DECISION-BASED MEDIAN FILTER USING K-NEAREST NOISE-FREE PIXELS

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ABSTRACT

Traditional median filter replaces each pixel in an image with the median value of their k-nearest pixels (commonly known as pixels in 2-D window). The problem associated with this approach is that the restored pixel is noise if median value of their k-nearest pixels is a corrupted pixel. To mitigate the above problem, this paper proposes a novel decision-based median filter that replaces each corrupted pixel with the median value of their k-nearest noise-free pixels. Advantages of the median filter using k-nearest noise-free pixels instead of k-nearest pixels are two facets: first, it guarantees that pixels after being restored must be noise-free, because the median filter operator is executed on noise-free pixels; second, the median filter using k-nearest noise-free pixels adaptively adjusts its window size for each pixel such that the number of noise-free pixels locating in the window increases up to k. To realize it, the median filter using k-nearest noise-free pixels firstly detects noise-free pixels in an image, then replaces each corrupted pixel with the median value of their k-nearest noise-free pixels. The proposed median filter is tested on four real images corrupted by different levels of salt-and-pepper noise. Experimental results confirm the effectiveness of decision-based median filter using k-nearest noise-free pixels.

***Index Terms*—** Decision-based median filter, image restoration, impulse noise, median filter, salt-and-pepper noise.

1. INTRODUCTION

Images are sometimes corrupted by impulse noise due to malfunctioning pixels in camera sensors and the transmission in noisy channels. One common approach to detecting impulse noise and restoring corrupted images is the median filter. The median filter performs to replace each pixel in an image with the median value of their k-nearest pixels. The median filter is very simple to implement and has a low computational cost and good noise diagnosing ability. Therefore, the median filter has been widely applied into image restoration. However, the median filter is not exempt from any drawbacks: First, a good performance of the median filter significantly relies on the proper number of the nearest pixels (or the proper size of window), that should be able to draw a good balance between the restoration of corrupted pixels and the smoothness of edges in restored images. Second, the median filter is implemented uniformly across all pixels in an image. This may lead to the smearing of image edges.

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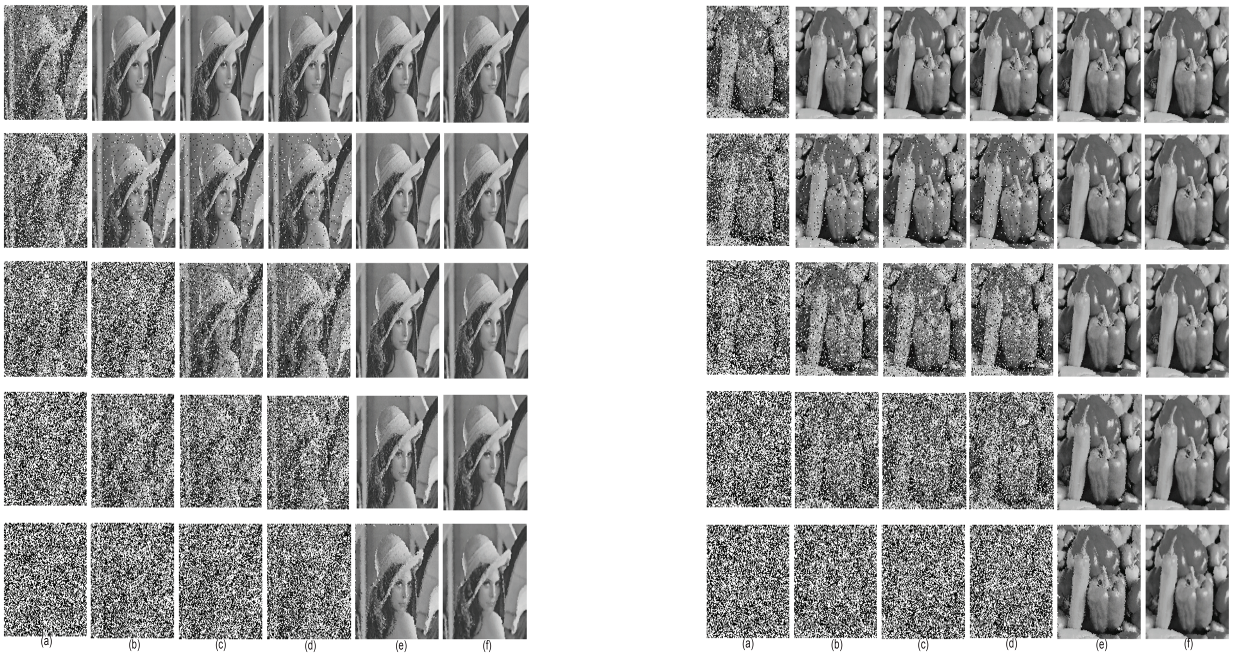
Many modifications of the median filter were proposed to mitigate the above two problems [1]-[2]. For example, the adaptive median filter was proposed that is able to adjust the number of the nearest pixels (or the size of window) according to the noise level [6]. Apart from the adaptive median filter, another modification of median filter is the decision-based median filter [1]-[4]. Decision-based median filter firstly detects possible corrupted pixels in an image, then replaces them with the median value of their k-nearest pixels, while still leaving noise-free pixels unchanged. Several recent studies have shown that decision-based median filter performs well for images corrupted by low-level noise [1][4]. However, the performance of decision-based median filter significantly degrades if more noise is added. This is because pixels locating in the neighborhood of a corrupted pixel may also be noise when images are corrupted by high-level noise. In this case, it is unreasonable to simply replace a corrupted pixel with the median value of their k-nearest pixels. Srinivasan and Ebenezer suggested using its neighborhood pixel as the replacement of a corrupted pixel if the median value of the k-nearest pixels is also a noisy pixel [4].

This paper proposes a novel decision-based median filter that replaces each corrupted pixel with the median value of their k-nearest noise-free pixels. Advantages of median filter using k-nearest noise-free pixels instead of k-nearest pixels are two facets: first, the pixel after being restored must be noise-free, because the median filter operator is executed on noise-free pixels; second, the median filter using k-nearest noise-free pixels can adaptively adjust its window size for each pixel according to the noise level such that the num-



(1) Lena image (2) Pepper image

Fig. 1. Restored results of different filters for Lena image and Pepper image under different noise level. (a) Corrupted images with different noise levels: 20% for images in the first row, 40% for images in the second row, 60% for images in the third row, 80% for images in the fourth row and 90% for images in the last row. (b) Restored images by adaptive median filter (AMF). (c) Restored images by relaxed median filter (RMF). (d) Restored images by switching median filter (SMF). (e) Restored images by fast decision-based median filter (PA). (f) Restored images by our proposed decision-based median filter.

ber of noise-free pixels locating in the window increases up to k. To realize it, the median filter using k-nearest noise-free pixels firstly detects noise-free pixels in an image, then replaces each corrupted pixel with the median value of their k-nearest noise-free pixels. Decision-based median filter using k-nearest noise-free pixels is tested on four real images corrupted by different levels of salt-and-pepper noise. Experimental results demonstrate its effectiveness.

The remainder of the paper is arranged as follows. Section II goes into details of describing decision-based median filter using k-nearest noise-free pixels. Our experimental results and their analysis are given in section III. Section IV concludes this paper.

2. DECISION-BASED MEDIAN FILTER USING K-NEAREST NOISE-FREE PIXELS

Before further illustration about decision-based median filter using k-nearest noise-free pixels, some notations used throughout this paper are given as follows: $x_{i,j}$ and $y_{i,j}$ denote the values of the pixel at the position (i, j) in the corrupted and restored images respectively. $S_{i,j}$ represents the set of the k-nearest pixels locating in the window of the pixel (i, j) with the window size w. Therefore, if $k = (2w + 1) \times (2w + 1)$ nearest pixels are taken into account when restoring the pixel (i, j), then the set $S_{i,j}$ contains the following pixels:

$$S_{i,j} = \{x_{i-w,j-w}, ..., x_{i,j}, ..., x_{i+w,j+w}\} \qquad (1)$$

where w is the size of window and k is the number of the nearest pixels that are taken into account.

2.1. Noise-free pixels detection

To determine whether a pixel (i, j) is noise-free or noise, the value of the pixel (i, j) is compared with the maximum and minimum values of the $(2w + 1) \times (2w + 1)$ nearest pixels. This is because the corrupted pixels can take only the maximum or minimum values in the dynamic range (0, 255) [3]-[4]. The maximum value in its $(2w+1)\times(2w+1)$ nearest pixels can be calculated as follows:

$$Maxx_{i,j} = \max\{x_{i-w,j-w}, ..., x_{i,j}, ..., x_{i+w,j+w}\} \qquad (2)$$

and the minimal value is equal to:

$$Minx_{i,j} = \min\{x_{i-w,j-w}, ..., x_{i,j}, ..., x_{i+w,j+w}\} \quad (3)$$

If a binary matrix B is employed to represent whether a pixel is noise or not, then the binary matrix B can be computed as follows:

$$B_{i,j} = \begin{cases} 1 & \text{if } Minx_{i,j} < x_{i,j} < Maxx_{i,j}; \\ 0 & \text{otherwise}; \end{cases} \quad (4)$$

Where the value 1 of $B_{i,j}$ denotes the pixel (i,j) is noise-free and the value 0 means that the pixel (i,j) is noise.

2.2. Decision-based median filter using k-nearest noise-free pixels

After the binary matrix B is obtained, the smallest window

$$S_{ij} = \{x_{i-w,j-w}, ..., x_{i,j}, ..., x_{i+w,j+w}\}$$

of the pixel (i,j) containing k noise-free pixels can be obtained by an iterative process based on the following two inequalities:

$$\sum\{B_{i-w,j-w}, ..., B_{i,j}, ..., B_{i+w,j+w}\} \geq k \quad (5)$$

and

$$\sum\{B_{i-w+1,j-w+1}, ..., B_{i,j}, ..., B_{i+w-1,j+w-1}\} < k \quad (6)$$

Then all noise-free pixels in the window S_{ij} can be detected and stored into a new set $S^*_{i,j}$:

$$S^*_{i,j} = \{x_{i+t_i,j+t_j} \mid B_{i+t_i,j+t_j} = 1, -w \leq t_i \leq w, -w \leq t_j \leq w\} \quad (7)$$

The pixels in $S^*_{i,j}$ are ranked and their median value is returned as the final pixel of the corrupted pixel (i,j). Therefore, decision-based median filter using k-nearest noise-free pixels replace the pixels in the original corrupted image with the following rule employed:

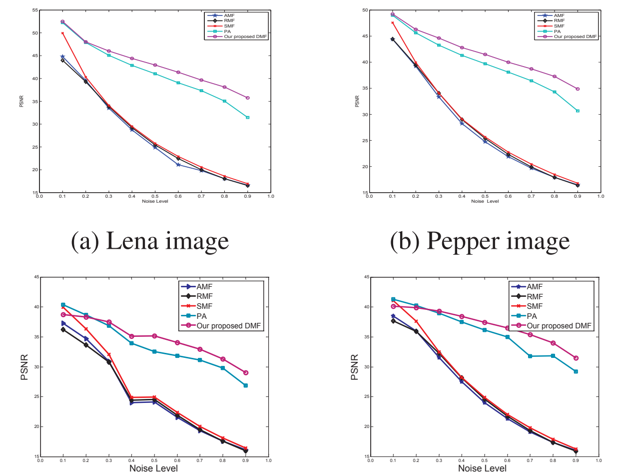
$$y_{i,j} = \begin{cases} \text{MEDIAN}(S^*_{i,j}) & \text{if } B_{ij} = 0; \\ x_{ij} & \text{if } B_{ij} = 1; \end{cases} \quad (8)$$

where $\text{MEDIAN}(S^*_{i,j})$ returns the median value of the pixels in the set $S^*_{i,j}$.

3. EXPERIMENTAL RESULTS AND THEIR ANALYSIS

In experiments, the proposed median filter was tested on four real images: Lena image, Pepper image, Cameraman image and Pig image corrupted by different levels of salt-and-pepper noise. Its results were compared with another four median filters: adaptive median filter (AMF) [6], relaxed median filter (RMF) [5], switching median filter (SWF) [1] and fast decision-based median filter (PA) [4]. The number of the nearest pixels k that are taken into account when restoring an image is set as 9 in experiments for RMF, SWF, PA and our proposed median filter.

Corrupted Lena image and Pepper image with different noise levels and their restored images obtained by the compared algorithms are shown in Figure 1. It can be observed from Figure 1 that AMF, RMF and SMF achieved good restored images if the noise level is 20%. However, their performances significantly degraded when noise levels increases up to 40% and the restored images became bad when noise levels were up to 60%. The restored images obtained by PA and our proposed median filter were much better than those obtained by AMF, RMF and SMF. Both of them achieved a very satisfactory restored image, even if the original image was corrupted by 90% salt-and-pepper noise. The performance of our proposed decision median filter are the best among all five compared median filters.

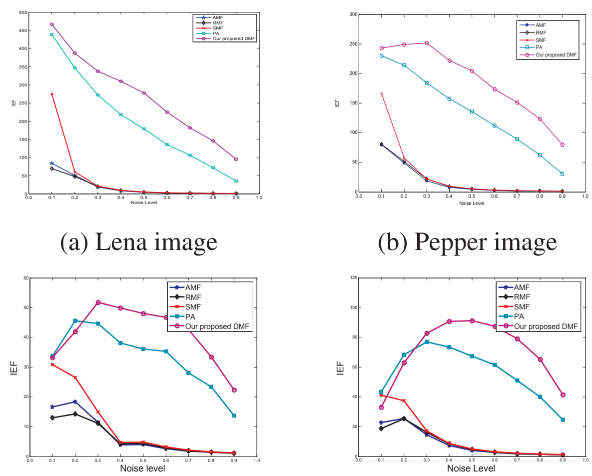


(a) Lena image (b) Pepper image

(c) Cameraman image (d) Pig image

Fig. 2. PSNR obtained by different filters under different noise levels.

To quantitatively compare the performances of five median filters, restoration qualities of their obtained restored images were measured by peak-signal-to-noise ratio (PSNR) and image enhancement factor (IEF) [4]. Experimental results were given in Figure 2 and Figure 3. It can be observed from Figure 2 and Figure 3 that the values of PSNR and IEF decreased very fast for AMF, RMF and SMF, if the noise level increased. For example, the values of PSNR are around 45 for AMF, RMF and SMF if the Lena image was corrupted by 10% noise. However, their values decreased to around 16 if the the noise level increased up to 80%. Another phenomenon that can be observed from Figure 2 and Figure 3 is our



(a) Lena image (b) Pepper image

(c) Cameraman image (d) Pig image

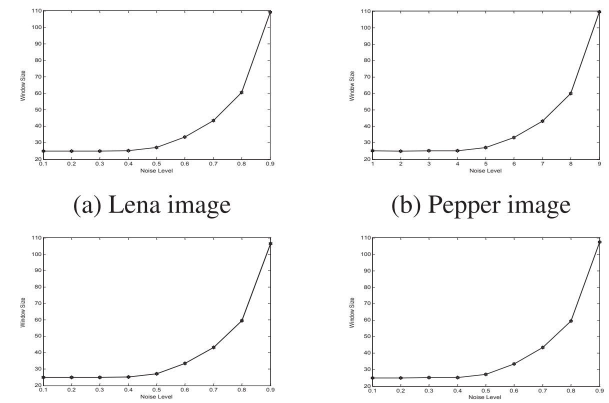
Fig. 3. IEF obtained by different filters under different noise levels.

proposed median filter worked well for images that were corrupted by high level noise and significantly outperformed PA and another three median filters. For example, the values of PSNR and IEF obtained by our proposed median filter were 34.8674 and 80.0766, when the Lena image was corrupted by 90% salt-and-pepper noise, that were much higher than 30.6626 of PSNR and 30.4122 of IEF obtained by PA, around 16.1223 of PSNR and 0.000 of IEF obtained by other three median filters. The same superiority of our proposed median filter can also be observed from the results of Pepper.tif image, Cameraman.tif image and Pig.tif image.

Finally, the average window size of our proposed median filter was studied. Experimental results were given in Figure 4. It is very interesting to be observed from Figure 4 that the window size of our proposed median filter increased a lot if the noise level increased. For example, the average window size of our proposed median filter was around 25 if 30% noise was added; while its value increased up to around 100 if 90% noise was added for Lena, Pepper, Cameraman and Pig images. The above experimental results tell us that our proposed median filter is able to adjust the window size according to the noise level. Another interesting phenomenon that can be observed from Figure 4 is the increasing curves of the window size for four different images are very similar. This phenomenon may let us know that the window size of our proposed median filter only relies on the noise level.

4. CONCLUSIONS

This paper has proposed a novel decision-based median filter using k-nearest noise-free pixels. We have described the decision-based median filter using k-nearest noise-free pixels into details. Moreover, we have tested the proposed decision-based median filter on two real images and compared its performance with other decision-based median filter. Experimental results have confirmed the effectiveness of the proposed decision-based median filter.



(a) Lena image (b) Pepper image

(c) Cameraman image (d) Pig image

Fig. 4. Average window Sizes obtained by our proposed decision-based median filter under different noise levels.

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