A NEW SELECTIVE FILTERING ALGORITHM FOR IMAGE DENOISING

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ABSTRACT

This paper proposes a simple but efficient selective filtering algorithm (SFA) for removing the impulse noise in images. Integrating the noise detector with the relationship between a pixel and its neighbors, the SFA is able to efficiently detect and remove noise pixels while well preserving information pixels. Experimental results and comparisons demonstrate that the proposed SFA outperforms several existing denoising methods with respect to the visual effects and quantitative measure results.

***Index Terms*—** image denoising, impulse noise, noise detection, selective filtering.

1. INTRODUCTION

Digital images are frequently contaminated by the impulse noise such as salt and pepper noise in the image acquisition processes, or during incorrect transmission and compression. Generally, the impulse noisy image can be described as [1]

$$x_{i,j} = \begin{cases} f_{i,j} & p = 1 - p_0 \\ s_{i,j} & p = p_0 \end{cases} \tag{1}$$

where $f_{i,j}, s_{i,j}$ denote the original and corrupted pixels, respectively; p_0 is the noisy probability. For the salt and pepper noise in the grayscale image, $s_{i,j} = \{0, 255\}$.

In order to restore the images corrupted by the impulse noise, many filters and methods have been employed. The median (MED) filter is a common tool to remove the impulsive noise due to its good denoising performance [2]. However, the MED may also remove some desirable details in images. Therefore, several MED extensions were then proposed for obtaining better denoising performance. Examples include the weighted median (WM) filter [3], center weighted median (CWM) filter [4], and recursive weighted median filter (RWMF) [5]. These filters assign weights to emphasize the desirable pixels, obtaining improved filtering performance. Nevertheless, they process each pixel in the sliding window without considering whether it is noise or not.

Recently, integrating with noise detectors, several filtering techniques have been developed. Some of them are based on the median filter, including the noise adaptive soft-switching median filter [6], contrast enhancement-based filter (CEF) [7], and modified decision based unsymmetric trimmed median filter (MDBUTMF) [8]. Using noise detectors, these methods are able to distinguish the noise pixels and noise-free pixels. Then the noise pixels are removed while the noise-free pixels remain unchanged. Others are based on the arithmetic mean filter. For example, the tolerance based selective arithmetic mean filtering technique [9, 10]. It uses the arithmetic mean filter to process the selected image pixels while ignoring the maximum and minimum pixel values. However, these techniques process an image using a single filter and may fail to remove the impulse noise in specific regions in the image.

This paper introduces a new image denoising algorithm using the selective filtering technique for removing the impulse noise. It includes three types of classic mean filters, namely the weighted, harmonic, and contraharmonic mean filters. According to the noise detection results, the proposed algorithm adaptively chooses an appropriate filter for removing the impulse noise in different regions within an image. Using several simple traditional filters, the SFA yields promising denoising results which are better than the several state of the arts.

The rest of this paper is organized as follows. Section 2 reviews three classic mean filters, which are used for the new selective filtering algorithm presented in Section 3. Simulation results and comparisons are shown in Section 4 and Section 5 reaches a conclusion.

2. BACKGROUND

A mean filter in image processing works in a way that it performs a filtering operation by applying an $N \times N$ sliding window to a source image and replacing the center pixel with a mean or weighted-mean value of the pixels within the sliding window. It is widely used for image smoothing. This section reviews three classic mean filters: the weighted, harmonic, and contraharmonic mean filters. They will be used in our proposed filtering algorithm.

Let S_{ij} be a set of pixel coordinates within a sliding window with the size of $N \times N$, centered at the point (i, j); $x(i, j)$

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be the pixel intensity value at the location of (i, j) in the noisy image; and $y(i, j)$ be the filtering output at the position (i, j).

The output of the weighted mean filter (WMF) is defined by,

$$y(i,j) = \frac{\sum\limits_{(s,t)\in S_{ij}} w(s,t)x(s,t)}{\sum\limits_{(s,t)\in S_{ij}} w(s,t)} \tag{2}$$

where $w(s, t)$ denotes the weight coefficient. The WMF is an extension of the arithmetic mean filter. Its output is a local average of the inputs with different weights for different positions. It can effectively remove the Gaussian noise and impulse noise with low density.

The harmonic mean filter (HMF) is defined as,

$$y(i,j) = \frac{MN}{\sum\limits_{(s,t)\in S_{ij}} \frac{1}{x(s,t)}} \tag{3}$$

The HMF works very well for removing the salt noise.

The contraharmonic mean filter (CHMF) is defined as,

$$y(i,j) = \frac{\sum\limits_{(s,t)\in S_{ij}} x(s,t)^{p+1}}{\sum\limits_{(s,t)\in S_{ij}} x(s,t)^{p}} \tag{4}$$

where p is a control parameter. The CHMF is able to efficiently eliminate the pepper noise when $p > 0$.

3. THE PROPOSED ALGORITHM

In this section, we introduce a novel selective filtering algorithm (SFA) for image denoising. Because image contents may change significantly in different regions within an image, one single denoising filter for the whole image may be no longer appropriate. The underlying fundamental of the proposed SFA is to select an appropriate filter to remove noise in different regions within an image. This filter selection changes adaptively according to the image contents. The new SFA is illustrated in Algorithm 1. Notice that all images in the rest of this paper denote grayscale images with pixel intensity values within $[0,\ 255]$.

For a noisy image X, set a sliding window W with the size of $N \times N$. Let $S = \{x_{k,l} | 0 < x_{k,l} < 255, x_{k,l} \in W\}$, that is, S is the set which contains all the pixels with intensity value greater than 0 and less than 255 in the sliding window. And let $m = |S|$ be the number of pixels in S, m_0 be a small number (threshold), and n_{dark} be the number of the pixels in the window whose intensity values are no more than 15. Analogously, n_{bright} denotes the number of the pixels in the window whose intensity values are between 240 and 255. Then, we defined three non-overlapping dark, bright and gray regions as follows:

(1) If $m < m_0 \wedge n_{dark} > n_{bright}$, the center pixel of the window belongs to **the dark region** in the image;

(2) If $m < m_0 \wedge n_{dark} < n_{bright}$, the center pixel of the window belongs to **the bright region** in the image;

(3) Otherwise, the center pixel of the window belongs to **the gray region** in the image.

Algorithm 1. The proposed selective filtering algorithm

Input: The input corrupted image X, with size of $K_1 \times K_2$
Set the sliding window size of $N \times N$, thresholds m_0 and T_0;
Set the initial value for the pixel numbers $m = 0, n_{dark} = 0, n_{bright} = 0$;
for $i = 1$ to K_1 **do**
  for $j = 1$ to K_2 **do**
    obtain the pixels within the sliding window with size of $N \times N$, centered at the pixel $x(i, j)$
    Calculate and update the number, m
    if $m \geq m_0$ **then**
      Apply the WMF in Eq. (2) to these selected pixels, obtaining $y(i, j)$;
    else
      Calculate and update the pixel numbers, n_{dark}, n_{bright}
      if $n_{dark} > n_{bright}$ **then**
        Apply the HMF in Eq. (3) to the sliding window, obtaining $y(i, j)$;
      else
        if $n_{dark} < n_{bright}$ **then**
          Apply the CHMF in Eq. (4) to the sliding window, obtaining $y(i, j)$;
        else
          Apply the WMF in Eq. (2) to all the pixels in the sliding window, obtaining $y(i, j)$;
        end if
      end if
      if $|y(i, j) - x(i, j)| \geq T_0$ **then**
        $x(i, j) \leftarrow y(i, j)$
      else
        leave the pixel value unchanged
      end if
    end if
  end for
end for
Output: The restored image, $y(i, j)$

The proposed SFA first segments the input image into the dark, bright and gray regions. Then, each pixel is assigned to one of these three regions. The WMF, HMF, and CHMF are then selected for removing noise in the gray, dark and bright regions, respectively.

The SFA also treats the salt and pepper noises separately. Notice that the salt noise (white spots) is more annoying in the dark regions in an image, the HMF, which is good at removing the salt noise, is utilized; On the other hand, because the pepper noise (black dots) is more revolting in the bright regions, the CHMF that can well suppress the pepper noise is then employed in the proposed SFA. Therefore, this new SFA can remove the impulse noise in the black and bright regions in an image while preserving the information pixels.

4. SIMULATION RESULTS

In this section, the proposed SFA has been applied to various grayscale images with different features to assess its denoising performance.

Filtering low corrupted images is more interesting because it requires precise detection of corrupted pixels to preserve details and edges in images [11]. We thus choose the noise density level no more than 50% for our simulations. Before simulations, several parameters should be predefined: the window size N, thresholds m_0 and T_0. According to our experiments, the window size does not effect the restoration results when the noise density is low. Besides, m_0 less than one third of the pixel number in the sliding window and $T_0 \in [15, 45]$ can obtain good denoising results. In this paper, the sliding window is set to 3×3, and the thresholds are set for $m_0 = 2$, $T_0 = 25$. Here, we select the Gaussian filter as an example of the center weighted mean filter in the proposed SFA. In our simulations, we also found that using the propose SFA iteratively can obtain better results, and repeat two times is the best choice.

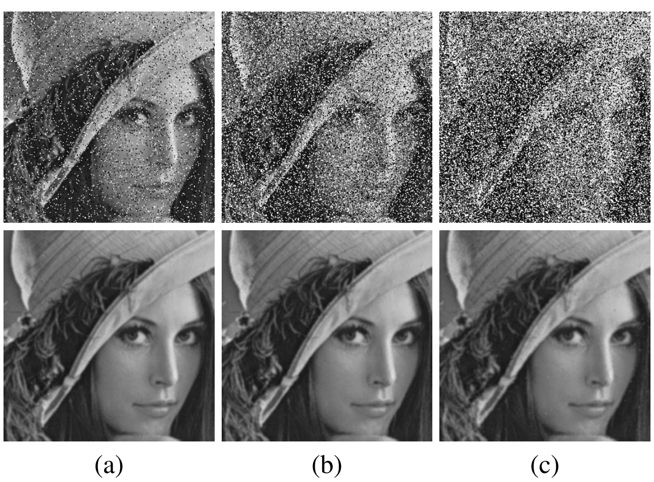

Fig. 1: Image restoration using the proposed SFA with different salt and pepper noise levels. the top row shows the corrupted images; the bottom row shows the corresponding restored images using the proposed SFA. (a) 10%; (b) 30%; (c) 50%.

Fig. 1 shows the corrupted images with different noise levels and their corresponding restoration results using the proposed SFA. As can be seen, all levels of the impulse noise have been completely removed.

The proposed SFA has been compared with several existing filtering methods such as the tolerance based selective arithmetic mean filtering technique (TSAMFT) [9], contrast enhancement-based filter (CEF) [7], and modified decision based unsymmetric trimmed median filter (MDBUTMF) [8].

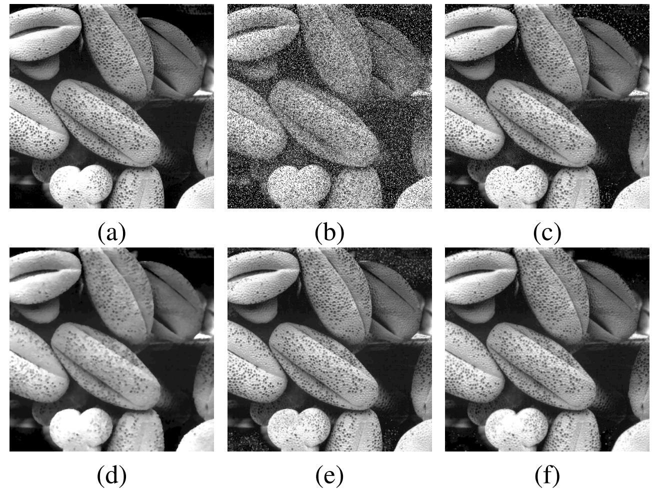

Fig. 2: Image restoration using different methods. (a)-(b) are the original and corrupted images; (c)-(f) are the restored images by different methods. (c) TSAMFT; (d) CEF; (e) MDBUTMF; (f) SFA.

Table 1: PSNR and SSIM Results for Different Filtering Methods

Noise	TSAMFT	CEF	MDBUTMF	SFA
	PSNR			
5%	33.17	25.84	31.06	**35.00**
10%	30.48	25.56	29.13	**33.60**
15%	28.49	25.33	27.56	**32.29**
20%	26.41	25.02	26.56	**31.23**
25%	24.68	24.74	25.35	**30.15**
30%	22.93	24.38	24.55	**30.12**
35%	21.77	23.88	23.48	**29.15**
40%	20.50	22.38	22.59	**27.88**
45%	19.21	20.10	21.93	**26.36**
50%	18.20	19.62	20.86	**24.88**
	SSIM			
5%	0.938	0.733	0.922	**0.979**
10%	0.887	0.725	0.908	**0.969**
15%	0.841	0.717	0.898	**0.959**
20%	0.802	0.707	0.888	**0.949**
25%	0.768	0.697	0.877	**0.937**
30%	0.734	0.687	0.864	**0.924**
35%	0.701	0.685	0.850	**0.909**
40%	0.662	0.665	0.836	**0.892**
45%	0.611	0.612	0.816	**0.870**
50%	0.552	0.533	0.789	**0.834**

The corrupted image in Fig. 2(b) contains 30% salt and pepper noise. This is a difficult case for removing the impulse noise because the original image contains a set of dark regions and several large bright areas with many small black dots. As can be seen from Fig. 2, the TSAMFT and MDBUTMF failed in the dark and bright regions. The CEF can remove the impulse noise, but it is over denoised, which causes a lot of blur effects on image edges. Fig. 2 (f) shows that the propose SFA not only removes the impulse noise efficiently but also preserves the details in background and bright regions.

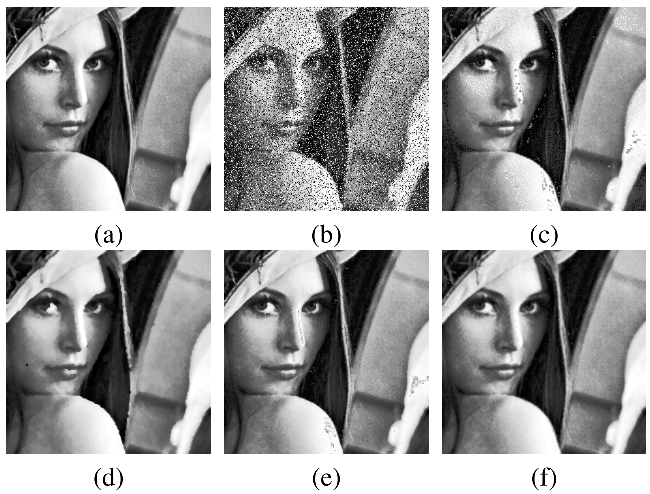

Fig. 3: Image restoration by using different filtering methods. (a)-(b) are the original and corrupted images; (c)-(f) are the restored images by applying different methods. (c) TSAMFT, (d) CEF, (e) MDBUTMF, (f) SFA.

To quantitatively evaluate the filtering performance, the peak signal to noise ratio (PSNR) and structural similarity (S-SIM) [12] are chosen to measure the restored results. Generally, the larger PSNR and SSIM value is, the better quality of the restored image will be.

The original image in Fig. 2(a) is corrupted by the salt and pepper noise with noise densities from 5% to 50%, respectively. The corrupted images are then processed by these four filtering methods. Table 1 shows the PSNR and SSIM scores of the restored results. As can be seen, the proposed SFA obtains the best values, which further demonstrates that the proposed SFA outperforms other three existing methods.

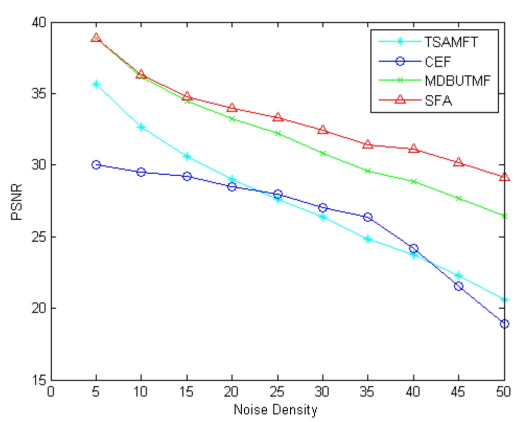

Fig. 4: PSNR measures of the restored results of different filtering methods.

The image in Fig. 3(a) is the 'face' image containing bright areas with pixel values close to 255 and dark area with pixel values equal to 0. So this is an another difficult case for salt and pepper noise removing. The corrupted image in Fig. 3(b) is generated by adding 30% salt and pepper noise to the original image in Fig. 3(a). As can be seen from the restored results, the TSAMFT and MDBUTMF fail to remove noise while bring additional distortions to the dark and bright areas. The CEF obtains a better restoration result but loses some details and edges. The proposed SFA removes the impulse noise while preserving the image edges and the detail information in the dark and bright areas.

Table 2: SSIM value of the Restoration Results of 'face' image for Different Filtering Methods

Noise	TSAMFT	CEF	MDBUTMF	SFA
5%	0.945	0.814	0.981	**0.982**
10%	0.903	0.809	0.969	**0.972**
15%	0.862	0.804	0.959	**0.961**
20%	0.829	0.796	0.946	**0.949**
25%	0.798	0.790	0.936	**0.937**
30%	0.758	0.780	0.921	**0.922**
35%	0.721	0.769	0.907	**0.911**
40%	0.667	0.748	0.889	**0.894**
45%	0.607	0.686	0.869	**0.873**
50%	0.529	0.626	0.843	**0.852**

Fig. 4 plots the PSNR measure of the restoration results of the 'face' image in Fig. 3(a) which was corrupted by the salt and pepper noise with noise densities varying from 5% to 50%, and Table 2 shows the corresponding SSIM scores. These quantitative results show that our proposed SFA gives the higher scores than the other three techniques.

5. CONCLUSION

This paper has introduced a novel selective filtering algorithm for image denoising. The new algorithm takes into account the relationship between image pixels and their neighborhoods. It adaptively segments the images into three different regions and then selects a specific filter to remove the impulse noise in each region. The propose SFA uses several simple filters to yield excellent denoising performance. Experimental results and comparisons have demonstrated that the proposed algorithm is able to efficiently remove the impulse noise while well preserving the edges, bright and dark areas in images. The proposed algorithm outperforms three existing denoising methods.

6. ACKNOWLEDGEMENT

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7. REFERENCES

[1] I. Pitas and A. N. Venetsanopoulos, *Nonlinear Digital Filters: Principles and Applications*, Kluwer, 1990.

[2] Rafael C. Gonzalez and Richard E. Woods, *Digital Image Processing*, Pearson Prentice Hall, 3 edition, 2008.

[3] D. R. K. Brownrigg, "The weighted median filter," *ACM Communication*, vol. 27, no. 8, pp. 807–818, 1984.

[4] S.-J. Ko and Y.H. Lee, "Center weighted median filters and their applications to image enhancement," *IEEE Transactions on Circuits and Systems*, vol. 38, no. 9, pp. 984–993, 1991.

[5] G.R. Arce and J.L. Paredes, "Recursive weighted median filters admitting negative weights and their optimization," *IEEE Transactions on Signal Processing*, vol. 48, no. 3, pp. 768–779, 2000.

[6] How-Lung Eng and Kai-Kuang Ma, "Noise adaptive soft-switching median filter," *IEEE Transactions on Image Processing*, vol. 10, no. 2, pp. 242–251, 2001.

[7] U. Ghanekar, A.K. Singh, and R. Pandey, "A contrast enhancement-based filter for removal of random valued impulse noise," *IEEE Signal Processing Letters*, vol. 17, no. 1, pp. 47–50, 2010.

[8] S. Esakkirajan, T. Veerakumar, A.N. Subramanyam, and C.H. PremChand, "Removal of high density salt and pepper noise through modified decision based unsymmetric trimmed median filter," *IEEE Signal Processing Letters*, vol. 18, no. 5, pp. 287–290, 2011.

[9] S. Kaisar, M. S. Rijwan, J. A. Mahmud, and M. M. Rahman, "Salt and pepper noise detection and removal by tolerance based selective arithmetic mean filtering technique for image restoration," *International Journal of Computer Science and Network Security*, vol. 8, no. 6, pp. 271–278, 2008.

[10] S. Deivalakshmi and P. Palanisamy, "Improved tolerance based selective arithmetic mean filter for detection and removal of impulse noise," in *2010 International Conference on Industrial and Information Systems (ICIIS)*, 2010, pp. 309–313.

[11] I. Aizenberg and C. Butakoff, "Effective impulse detector based on rank-order criteria," *IEEE Signal Processing Letters*, vol. 11, no. 3, pp. 363–366, 2004.

[12] Wang Zhou, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: from error visibility to structural similarity," *IEEE Transactions on Image Processing*, vol. 13, no. 4, pp. 600–612, 2004.