BOUNDARY BASED PROGRESSIVE SWITCHING MEDIAN FILTER FOR THE REMOVAL OF IMPULSE NOISE IN HIGHLY CORRUPTED IMAGES

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ABSTRACT: **Boundary Based Progressive Switching Median (BPSM) filter is a median-based filter proposed to restore images corrupted by salt and pepper noise and to preserve boundaries in image. The algorithm is followed by the following three steps: 1) an algorithm is used before filtering, to detect the corrupted pixels called impulse (salt and pepper)detection 2) The detection of impulse and filtering of noise are applied step by step process through several iterations, called progressive.3)boundary updating is done to preserve edge information. Simulation results reveals that the proposed algorithm is superior than Progressive Switching Median (PSM) filters and is particularly effectual for the cases where the images are very highly corrupted in boundaries.**

GENERAL TERMS: **Image enhancement, impulse detection, PSM filter, nonlinear filter.**

KEYWORDS: **Impulse noise, salt and pepper noise, boundary updating.**

I. INTRODUCTION

Impulse noises are generated by errors in communication channels and sensors used to acquire the images. This leads to corrupted images that lose the edge information .So it is essential to eliminate noise in the images before processing the other steps in image processing, such as edge detection, image segmentation and object recognition [1]. For this purpose, many linear and non linear digital filters have been proposed. In the past years, median-based filters play a vital role in elimination of noise due to its simplicity in implementation. Nevertheless, median filters are implemented uniformly across the image that modifies both noise pixels and undistorted pixels. To avoid the damage of undistorted pixels, the switching scheme is introduced, where impulse detection algorithms are implemented before filtering and the impulse detection results are used to control whether a pixel should be modified or not[2][3]. However, when the images are very highly corrupted, many impulses are difficult to detect and impossible to eliminate [4]. In such case, the error will propagate around their neighbourhood pixels and fins difficult in preserving information on edges [5]. In this paper, we present a new median-based switching filter, called boundary based progressive switching median (BPSM) filter, where both the impulse detector and the noise filter are applied progressively in iterative manners and boundaries are updated to preserve the edges. .The subsequent iterations of noise pixels are processed with the help of previous iterations. In such a method some impulse pixels located in the middle of large noise blotches can also be properly detected and filtered. Therefore, better restoration results are expected, particularly for the cases where the images are highly corrupted on edges.

II. BPSM FILTER

In our proposed method, impulse detector is developed by an image that possesses a smooth varying function, and also separated by edges. Our proposed algorithm consider only salt & pepper impulsive noise which means: 1) only some image pixels are corrupted by noise while other pixels are undistorted and 2) a noise pixel takes either takes a positive impulse or a negative impulse. In this paper, we use noise ratio $R(0 \leq R \leq 1)$ to represent that image is corrupted by 50% of impulse noise, Of these 25% of the pixels in the image are corrupted by positive impulses(salt) and 25% of the pixels by negative impulses(pepper). The processing steps involves in BPSM are a) Impulse detection. b) Noise filtering c) Boundary updation. . Fig. 1 shows a general framework of BPSM that preserve edges when the noise pixels are not densely distributed in the image.

A. IMPULSIVE NOISE DETECTION*:*

In our method, we generate two image sequences during the impulse detection procedure. The first is a sequence of gray scale binary images, $\{\{y_i^{(0)}\}, \{y_i^{(1)}\},.......\{y^{(N)}\},....\}$ where $\{y_i^{(0)}\}$ indicates the initial binary noise image to be detected, $y_i^{(0)}$ denotes the pixel value at position (i,j) in the initial noisy image and $y_i^{(n)}$ represents the pixel value at position(i,j) in the image after the N-th iteration. The binary flag sequence is generated as ,$\{\{f_i^{(1)}\},\{f_i^{(2)}\},...............\{f_i^{(N)}\}......\}$, where the binary value $f_i^{(n)}$ is used to indicate whether the pixel at position (i,j) has been detected as an impulse, i.e., $f_i^{(N)} = 0$ means the pixel at position (i,j) is good and $f_i^{(n)} = 1$ means it has been found to be an impulsive noise. Before the initial iteration, we do the assumption as all the image pixels are good (i.e) $f_i^{(N)}=0$.

For the N-th iteration (n=1,2,3..........),the median values for pixels of the samples is given by the $W_D \times W_D$ window size centered about it.
Median is given by

$$C_i^{(N-1)} = \mathrm{Medi}\{y_i^{(N-1)}\}. \qquad (1)$$

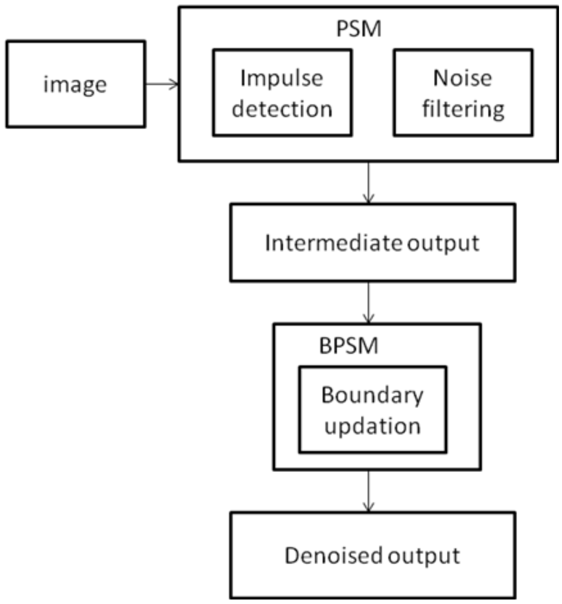


Fig.1 Framework of Boundary Based Progressive Switching Median Filter.

The flag sequences can be detected by performing the difference between $C_i^{(N-1)}$and $y_i^{(N-1)}$.

$$f_i^{(N)} = \begin{cases} f_i^{(N-1)}, & \text{if } |y_i^{(N-1)} - C_i^{(N-1)}| < T_D \\ 1, & \text{else} \end{cases} \qquad (2)$$

Where T_D is a predefined threshold value. If a pixel is detected as an impulse noise , the value of $y_i^{(N)}$ is modified as.

$$y_i^{(N)} = \begin{cases} C_i^{(N-1)}, & \text{if } f_i^{(N)} = f_i^{(N-1)} \\ y_i^{(N)}, & \text{if } f_i^{(N)} \neq f_i^{(N-1)} \end{cases} \qquad (3)$$

here flag sequence $f_i^{(N)}$ is used for our noise filtering. The impulse detection mentioned in our method is first introduced in switch I scheme[6]. In progressive switching median filter(PSM) the impulses are detected progressively through several iterations[7].

B. NOISE FILTERING*:*

Similar to impulse detection procedure, the noise filtering procedure also generates a gray scale image flag sequence,$\{\{w_i^{(0)}\}, \{w^{(1)}\},.......\{w_i^{(N)}\},........\}$ and a binary flag image sequence, $\{\{b_i^{(1)}\},\{b_i^{(2)}\},...............\{b_i^{(N)}\}......\}$, Like impulse detection procedure,in the gray scale image sequence, the pixel in (i,j) position (i.e) $w_i^{(N)}$ is to be filtered and to represent the pixel value at position (i,j)in the image after the n^{th} iteration. In a binary gray scale flag sequence image $\{b_i^{(N)}\}$, the value $b_i^{(N)}=0$, indicates the pixel (i,j) is good and $b_i^{(N)}=1$,indicates it is an impulse, which is to be filtered. If we compare with the impulse detection procedure ,the initial flag sequence image $\{b_i^{(N)}\}$ is not a blank image.

In the N-th iteration (N=1,2,......),for each pixel $w_i^{(N-1)}$, similar to impulse detection procedure we first calculate its median value $C_i^{(N-1)}$ of a $W_F \times W_F$ window centered about it. However, the median value here is selected from undistorted image pixels with $b_j^{(N-1)} = 0$ in the window. Unlike the impulse detection procedure here we find the median values for odd and even number of pixels.

Let K denote the number of all the pixels with $b_j^{(N-1)} = 0$ in the $W_F \times W_F$ window. If K is odd, then

$$C_i^{(N-1)} = \text{Medi}\{w_i^{(N-1} \, |g_j^{(n-1)} = 0 \qquad (4)$$

If M is even but not to be 0,then

$$C_i^{(N-1)} = \{\text{Medi}_{LM}\{ w_i^{(N-1)} | \, b_j^{(N-1)} = 0\} + \{\text{Med}_{RM}\{w_i^{(N-1)} |b_i^{(N-1)}=0\}/2 \qquad (5)$$

where Medi_{LM} and Medi_{RM} denote the left and the right median values, respectively. That is, Medi_{LM} is the $(K/2)^{th}$ largest value and Medi_{RM} is the (K/2+1)th largest value of the given data. If K is greater than zero,the value of $w_i^{(N)}$ is modified only when the pixel (i,j) is an impulse

$$y_i^{(N)} = \begin{cases} C_i^{(N-1)} & \text{if } b_i^{(N-1)}=1; \quad K>0 \\ w_i^{(N-1)} & \text{else} \end{cases} \qquad (6)$$

If the impulse pixel is modified, for further iterations it is considered as a good pixel .

$$b_i^{(N-1)} = \begin{cases} b_i^{(N-1)} & \text{if } y_i^{(N)} = y_i^{(N-1)} \\ 0 & \text{if } y_i^{(N)} = C_i^{(N-1)} \end{cases} \qquad (7)$$

The procedure stops after the N_I- th iteration if all of the noise pixels have been modified, i.e.,

$$\sum g_i^{(N_I)} = 0 \qquad (8)$$

Then the restored image $\{y_i^{(N)}\}$ is obtained as output.

C. BOUNDARY UPDATION:

The original test images are corrupted with fixed valued salt-pepper impulses. The impulse noise corrupts the edge information more. Hence image restoration becomes quite difficult. So the boundaries in the images are updated. To perform boundary updation in PSM filter, two parameters must be calculated. The boundary values are updated using the following algorithm.

y(i-1,j-1)	*y(i,j-1)*	*y(i+1,j_1)*
y(i-1,j)	*y(i,j)*	*y(i+1,j)*
y(i-1,j+1)	*y(i,j+1)*	*y(i+1,j+1)*

Fig 2: Representation of pixels in 3×3 window.

For 3 X 3 window size represented in fig 2.,
Vertical median,

$$V_v = y(i,j) - (y(i,j-1) + y(i,j+1))/2 \qquad (9)$$

Horizontal median,

$$V_h = y(i,j) - (y(i-1,j) + y(i+1,j))/2 \qquad (10)$$

$V_v < V_h$ →vertical edge
$V_v > V_h$ →horizontal edge

By this BPSM algorithm, the quality of the image was enhanced by preserving the edges, so far we can use the filtered image for further processing.

III. IMPLEMENTATION AND SIMULATION

In our experiments the original test images are corrupted with fixed valued salt–pepper impulses, where the corrupted pixels take on the values of either 0 or 255 with equal probability.

To implement the BPSM algorithm, three parameters must be pre- determined. They are the filtering window size W_F , the impulse detection window size W_D, and the impulse detection threshold T_D.

$$PSNR=10*\log10((255)^2/N) \quad (11)$$

Where N is the size of the image.

Our experiments show that almost all the best restoration results are obtained when the window size is not smaller than 3(W_F=3).

NOISE LEVEL (dB)	MEDIAN FILTER		PSM FILTER		BPSM FILTER	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
0.2	18.4846	60.7	18.3577	67.3	31.8081	97.5
0.3	17.6127	56	18.2383	66.2	28.728	95.1
0.4	16.1569	48	18.1028	64.8	25.955	91.3
0.5	14.247	36.6	17.8774	62.7	23.337	85.4
0.6	12.1373	24.6	17.5459	59.4	21.0644	77.4
0.7	10.3	15.0	16.8623	53.9	18.7897	65.7
0.8	8.73649	8.9	15.3355	42.7	16.4974	48.7
0.9	7.4172	3.8	12.0879	20.6	14.193	27.2

Table.1 Tabulation of PSNR and SSIM for median,PSM, BPSM filters

Table.1 shows the peak signal to noise ratio(PSNR) and Structural Similarity Index Matrix(SSIM) of median filter, PSM filter and BPSM filter for various noise levels.

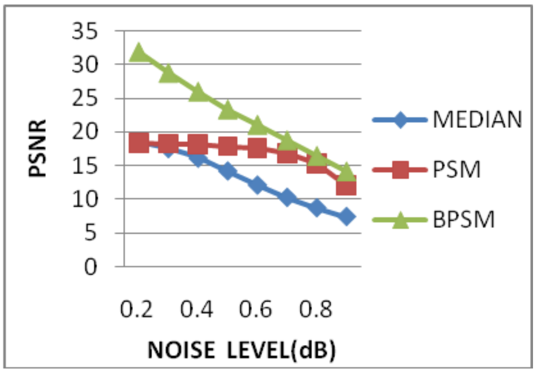


Fig.3 Graph which shows the effect of PSNR with respect to noise level in dB for Median, PSM, BPSM filter.

When comparing the PSNR values of various filters, the proposed BPSM filter shows better PSNR for highly corrupted images. This is graphically represented in the fig.3.

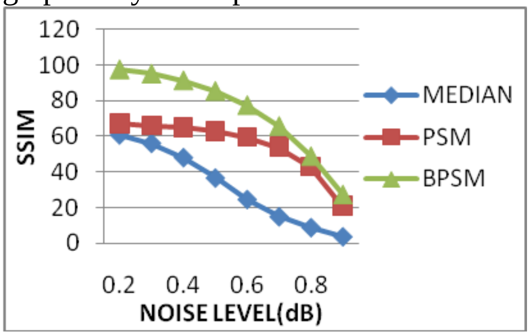
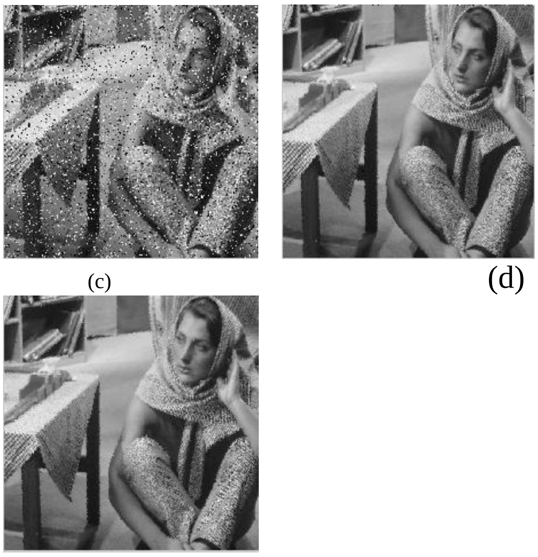


Fig.4 Graph which shows the SSIM with respect to noise level in dB for Median ,PSM, BPSM filter.

Fig.4 Illustrates Structural Similarity Index Matrix(SSIM) with respect to noise level for median filter, PSM filter and BPSM filter. Our experiments shows better result for window size not smaller than 3 and also for highly corrupted images. For example,noise level=0.5dB BPSM filter has PSNR with 23.337 and SSIM with 85.4.

(a) (b)



(c) (d)

(e)

Fig .5 Restoration results of different median filters a) Original image b) Corrupted image with 50% of salt and pepper noise c) Median filtered image d) PSM filtered image e) BPSM filtered image

From Fig.5 , we can observe that, for image "barbara" W_D =3 is more suitable for low noise ratio and W_D =5 is better for high noise ratio, with PSNR of 23.337. The structural similarity of ground truth image and filtered image is about 83%.

IV CONCLUSION AND RESULTS

We test our BPSM algorithm and compare it with other well known median filter and PSM filter for better performance analysis. The experiments are carried out on several 512, 8 bits/pixel gray scale images. We provide the PSNR and SSIM performance for the original test image "Barbara" is corrupted with different impulse noise ratios.

The PSNR curves demonstrate that our BPSM algorithm is better than other median-based methods, especially with high noise ratio. We show the restoration results of different filtering methods for test image "Barbara" highly corrupted with 50% impulse noise. Both the simple 3×3 window, median filter and the PSM filter can preserve image details but many noise pixels are remained in the image. The BPSM filter performs better than simple median filter, because when comparing with other median filters boundary of the image content is preserved. 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 PSM filter does not modify good pixels in the image, it maintains image details better than the iterative median filter, but boundaries are not preserved in PSM. Dramatic restoration results are obtained by our BPSM filter. It can remove almost all of the noise pixels while preserve image details very well and boundaries are preserved.

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