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Simple Adaptive Switching Median Filter for the Removal of Impulse Noise from corrupted images

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Abstract

This paper presents a simple, yet efficient way to remove impulse noise from digital images. Linear and nonlinear filters have been proposed earlier for the removal of impulse noise; however the removal of impulse noise often brings about blurring which results in edges being distorted and poor quality. Therefore the necessity to preserve the edges and fine details during filtering is the challenge faced by researchers today. The proposed method consists of noise detection followed by the removal of detected noise by Adaptive median filter using selective pixels that are not noise themselves in gray level images. Noise detection is based on only the two intensity values i.e. 0 & 255; the pixels are roughly divided into two classes, which are "noise-free pixel" and "noise pixel". In impulse noise elimination, only the "noise-pixels" are processed. The "noise-free pixels" are copied directly to the output image. The method adaptively changes the size of the median filter based on the number of the "noise- pixels" in the neighbourhood. For the filtering, only "noise-free pixels" are considered for the finding of the median value. Computer simulations were carried out to analyse the performance of the proposed method.

Keywords: *salt-and-pepper noise, impulse noise, noise detection & elimination, nonlinear filter, median filter, adaptive filter.*

1. Introduction

During image acquisition through faulty camera sensors, noisy communication channels, and faulty memory locations in hardware digital images are normally corrupted by many types of noise. The interference of noise in images might affect the results for some processing, such as edge detection, image segmentation, data compression and object recognition. Therefore, the process of image restoration or noise filtering should be taken on the image before other image processing takes place [4]. Since signals are nonlinear in nature, it is evident that nonlinear filters are generally superior to linear filters in terms of impulse noise removal. Impulse noise, also known as salt-and-pepper noise, randomly and sparsely corrupts pixels to two intensity levels. When the signal is quantized into L intensity levels, the corrupted pixels are generally digitized into either two extreme values, which are the minimum or maximum values in the dynamic range (i.e. 0 or L-1). The corrupted pixels are either set to a maximum value or zero value, giving the image a "salt-and-pepper" like appearance causes white and black points appears in digital grayscale images while the unaffected pixels always remain unchanged[1,3].

Median filter is one of the order-statistic filters, which falls in the group of nonlinear filter. Median based filters are the popular methods to be employed for reducing the impulse noise level from corrupted images. This is because of their simplicity and capability to preserve edges. The conventional median works in spatial domain, and based on windowing process, using a filter size of $WM\times WN$. Normally WM and WN are both in odd dimensions. Given an input image f, the filtered image g is defined by:

$$g(x,y) = \underset{(s,t)\epsilon Sxy}{median}\,\{f(s,t)\} \quad (1)$$

Where (x,y) are the coordinates of the pixel located at the center of the contextual region Sxy defined by $WM\times WN$, and (s,t) are the coordinates of the pixels belong to that region. This means that filtered pixel is the median value of the data contained in the contextual region. Median filter replaces the centre value of a filtering window with the median of all the pixel values inside the window [2]. But analysis of different sources dedicated to median filtering as defined in (1) shows, that the classic median filter has a set of disadvantages like signal weakening (object's counters and edges are blurred in image), affecting to non corrupted ("good") image pixels[5-8]. The difference modifications of median filter have been purposed to eliminate this disadvantages of median filtering.

One of the branches of median based filter is the switching scheme approach mean splitting of noise removal procedure into two main stages [10, 18]:

1. Preliminarily detection of noise corrupted pixels of digital image.
2. Filtering of noise pixels or impulses which have been detected in first stage of processing using information about gathered image properties. Other pixels, which are considered as "*noise-free pixels*", are kept unchanged.

Another type of the median based filter is adaptive median filter, such as the work by [5] and [19]. The size of the median filter (window) applied to the individual pixel is determined based on the approximation of the local noise level. Bigger filter is applied to the areas with high level of noise, and smaller filter is applied to the areas with low level or noise. For example, approximate the "*noise pixels*" based on the minimum, maximum and median intensity values contained inside a local window and then started with a smaller window size first, and increase the size until certain conditions are met.

In this paper, we present a new median filter based technique, which is a hybrid of adaptive median filter and switching median filter. This proposed method is fast, simple, and adaptable to the local noise level. The method can remove the impulse noise effectively from the image, and at the same time can preserve the details inside the image, even when the input image is very highly corrupted by the noise.

The peak signal to noise ratio has been used for numeric estimation of algorithm's efficiency in this work. This criterion is shown in expression (2):

$$PSNR = 10 \log_{10} \frac{(255)^2}{MSE} \quad (2)$$

where

$$MSE = \frac{1}{N} \sum_i (\mu i - \varphi i)^2$$

where N – number of pixels in processed image, μi and φi - pixel's brightness at position i in restored and original images respectively.

This paper is organized as follows. Section 2 describes the proposed method in details. Section 3 presents our results and discussions. Section 4 concludes the paper.

2. The Proposed Method

Our proposed method is a merging of adaptive median filter with switching median filter. We use the adaptive median filter in order to enable the flexibility of the filter to change it size accordingly based on the approximation of local noise density. We use switching median filter order to speed up the process, because only the noise pixels are filtered. In addition to this, switching median filter also allows local details in the image to be preserved. We divide this method into two stages, which are the noise detection, and the noise cancellation. These two methods are described in the following subsections. In order to implement this method, we need three 2D arrays of the same size to hold the pixel values of the input image *f*, the output image *g*, and the mask to mark the "*noise pixels*" ω. The dimensions of these arrays are equal to the dimensions of *f* (i.e. *M*×*N*).

2.1. Stage 1: Noise Detection

The main purpose of this stage is to identify the "*noise pixel*". In our method, we assume 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). Thus, in this stage, at each pixel location (*x*,*y*), we mark the mask ω by using the following equation:

$$\omega(x,y) = \begin{cases} 1 & : f(x,y) = L-1\ (i.e. 255) \\ 1 & : f(x,y) = 0 \\ 0 & : otherwise \end{cases} \quad (3)$$

where the value 1 presents the "*noise pixel*" and the value 0 presents the "*noise-free pixel*". The noise mask ω will be used in the following stage, which is for the noise removal.

2.2. Stage 2: Noise Cancellation

In this stage, we filter the input image *f*, and produce the filtered image *g*. Similar to many switching median filter methods, the output is defined as:

$$g(x, y) = [1 - \omega(x, y)]\, f(x, y) + \omega(x, y) p(x, y) \quad (4)$$

where ω is the noise mask, defined by (3) in Stage *1*, where *p* is the median value obtained from our adaptive method. The determination of *p* will be explained later. As ω (*x*,*y*) only can take value of either 0 or 1, as defined by (3) the output value *g*(*x*,*y*) is either equal to *f*(*x*,*y*) or *p*(*x*,*y*). Thus, the calculation of *p*(*x*,*y*) is only done when *f*(*x*,*y*) is a "*noise pixel*" (i.e. ω (*x*,*y*) = 1). For the "*noise-free pixel*" (i.e. ω (*x*,*y*) = 0), the value of *f*(*x*,*y*) is copied directly as the value of *g*(*x*,*y*). This significantly speeds up the process, because not all pixels need to be filtered. Thus, alternatively, *g*(*x*,*y*) can be re-written as:

$$g(x, y) = \begin{cases} f(x,y) & : \omega(x,y) = 0 \\ p(x,y) & : otherwise \end{cases} \quad (5)$$

We use the adaptive methodology to determine *p*(*x*,*y*). This means that the size of the filter used at every pixel location is changing accordingly to the local information. For the filtering process we only consider the square filters with odd dimensions, as given by (6).

$$W = WM = WN = 2R + 1 \qquad (6)$$

where R takes any positive integer value.

As the samples for the calculation of $p(x,y)$, our method uses only "*noise-free pixels*" that are contained in the contextual region, defined by the area of $W \times W$ (i.e. the filter size), This procedure ensures that the value of $g(x,y)$ will not be affected by the noise. Our method is an adaptive, where the size of the filter is not fixed. To determine the value of $p(x,y)$, in our proposed method, we have set the rules that if the maximum number of "*noise-pixels*" in 3×3 filter size is less than 4 then remaining 5 "*noise-free pixels*" (except centre pixel) are good enough to present the local information of the image properly. If the maximum number of "*noise- pixels*" in 3×3 filter size is equal or greater than four then remaining "*noise-free pixels*" (except centre pixel) are not good enough to present the local information of the image properly therefore filter size increase to 5×5. But it is needed for 5×5 filter size is that the "*noise-free pixels*" should be greater than eight. If a large sample size is taken, this also cannot present the local information because the samples come from many objects in the image. Thus, a large sample size, although requires more computational time, tends to introduce distortions.

Our novel adaptive method for finding $p(x,y)$ is described by the following algorithm. For each pixel location (x,y) with $\omega(x,y)=1$ (i.e. "*noise pixel*"), do the following:

1. Initialize the size of the filter $W = 2R+1$, where $R=1$
2. Compute the number of "*noise- pixels*" contained in the contextual region defined by this $W \times W$ filter.
3. If the number of "*noise-pixels*" is less than four pixels, go to step 5 otherwise increase the size of the filter by two (i.e. $W = W+2$)
4. If in increased size of the filter the number of "*noise-free pixels*" is greater than eight, go to step 5 otherwise increase the size of the filter by two (i.e. $W = W+2$). Calculate the value of $p(x,y)$ based on the *noise-free pixels*" contained in $W \times W$ window.
6. Update the value of $g(x,y)$ using (3) or (4)

3. Experimental Results

In this section we present a comparative analysis of the proposed method (ASMF) with different algorithms. In order to demonstrate the performance of our method, we also implemented Simple Median filter (SMF) with 3 X 3 window size, Center Weighted Median (CWM) filter with 3 X 3 window size & center weight of 3, Iterative Median (IM) filter with 3 X 3 window size & 3 iterations, and Iterative Switch Median (ISWM) filter. As our method is a mixing of a switching median filter and an adaptive median filter, we implemented the methods proposed by Denis [18], "An Improved Switching Median Filter for Impulse Noise Removal" and by Haidi [19], "Simple Adaptive Median Filter for the Removal of Impulse Noise from Highly Corrupted Images". Method [18] is a switching median method, while method [19] is an adaptive median method.

In our analysis we shall use the following criteria:

1. A metric for quality assessment of the restored images – PSNR.

2. Visual quality of the restored test images.

Table 1 shows PSNR (db) performances of proposed algorithm with SMF, CWM, IM, and ISWM & Table 2 shows PSNR (db) performances of proposed algorithm with IPSM and SAMF for 'Lena' image corrupted with different impulse noise density.

Table 1: PSNR (db) performances of proposed algorithm with SMF, CWM, IM, and ISWM for 'Lena' image corrupted with different impulse noise density

N.D.	SMF	CWM	IM	ISWM	PM
10%	33.12	33.71	32.19	36.46	49.14
20%	28.95	29.71	30.53	32.90	45.55
30%	23.79	24.49	29	30	43.24
40%	18.99	20	26.75	27.20	41.65
50%	15.26	16.41	22.48	23.12	40
60%	12.37	13.19	17.79	17.90	39
70%	10	10.61	13.46	13.51	37.48

Table 2: PSNR (db) performances of proposed algorithm with IPSM and SAMF for 'Lena' image corrupted with different impulse noise density.

Noise Density	IPSM	SAMF	PM
10%	36.64	48.40	49.14
20%	33.89	44.90	45.55
30%	32.26	42.70	43.24
40%	31	41.10	41.65
50%	30.17	39.83	40
60%	29.52	38.74	39
70%	29	37.55	37.48

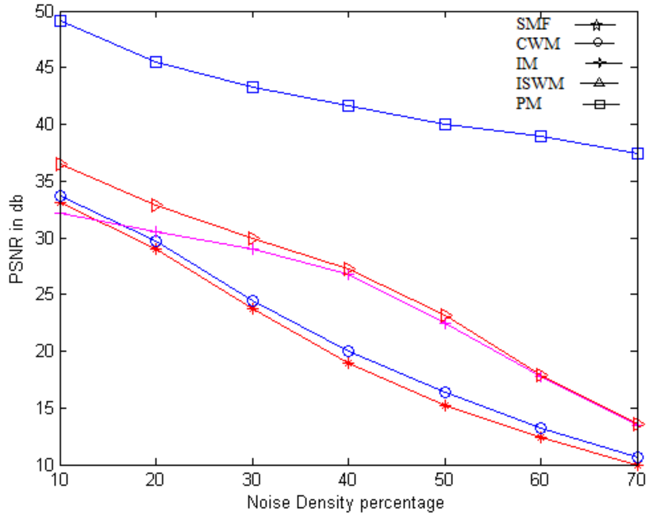

Figure 1: PSNR (db) plot of proposed algorithm with SMF, CWM, IM, and ISWM for 'Lena' image corrupted with different impulse noise density

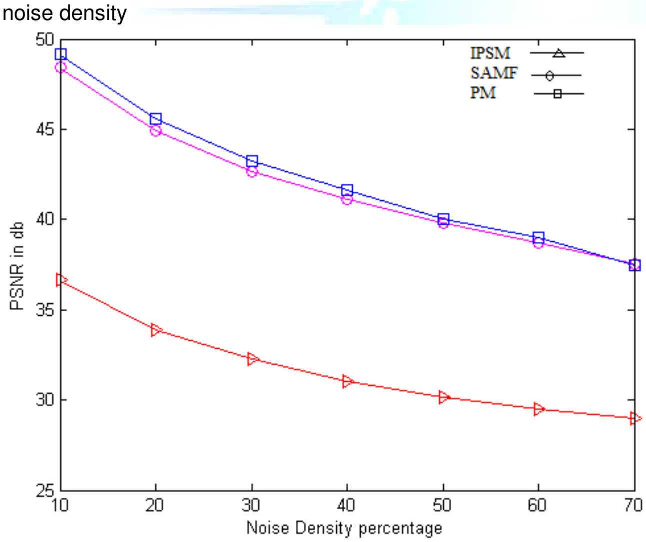

Figure 2: PSNR (db) plot of proposed algorithm with IPSM and SAMF for 'Lena' image corrupted with different impulse noise density

Figure 1 & 2 shows PSNR (db) plot of proposed algorithm with SMF, CWM, IM, ISWM, IPSM and SAMF for 'Lena' image corrupted with different impulse noise density. From figure 2 we can draw a conclusion that the Proposed Simple Adaptive Switching Median filter algorithm provides relatively good results of filtration and performs robustness against noise which is demonstrated by the declivity of this algorithm's PSNR curve.
The results of the restoration of test image 'Lena' which was corrupted by 60% impulse noise is presented in figure 3 from this we can draw the following basic conclusions:

1. Classic median filter and center weighted median filter remove impulses but add visually seen significant distortions into original images which cause the blurring of objects edges and the blurring of a whole image;

2. In the terms of the criterion PSNR, Proposed Filter algorithm is more efficient then IPSM and SAMF

3. It's possible to notice visual differences in the quality of image restoration. Proposed algorithm provides the best visual quality of restored images among all of considered algorithms. It is expressed in preserving of tiny details, edges in the images processed by this filter. Also the blurring injected into image during processing by proposed algorithm is insignificant.

4. Conclusion

The new impulse noise removal algorithm proposed in this work have good characteristics for impulse noise removal and may be supplied in different devices for digital image and video processing, which work in high noise environment. In Figure 3, we show the restoration results of different filtering methods for test image "lena" highly corrupted with 60% impulse noise. Both the simple 3x3 median filter and the switch median filter can preserve image details but many noise pixels are remained in the image. The CWM filter performs better than simple median filter, but it still influences good pixels and misses many impulse pixels. The iterative median filter removes most of the impulses, but many good pixels are also modified, resulting in blurring of the image. Since the iterative switch median filter does not modify good pixels in the image, it maintains image details better than the iterative median filter, but many noise blotches still remained in the image In most cases described algorithm almost completely removes a salt-and-pepper noise from corrupted digital images and efficiently preserves edges and contours in images. So the information stored in digital image is not losing during noise removing even if noise has large density. The method is actually a hybrid of the adaptive median filter and switching median filter. One of the advantages of this method is that this method does not need the threshold parameter.

Figure3: Restoration results of different filters (a) Original test image “Lena” (b) Corrupted image with 60% salt & pepper noise(c) Median filter with 3 X 3 window size (d) CWM filter with 3 X 3 window size & center weight of 3(e) Iterative Median filter with 3 X 3 window size & 3 iterations (f) Iterative Switch Median filter (g) Improved Progressive Switching Median filter. (h) Simple Adaptive Median Filter (i) Proposed Filter

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