Progressive Switching Median Filter for the Removal of Impulse Noise from Highly Corrupted Images

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***Abstract*— A new median-based filter, progressive switching median (PSM) filter, is proposed to restore images corrupted by salt–pepper impulse noise. The algorithm is developed by the following two main points: 1) switching scheme—an impulse detection algorithm is used before filtering, thus only a proportion of all the pixels will be filtered and 2) progressive methods—both the impulse detection and the noise filtering procedures are progressively applied through several iterations. Simulation results demonstrate that the proposed algorithm is better than traditional median-based filters and is particularly effective for the cases where the images are very highly corrupted.**

***Index Terms*— Image enhancement, impulse detection, median filter, nonlinear filter.**

I. Introduction

Images are often corrupted by impulse noise due to errors generated in noisy sensors or communication channels. It is important to eliminate noise in the images before some subsequent processing, such as edge detection, image segmentation and object recognition. For this purpose, many approaches have been proposed [1]. In the past two decades, median-based filters have attracted much attention because of their simplicity and their capability of preserving image edges [1]–[4]. Nevertheless, because the typical median filters are implemented uniformly across the image, they tend to modify both noise pixels and undisturbed good pixels. To avoid the damage of good pixels, the switching scheme is introduced by some recently published works [3]–[7], where impulse detection algorithms are employed before filtering and the detection results are used to control whether a pixel should be modified. Fig. 1 shows a general framework for such kinds of algorithms which proved to be more effective than uniformly applied methods when the noise pixels are sparsely distributed in the image. However, when the images are very highly corrupted, a large number of impulse pixels may connect into noise blotches. In such cases, many impulses are difficult to detect, thus impossible to be eliminated. In addition, the error will propagate around their neighborhood regions.

In this paper, we present a new median-based switching filter, called progressive switching median (PSM) filter, where both the impulse detector and the noise filter are applied progressively in iterative manners. The noise pixels processed in the current iteration are used to help the process of the other pixels in the subsequent iterations. A main advantage of such a method is that some impulse pixels located in the middle of large noise blotches can also be properly detected and filtered. Therefore, better restoration results are expected, especially for the cases where the images are highly corrupted.

II. PSM Filter

A. Impulse Detection

Similar to other impulse detection algorithms, our impulse detector is developed by a *prior* information on natural images, i.e., a noise-free image should be locally smoothly varying, and is separated by edges [4]. The noise considered by our algorithm is only salt–pepper impulsive noise which means: 1) only a proportion of all the image pixels are corrupted while other pixels are noise-free and 2) a noise pixel takes either a very large value as a positive impulse or a very small value as a negative impulse. In this paper, we use noise ratio $R (0 \le R \le 1)$ to represent how much an image is corrupted. For example, if an image is corrupted by $R = 30\%$ impulse noise, then 15% of the pixels in the image are corrupted by positive impulses and 15% of the pixels by negative impulses.

Manuscript received April 30, 1997; revised June 12, 1998. This work was supported in part by the UGC Fund, Hong Kong. This paper was recommended by Associate Editor A. Nishihara.

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Publisher Item Identifier S 1057-7130(99)01479-2.

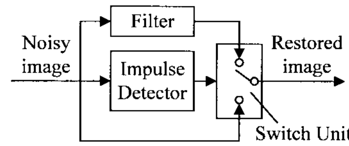

Fig. 1. A general framework of switching scheme-based image filters.

Two image sequences are generated during the impulse detection procedure. The first is a sequence of gray scale images, $\{\{x_i^{(0)}\}, \{x_i^{(1)}\}, \cdots, \{x_i^{(n)}\}, \cdots\}$, where the initial image $\{x_i^{(0)}\}$ is the noisy image to be detected, $x_i^{(0)}$ denotes the pixel value at position $\boldsymbol{i} = (i_1, i_2)$ in the initial noisy image and $x_i^{(n)}$ represents the pixel value at position $\boldsymbol{i}$ in the image after the nth iteration. The second is a binary flag image sequence, $\{\{f_i^{(0)}\}, \{f_i^{(1)}\}, \cdots, \{f_i^{(n)}\}, \cdots\}$, where the binary value $f_i^{(n)}$ is used to indicate whether the pixel $\boldsymbol{i}$ has been detected as an impulse, i.e., $f_i^{(n)} = 0$ means the pixel $\boldsymbol{i}$ is good and $f_i^{(n)} = 1$ means it has been found to be an impulse. Before the first iteration, we assume that all the image pixels are good, i.e., $f_i^{(0)} \equiv 0$.

In the nth iteration $(n = 1, 2, \cdots)$, for each pixel $x_i^{(n-1)}$ we first find the median value of the samples in a $W_D \times W_D$ (W_D is an odd integer not smaller than 3) window centered about it. If we use Ω_i^W to represent the set of the pixels within a $W \times W$ window centered about $\boldsymbol{i}$

$$\Omega_i^W = \{\boldsymbol{j} = (j_1, j_2) | i_1 - (W-1)/2 \le j_1 \le i_1 + (W-1)/2, \quad i_2 - (W-1)/2 \le j_2 \le i_2 + (W-1)/2\} \tag{1}$$

then we have

$$m_i^{(n-1)} = \mathrm{Med}\{x_j^{(n-1)} | \boldsymbol{j} \in \Omega_i^{W_D}\}. \tag{2}$$

The difference between $m_i^{(n-1)}$ and $x_i^{(n-1)}$ provides us with a simple measurement to detect impulses

$$f_i^{(n)} = \begin{cases} f_i^{(n-1)}, & \text{if } |x_i^{(n-1)} - m_i^{(n-1)}| < T_D \\ 1, & \text{else} \end{cases} \tag{3}$$

where T_D is a predefined threshold value. Once a pixel $\boldsymbol{i}$ is detected as an impulse, the value of $x_i^{(n)}$ is subsequently modified

$$x_i^{(n)} = \begin{cases} m_i^{(n-1)}, & \text{if } f_i^{(n)} \ne f_i^{(n-1)} \\ x_i^{(n-1)}, & \text{if } f_i^{(n)} = f_i^{(n-1)}. \end{cases} \tag{4}$$

Suppose the impulse detection procedure is stopped after the N_Dth iteration, then two output images—$\{x_i^{(N_D)}\}$ and $\{f_i^{(N_D)}\}$ are obtained, but only $\{f_i^{(N_D)}\}$ is useful for our noise filtering algorithm.

It should be mentioned that the impulse detection measurement used here is first introduced by Sun and Neuvo in their switch I scheme [4]. The difference between our method and Sun and Neuvo's algorithm is that our method is iteratively applied, so that the impulses are detected progressively through several iterations. Later simulation results show that our algorithm performs better when the noise ratio is high.

B. Noise Filtering

Like the impulse detection procedure, the noise filtering procedure also generates a gray scale image sequence, $\{\{y_i^{(0)}\}, \{y_i^{(1)}\}, \cdots, \{y_i^{(n)}\}, \cdots\}$, and a binary flag image sequence $\{\{g_i^{(0)}\}, \{g_i^{(1)}\}, \cdots, \{g_i^{(n)}\}, \cdots\}$. In the gray scale image sequence, we still use $y_i^{(0)}$ to denote the pixel value at position $\boldsymbol{i}$ in the noisy image to be filtered and use $y_i^{(n)}$ to represent the pixel value at position $\boldsymbol{i}$ in the image after the nth iteration. In a binary flag image $\{g_i^{(n)}\}$, the value $g_i^{(n)} = 0$ means the pixel $\boldsymbol{i}$ is good and $g_i^{(n)} = 1$ means it is an impulse that should be filtered. A difference between the impulse detection and noise-filtering procedures is that the initial flag image $\{g_i^{(0)}\}$ of the noise-filtering procedure is not a blank image, but the impulse detection result $\{f_i^{(N_D)}\}$, i.e., $g_i^{(0)} \equiv f_i^{(N_D)}$.

In the nth iteration $(n = 1, 2, \cdots)$, for each pixel $y_i^{(n-1)}$, we also first find its median value $m_i^{(n-1)}$ of a $W_F \times W_F$ (W_F is an odd integer and not smaller than 3) window centered about it. However, unlike that in the impulse detection procedure, the median value here is selected from only good pixels with $g_j^{(n-1)} = 0$ in the window. Let M denote the number of all the pixels with $g_j^{(n-1)} = 0$ in the $W_F \times W_F$ window. If M is odd, then

$$m_i^{(n-1)} = \mathrm{Med}\{y_j^{(n-1)} | g_j^{(n-1)} = 0, \boldsymbol{j} \in \Omega_i^{W_F}\}. \tag{5}$$

If M is even but not 0, then

$$\begin{aligned} m_i^{(n-1)} = \ &(\mathrm{Med}_L\{y_j^{(n-1)} | g_j^{(n-1)} = 0, \boldsymbol{j} \in \Omega_i^{W_F}\} \\ &+ \mathrm{Med}_R\{y_j^{(n-1)} | g_j^{(n-1)} = 0, \boldsymbol{j} \in \Omega_i^{W_F}\})/2 \end{aligned} \tag{6}$$

where Med_L and Med_R denote the left and the right median values, respectively. That is, Med_L is the $(M/2)$th largest value and Med_R is the $(M/2+1)$th largest value of the sorted data. The value of $y_i^{(n)}$ is modified only when the pixel $\boldsymbol{i}$ is an impulse and M is greater than 0:

$$y_i^{(n)} = \begin{cases} m_i^{(n-1)} & \text{if } g_i^{(n-1)} = 1\ ;\ M > 0. \\ y_i^{(n-1)} & \text{else.} \end{cases} \tag{7}$$

Once an impulse pixel is modified, it is considered as a good pixel in the subsequent iterations

$$g_i^{(n)} = \begin{cases} g_i^{(n-1)} & \text{if } y_i^{(n)} = y_i^{(n-1)} \\ 0 & \text{if } y_i^{(n)} = m_i^{(n-1)}. \end{cases} \tag{8}$$

The procedure stops after the N_Fth iteration when all of the impulse pixels have been modified, i.e.,

$$\sum_i g_i^{(N_F)} = 0. \tag{9}$$

Then we obtain the image $\{y_i^{(N_F)}\}$ which is our restored output image.

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. Mean square error (MSE) is used to evaluate the restoration performance. MSE is defined as

$$\mathrm{MSE} = \frac{1}{N} \sum_i (u_i - v_i)^2 \tag{10}$$

where N is the total number of pixels in the image, u_i and v_i are the pixel values at position $\boldsymbol{i}$ in the original and the test images, respectively.

To implement the PSM algorithm, four parameters must be predetermined. They are the filtering window size W_F, the impulse detection window size W_D, the impulse detection iteration number N_D and the impulse detection threshold T_D. Our experiments show

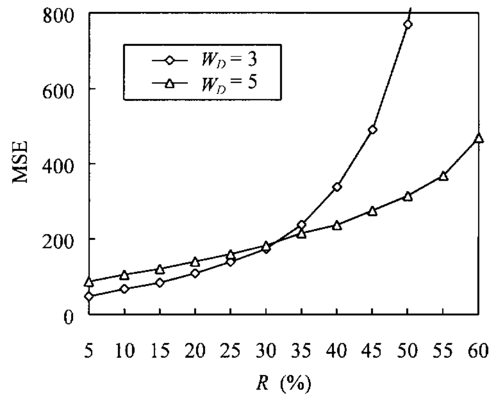

Fig. 2. The effects of W_D with respect to MSE, where $W_F = 3$, $N_D = 3$, and $T_D = 50$.

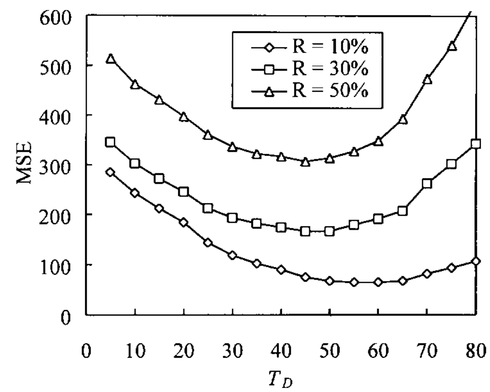

Fig. 3. The effects of T_D with respect to MSE. For R = 10%, $W_F = 3$, $W_D = 3$, and $N_D = 3$; for R = 30%, $W_F = 3$, $W_D = 5$, and $N_D = 3$; for R = 50%, $W_F = 3$, $W_D = 5$, and $N_D = 3$.

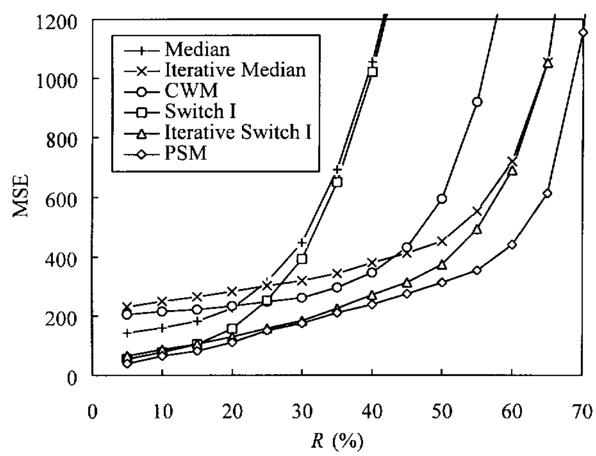

Fig. 4. A comparison of different median-based filters for the restoration of corrupted image "bridge" under a large range of impulse noise ratio.

that almost all the best restoration results are obtained when $W_F = 3$ and $N_D = 3$. In addition, these two parameters are not sensitive to noise rate and image type. Therefore, we simply set both W_F and N_D to be 3. The other two parameters, W_D and T_D, are sensitive to how much the image is corrupted. From Fig. 2, we can observe that, for image "Bridge," $W_D = 3$ is more suitable for low noise ratio and $W_D = 5$ is better for high noise ratio, with a cross point at about $R = 30\%$. The experiments on some other images give similar conclusion except that the cross point may be a little bit lower or higher such as $R = 25\%$ or $R = 35\%$. The influence of T_D is investigated in Fig. 3. It appears that the best T_D is decreasing with

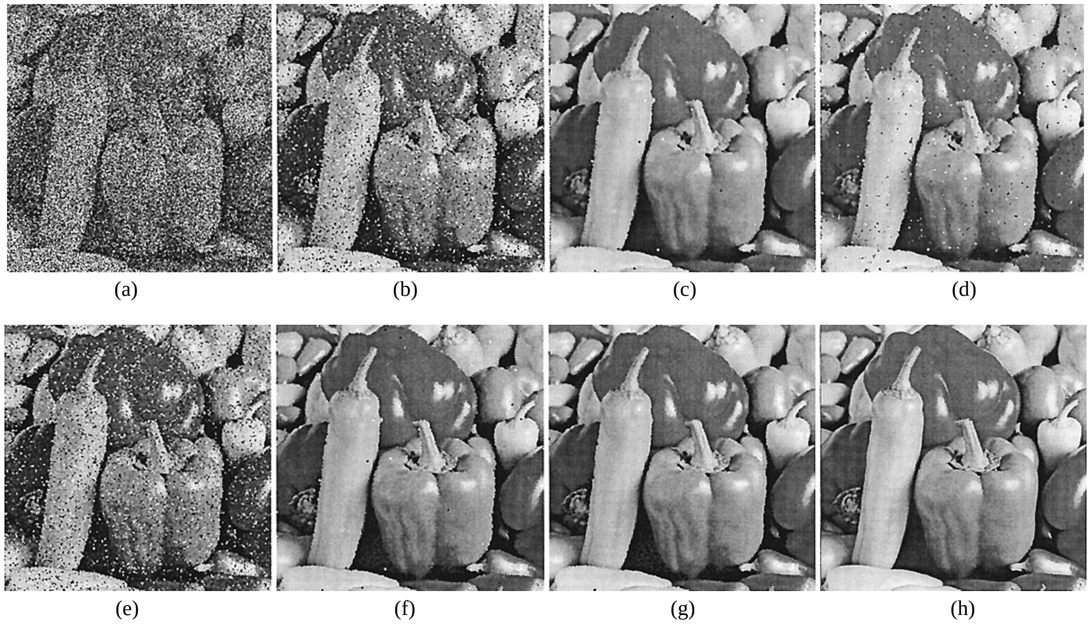

Fig. 5. Restoration results of different median-based filters. (a) Corrupted image "peppers" with 50% salt–pepper noise. (b) Median filter with 3×3 window size. (c) Iterative median filter with 3×3 window size and 8 iterations. (d) CWM filter with 5×5 window size and a center weight of 3. (e) Switch I median filter with 3×3 window size. (f) Iterative switch I median filter with 3×3 window size and 8 iterations, where the noise detection threshold is 40. (g) The PSM filter. (h) Original image of "peppers."

the increase of R. To determine W_D and T_D, we first make a rough estimation on the noise ratio, which again uses the impulse detection measurement of Sun and Neuvo's switch I scheme [4]. Initially, we set

$$N_I = 0 \tag{11}$$

where N_I is the number of impulses that have been detected. For each pixel x_i, we find the median value of the samples in the 3×3 window centered about it

$$m_i = \mathrm{Med}\{x_j | \boldsymbol{j} \in \Omega_i^3\}. \tag{12}$$

The difference between m_i and x_i is used to make a decision on whether it is an impulse

$$\text{if} \quad |m_i - x_i| \le T_I, \quad \text{then} \quad N_I + 1 \rightarrow N_I \tag{13}$$

where the threshold T_I is predefined as 40 in our experiments. After all the pixels in the image have been scanned once, we give an estimation of the noise ratio as

$$\hat{R} = N_I / N \tag{14}$$

where N is the total number of pixels in the image. Then W_D and T_D are defined according to $\hat{R}$

$$W_D = \begin{cases} 3, & \text{if } \hat{R} \le T_R \\ 5, & \text{if } \hat{R} > T_R \end{cases} \tag{15}$$

$$T_D = a + b \cdot \hat{R}. \tag{16}$$

According to our experimental results, we choose T_R, a, and b as 25%, 65, and -50, respectively.

Although our parameter preselection scheme brings about several new parameters, the restoration results are experimentally less sensitive to them, thus only rough estimations are needed. This is important for the usage of the PSM filter in real applications, where statistical information about the given corrupted images may be unavailable. While our parameter selection is based on the experiments on a small set of images such as "bridge" and "Lena," the results on other images are also good.

We test our PSM algorithm and compare it with other well known median-based filters, which are the simple median filters, the iterative median filter (iteratively apply the simple median filter), the center weighted median (CWM) filter, the switch I median filter, and the iterative switch I median filter (iteratively apply the switch I median filter). The experiments are carried out on several 512×512, 8 bits/pixel gray scale images. We provide the MSE performance in Fig. 4 where the original test image "bridge" is corrupted with different impulse noise ratios ranging from 5% to 70%. The MSE curves demonstrate that our PSM algorithm is better than other median-based methods, especially when noise ratios are high. In Fig. 5, we show the restoration results of different filtering methods for test image "peppers" highly corrupted with 50% impulse noise. Both the simple 3×3 median filter and the switch I 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 I 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. Dramatic restoration results are obtained by our PSM filter. It can remove almost all of the noise pixels while preserve image details very well.

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