If the value is less than 1 then it indicates a denser region, while values significantly larger than 1 indicate outliers.

1	1	1.1607	1.9938	1.0375	1
1	0.9211	3.4087	1.2971	1.0889	2.9524
1.89	0.9956	29.080	1	1	0.9762
1.7799	0.9787	1	20.7	1	1
1.7177	1.8329	1.0779	1	1	0.9524
0.9609	0.984	1	0.984	1	1

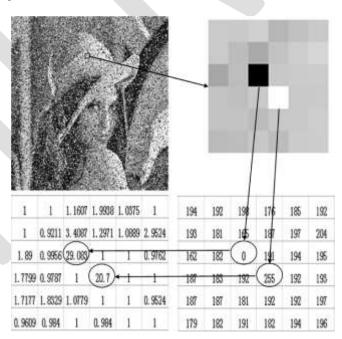| 194	192	198	176	185	192
198	181	165	187	197	204
162	182	0	191	194	195
187	183	192	255	192	198
187	187	181	192	192	197
179	182	191	182	194	196

Fig.2 LOF calculation example: The left top shows Lena image corrupted with 20% SPN noise; the right top shows 6×6 pixels portion; the right bottom shows gray level values of pixel and left bottom shows corresponding LOF.

Here we consider image as a dataset, every pixel in the image is treated as an object in the dataset, and the intensity difference of two pixels is taken as the distance of two objects, so we can calculate the LOF values of pixels. If a pixel is corrupted by

impulse noise, it would be likely different from surrounding pixels in gray level value, i.e. it may belong to another cluster. Thus, we can use LOF to express this characteristic. We define dataset as window (in our experiment, k=3, L=4) centered on pixel.

We gave a case of LOF calculation as shown in fig.2. In this example "Lena" image is contaminated with 20% salt and pepper noise. Only the 6×6 pixels area is displayed due to lack of space. There are two noises, one is salt noise and the other is pepper noise. The gray values of these two noisy pixels are 0 and 255 respectively, and the corresponding LOF values are 29.083 and 20.7, but the LOF values of other pixels in this area are relatively small, this shows that noisy pixels have different LOF values. So we can conclude that noise detection using LOF is possible. In addition, the median and mean of the LOF of all image pixels are approximately equal to 1 if there is no noise in an image.

Since local outlier factor of pixels at edge are different. Thus, it considers edge pixels as noise and miss-detect some noise pixels also. So false alarm rate and miss detection rate are high. To reduce the false alarm rate and miss-detection rate and to further improve image we have proposed a method in this paper.

PROPOSED SCHEME

Basic rule: If the LOF of an image pixel is greater than a threshold Ta then it may be corrupted, the larger the LOF of p is, and the more likely it is corrupted.

$$\text{Class (p)} = \begin{cases} \text{noise candidate} & \text{if } \text{LOF}\big(g(i,j)\big) > Ta \\ \text{noise} & \text{if } \text{LOF}\big(g(i,j)\big) > Tb \end{cases}$$

where Ta and Tb are given threshold, $g_{i,j}$ is the gray value of pixels at coordinate (i, j) of a digital image. Because of the diversity of the LOF values of the image pixels we find that fixed Ta and Tb are not universal. A simple but effective adaptive method according to local small neighborhood relativity principle of natural image is to use the mean of LOF values of all pixels in p's neighborhood. That is

$$Ta = \alpha M \text{ and } Tb = \beta M$$

α and β: given parameters (in our experiments α=2, β=6.5),
M: mean of the LOF value of all pixels in a 9×9 window.

A. Detection Stage

Noise detection strategy utilizes local outlier factor. If pixel is a noise candidate, then it will be validated by BDND method proposed by Ng [4]. The algorithm steps are given below:
1) Calculate the Local Outlier Factor of every pixel p in an image.

2) Classify p by LOF $(g_{i,j})$ and boundary discriminative method:
   a) If LOF $(g_{i,j})$ >Ta, then p is classified as noise candidate,else, impose a 21× 21 window centered on pixel p.
   b) Sort the pixels lie in the given window to an ordered vector Vo and find the median value med.
   c) Compute the difference vector of Vo, and then find the pixels which correspond to the maximum differences in the intervals of [0, med] and (med, 255], and set these two pixel's intensities as the decision boundaries b1 and b2 respectively.
   d) If b1< $g_{i,j}$ ≤b2 , then p is noise-free, else, p is classified as noise candidate.
3) Validate the noisy candidates:
   If LOF $(g_{i,j})$ > Tb, then p is noise, else, validate the noisy candidates by imposing a 3× 3 window, and repeat steps (b)–(d).

B. Filtering Stage

1.) To reduce false alarming at the edges of image the following steps are performed:
   a) Get the edges of image using sobel operator
   b) Divide edge image into blocks of 3×3.
   c) For each 3×3 block if the block has more than two edge pixels then declare it genuine and remove edge information at that point.
2.) To filter the corrupted image, we use a weighted median filter with 5×5 window as in [5] with four different directions. The weight of a pixel is computed on the basis of standard deviation in four directions.
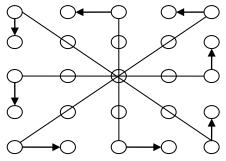
Fig. 3 5×5 mask for filtering

S is the set of pixels in the direction with minimum standard deviation.

$$w_{i,j} = \begin{cases} 2, & \text{if } g(x + i, y + j) \in S \\ 1, & \text{otherwise} \end{cases}$$

3.) The noisy pixel is restored by computing median as:

$$m(x, y)= \text{median}\{ w_{i,j} \lozenge g_{x+i, y+j} \}; \ -1 \leq \ i, j \leq +1$$

where operator $\lozenge$ denotes repetition operation. The output of the filter is:

$$\hat{g}(x, y) = a_{x, y}\, g + (1 - a_{x, y})\, m(x, y)$$

$$a_{x, y} = \begin{cases} 0, & \text{if } g(x, y) \text{ is corrupted} \\ 1, & \text{otherwise} \end{cases}$$

SIMULATION RESULTS

The existing and proposed algorithms are simulated in MATLAB 7.11 R2010b (32 bit). Experiments are performed with various images including both colored and gray scale images. To compare the performance, the images are corrupted with additive SPN. The density is varied from 45% to 75% in different images. The corrupted images are restored using both LOFBDND and the proposed algorithm.

A. Comparison of detection and filtering stage

Performance of the algorithms at detection stage is quantitatively measured in terms of FA and MD. In our testing, Miss-detection number (MD) represents the number of noise being miss-detected and false alarm number (FA) represents the number of noise free pixels that are misclassified as noise. At filtering stage the existing and proposed algorithms are compared in terms of PSNR and MAE.

$$\textbf{PSNR in db} = 10 \log_{10}\left(\frac{255}{\textbf{MSE}}\right)$$

$$\textbf{MSE} = \frac{\sum i \sum j \{Y(i,j) - \hat{Y}(i,j)\}^2}{M \times N}$$

$$\textbf{MAE} = \frac{\sum i \sum j \{Y(i,j) - \hat{Y}(i,j))\}}{M \times N}$$

Where PSNR stands for Peak Signal to Noise Ratio, MSE stands for Mean Squared Error, MAE stands for Mean Absolute Error, FA and MD for false alarm and miss-detection rate respectively. Y denotes the original image; Ŷ denotes the denoised image. In this text we have presented the comparative performance of 5 different images (Table 1). Figure numbers in first column of the table refers to the experimental outcomes displayed on the next page. From Table 1 we can see that our proposed detection algorithm is better on all parameters. At detection stage it maintains rather low miss-detection rate and false alarm rate than existing algorithm.

There is also increase in PSNR (peak signal to noise ratio) in each case and the proposed algorithm has lower MAE (mean absolute error) as well.

B. *Comparison of Visual Performance*

The images used in the tabulation are shown in figure 4 to figure 8 below. In all figures, top left is the original image, top right is the noisy image with additive SPN, bottom left is the denoised image generated by LOFBDND and bottom right is the denoised image generated by the proposed algorithm.

TABLE I: RESULT COMPARISON FOR TEST IMAGES

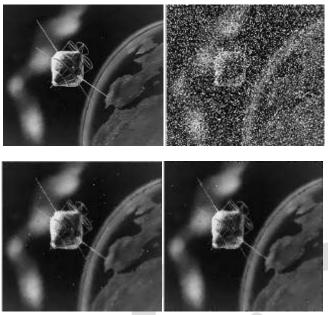| Image	Parameter	LOFBDND	Proposed Algorithm
Image 1 (figure 3)	PSNR	46.33	48.25
	MAE	0.145	0.127
	FA	83	28
	MD	96	19
Image 2 (figure 4)	PSNR	41.31	42.71
	MAE	0.268	0.238
	FA	48	11
	MD	70	17
Image 3 (figure 5)	PSNR	31.85	33.53
	MAE	0.759	0.642
	FA	206	72
	MD	172	55
Image 4 (figure 6)	PSNR	35.93	37.88
	MAE	1.09	0.86
	FA	77	29
	MD	64	13
Image 5 (figure 7)	PSNR	31.65	33.08
	MAE	1.938	1.683
	FA	89	26
	MD	64	21

Fig.4 Test Image 1

Visual analysis of the images also reveals that the issue reported earlier is corrected to a great extent by the proposed algorithm i.e. by using proposed algorithm we get less noise along edges and there is also improvement in quality of image. As we can see in test image 1 that noise along the edges and also in other parts get reduced. We have used satellite images in our experiments because edges are clearer in these images.
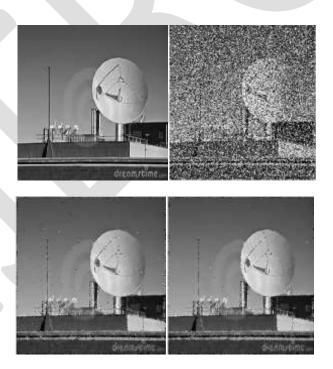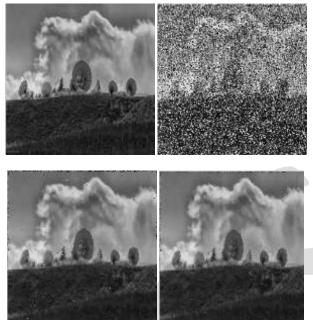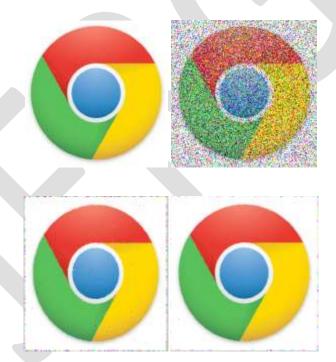

Fig. 5 Test Image 2

Fig.6 Test Image 3
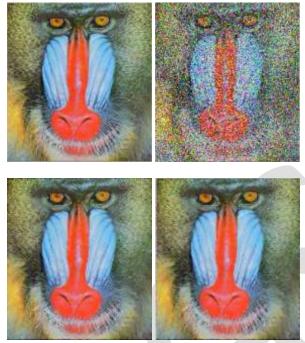

Fig. 7 Test Image 4

Fig. 8 Test Image 5

CONCLUSION AND FUTURE WORK

In this paper, an improved LOFBDND method is proposed to restore the images which are corrupted with high density SPN. The proposed algorithm tries to identify noisy pixels and restore them properly and do not give false alarms at pixels those are present on edges. A quantitative comparison of proposed algorithm is also done with the existing noise removal algorithms in terms of PSNR, MAE, FA, and MD. Simulation of the proposed algorithm is done in MATLAB 7.11 R2010b (32 bit). The Operating System is Windows XP Professional (Service Pack 3). The performance of the algorithm has been tested on both color and gray-scale images at varying noise densities. It is evident from the experimental results that proposed algorithm gives better performance both visibly and quantitatively.

This work can be carried further for improvement of the quality of the output image. Filtering stage can be improved by using cascading windows or by using open close sequence filter.

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