Improved Radiometric Based Method for Suppressing Impulse Noise from Corrupted Images

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Summary

A novel filter is introduced in this paper to improve the ability of radiometric based method on suppressing impulse noise. Firstly, a new method is introduced to design the impulsive weight by measuring how impulsive a pixel is. Then, the impulsive weight is combined with the radiometric weight to obtain the evaluated values on each pixel in the whole corrupted image. The impulsive weight is mainly designed to suppress the impulse noise, while the radiometric weight is mainly designed to protect the noise-free pixel. Extensive experiments demonstrate that the proposed algorithm can perform much better than other filters in terms of the quantitative and qualitative aspects.

Key words: radiometric, impulsive, noise, adaptively, filter

Introduction

Images are frequently corrupted by impulse noise that is generated in noisy sensors and communication channels [1]. Since the impulse noise may decrease the perceptual quality of the images, it is important to remove the impulse noise from the corrupted images before the subsequent image processing and analysis, e.g., edge detection, image segmentation, image retrieval and image compression. For a gray processing and analysis, e.g., edge detection, image segmentation, and noise-free pixel. Extensive experiments demonstrate that the proposed algorithm can perform much better than other filters in terms of the quantitative and qualitative aspects.

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1. Introduction

Images are frequently corrupted by impulse noise that is generated in noisy sensors and communication channels [1]. Since the impulse noise may decrease the perceptual quality of the images, it is important to remove the impulse noise from the corrupted images before the subsequent image processing and analysis, e.g., edge detection, image segmentation, image retrieval and image compression. For a gray

\[ u_{i,j} = \begin{cases} n_{i,j} & \text{with probability } p \\ s_{i,j} & \text{with probability } 1 - p \end{cases} \]

where \( n_{i,j} \) and \( s_{i,j} \) are the noise and the noise-free pixel value. For the fixed-valued noise, noise pixel \( n_{i,j} \) takes the value either 0 or 255, see [2]. For the random-valued noise, noise pixel \( n_{i,j} \) takes the random value in the range of \([0, 255]\), see [3]. Noise suppression on the random-valued impulse noise is much more difficult than that on the fixed-valued impulse noise because the gray difference between a noise and the noise-free pixel in the fixed-valued impulse noise is much more significant than that in the random-valued impulse noise. Therefore, this work is mainly designed to remove the random-valued impulse noise from the whole corrupted image.

Nonlinear filters have been successfully applied to smooth the impulse noise due to their good performances in edge preservation and noise rejection [4]. Among many classes of nonlinear filters, the median and order statistic based filters are well-known nonlinear filters for suppressing the impulse noise [5]–[10]. Despite their better efforts on smoothing the noise, they often tend to blur the fine details and alter the clean pixels. Therefore, switching based median filters are proposed to improve the performance of the median and order statistic based filters [11]–[17]. However, since the decision rule typically employs a single threshold for the whole image, the strategy of using such switching based filters may present difficulties in obtaining a robust decision measure, especially when the noise corruption is high.

Due to the large gray difference between the impulse noise and noise-free pixel, it has been proved that the radiometric based filters cannot suppress impulse noise [18]–[20]. Therefore, a new method is introduced to solve the drawbacks of the radiometric based filters. Firstly, a new method is introduced to design the impulsive weight by measuring how impulsive a pixel is. Then, the impulsive weight is combined with the radiometric weight to suppress the impulse noise and protect the noise-free pixel from the whole corrupted image. Several experimental results demonstrate that the proposed method can work much better than many other nonlinear filters in terms of the quantitative and qualitative aspects.

The outline of this paper is described as follows. Firstly, algorithm about the proposed method is introduced in Sect. 2. Secondly, simulation results between the proposed method and other compared methods are shown in Sect. 3. Finally, the conclusions are drawn in Sect. 4.

2. Algorithm about the Proposed Method

In this section, a new method is firstly introduced to design impulsive weight by measuring how impulsive a pixel is. Then, the radiometric weight and the impulsive weight is combined together to suppress the impulse noise and protect the noise-free pixels from the whole corrupted image.

2.1 New Method for Designing Impulsive Weight

Let \( x = (i, j) \) denote the coordinate of image \( u \), and let \( \Omega^{(N)}_{u_{i,j}} = \{(t + s, j + t) : -N \leq s, t \leq N; s, t \neq 0\} \) denote the neighbor positions about \( x \) in a filter window. For each filter window sized \((2N + 1) \times (2N + 1)\), the total number of

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neighbor positions is \((2N + 1)^2 - 1\). Figure 1 shows a \(3 \times 3\) filter window which will be used through this whole work with \(N = 1\).

Let \(c_x\) and \(f_x\) denote the number of “close” and “further” neighbor pixels which have the absolute gray differences to the center pixel \(u_x\) not-exceeding and exceeding threshold \(T\) [15], respectively. That is to say, \(c_x\) and \(f_x\) count these neighbor pixels, satisfying and un-satisfying the condition of \(|u_y - u_x| \leq T : y \in \Omega_{x,j}^{(N)}\), respectively. Here, threshold \(T\) is set as \(T = 5\) in the whole work, the same as the threshold \(d\) in [15]. Since there are \((2N + 1)^2 - 1\) neighbor positions in a filter window, the sum of \(c_x\) and \(f_x\) is \((2N + 1)^2 - 1\), i.e., \(f_x + c_x = (2N + 1)^2 - 1\). Since both of \(c_x\) and \(f_x\) lie in the integer range of \([1 : 8]\) when the filter window is sized \(3 \times 3\), \(m_x\), defined as follows, is used to measure how impulsive a pixel is:

\[
m_x = \begin{cases} 
\sum_{k=1}^{c_x} d_{(x,y)}^{(k)} & \text{if } c_x \geq f_x; \\
\sum_{k=c_x+1}^{8} d_{(x,y)}^{(k)} & \text{if } c_x < f_x; 
\end{cases}
\]

(2)

where \(d_{(x,y)}^{(k)}\) denote the \(k\)th smallest gray difference value \(d(x,y)\), i.e., \(d_{(x,y)}^{(1)} \leq d_{(x,y)}^{(2)} \leq \cdots \leq d_{(x,y)}^{(2(N+1)^2-2)} \leq d_{(x,y)}^{(2(N+1)^2-1)}\). \(d(x,y)\) is defined as the absolute gray difference between \(u_x\) and \(u_y\) as following:

\[
d(x,y) = |u_x - u_y| : y \in \Omega_{x,j}^{(N)}
\]

(3)

When the center of filter window is noise-free, \(c_x \geq f_x\) because many noise-free pixels in the neighbor positions have small gray differences between \(u_x\). Therefore, \(m_x\) will be small because Eq. (2) sums the small ascending-sorted absolute gray differences. Seen from an example of noise-free pixel in Fig. 2 (a), the ascending-sorted absolute gray differences, between \(u_x\) and \(u_y\) : \(y \in \Omega_{x,j}^{(1)}\), are {61, 62, 63, 64, 65, 66, 67, 68}. \(c_x = 0\) and \(f_x = 3\) when \(T = 5\). Since \(c_x < f_x\), \(m_x = 1 + 2 + 3 + 4 + 5 = 15\) according to Eq. (2).

When the center of filter window is corrupted by impulse noise, \(c_x < f_x\) because many noise-free pixels in the neighbor positions have large gray differences between \(u_x\). Therefore, \(m_x\) will be large because Eq. (2) sums the large ascending-sorted absolute gray differences. Seen from an example of the noise pixel in Fig. 2 (b), the ascending-sorted absolute intensity differences, between \(u_x\) and \(u_y\) : \(y \in \Omega_{x,j}^{(1)}\), are {61, 62, 63, 64, 65, 66, 67, 68}. \(c_x = 0\) and \(f_x = 8\) when \(T = 5\). Since \(c_x < f_x\), \(m_x = 61 + 62 + 63 + 64 + 65 + 66 + 67 + 68 = 516\) according to Eq. (2).

From the above discussion, Eq. (2) make large value on the impulse noise and small value on the noise-free pixel in the whole corrupted image. Figure 3 displays the mean measurement \(m_x\) on Lena and Peppers images, corrupted by

![Fig. 1](image1.png) 3 \times 3\) filter window used through this work.

![Fig. 2](image2.png) Examples about the noisy and noise-free pixels: (a) noise-free pixel; (b) noisy pixel.

![Fig. 3](image3.png) Mean measurements of the proposed method on the noisy and noise-free pixels for the Lena and Peppers images corrupted by random-valued impulse noise with different corruption ratios: (a) Lena; (b) Peppers.
random-valued impulse noise with different ratios. The upper dashed and lower solid lines represent the mean measurement for the noise and noise-free pixels, respectively. Seen from Fig. 3, the noise pixels consistently have much higher mean values than the noise-free pixels, especially when the image is lightly corrupted. It would be relatively simple to introduce this measurement \( m_x \) into many existing filtering techniques, allowing them to detect the impulse noise in a noise image. Below it is used to design the impulsive weight \( \omega I(x) \) as following:

\[
\omega I(x) = e^{-\frac{m_x^2}{\sigma_I^2}} \tag{4}
\]

where \( \sigma_I \) parameter determines the approximate threshold above which to penalize the high \( m_x \) value. Seen from Eq. (4), since \( m_x \) on the noise and noise-free pixel is large and small respectively according to Eq. (2), their corresponding impulsive weight \( \omega I(x) \) will be small and large as the result.

2.2 Reviewing Radiometric Weight

As described in [18], radiometric weight \( \omega R(x, y) \) between \( x \) and its neighbors \( y \in \Omega_{i,j}^{(N)} \) is defined as follows:

\[
\omega R(x, y) = e^{-\frac{1}{2} \left( \frac{m_x - m_y}{\sigma_R} \right)^2} \tag{5}
\]

where \( \sigma_R \) parameter determines the approximate threshold above which to penalize the gray difference between \( u_x \) and \( u_y \) in the filter window. When the center of filter window is noise-free, since noise-free pixels in the neighbor positions have small gray differences between \( u_x \) and \( u_y \), \( \omega R(x, y) \) will be large and \( u_y \) cannot be smoothed out by weighting these noise-free pixels heavily with such large \( \omega R(x, y) \) values. When the center of filter window is corrupted by impulse noise, since noise-free pixels in the neighbor positions have large gray differences between \( u_x \), \( \omega R(x, y) \) will be small and \( u_y \) cannot be smoothed out by weighting these noise-free pixels lightly with such small \( \omega R(x, y) \) values. For example, let us consider a filter window with black impulse noise in the center and the white pixels in several neighbor positions. Due to the large gray differences between \( u_x \) and \( u_y \), \( \omega R(x, y) \) will be small and the center black impulse noise may remain black impulse when the white pixels in the neighbor positions are lightly weighted by such small \( \omega R(x, y) \) values.

2.3 Weight Function of the Proposed Method

Let \( \omega(x, y) \) denote the proposed weight between the center pixel \( u_x \) and its neighbors \( u_y : y \in \Omega_{i,j}^{(N)} \) in the filter window, and let \( o_{i,j} \) denote the proposed output as following:

\[
o_{i,j} = \frac{\sum_{y \in \Omega_{i,j}^{(N)}} \omega(x, y) u_y}{\sum_{y \in \Omega_{i,j}^{(N)}} \omega(x, y)} \tag{6}
\]

where

\[
\omega(x, y) = \omega R(x, y)^{1-J(x,y)} \omega I(y)^{J(x,y)} \tag{7}
\]

where \( J(x, y) = 1 - e^{-(\max(m_x, m_y))^2/2\sigma^2} \) \tag{8}

where \( \sigma_I \) parameter determines the approximate threshold above which to penalize the measurement between the center pixel and its neighbors in the filter window.

When the center of filter window is corrupted by impulse noise, \( m_x \) is large according to Eq. (2) and weights between its neighbors \( \omega(x, y) : y \in \Omega_{i,j}^{(N)} \) can be described as following:

(1) For the noise pixel \( u_y \) in neighbor position, since \( m_x \) and \( m_y \) are both large as described in Eq. (2), \( J(x, y) \approx 1 \) and \( 1 - J(x, y) \approx 0 \) according to Eq. (8). Then, \( \omega R(x, y)^{1-J(x,y)} \approx 1 \), \( \omega I(y)^{J(x,y)} \approx \omega I(y) \) and \( \omega(x, y) \approx \omega I(y) \) according to Eq. (7). Since \( m_y \) is large, \( \omega I(y) \) will be so large according to Eq. (4) that noise pixel will be weighted lightly to the output value \( o_{i,j} \) according to Eq. (6).

(2) For the noise-free pixel \( u_y \) in neighbor position, although \( m_y \) is small as described in Eq. (2), \( m_x \) is large. Therefore, \( J(x, y) \approx 1 \) and \( 1 - J(x, y) \approx 0 \) according to Eq. (8). Then, \( \omega R(x, y)^{1-J(x,y)} \approx 1 \), \( \omega I(y)^{J(x,y)} \approx \omega I(y) \) and \( \omega(x, y) \approx \omega I(y) \) according to Eq. (7). Since \( m_y \) is small, \( \omega I(y) \) will be so large according to Eq. (4) that noise-free will be weighted heavily to the output value \( o_{i,j} \) according to Eq. (6).

From above all, when the center of filter window is corrupted by impulse noise, noise-free pixels in some neighbor positions will be weighted heavily by their corresponding large impulsive weight, and noise pixels in the other neighbor positions will be weighted lightly by their corresponding small impulsive weight. Therefore, impulse noise can be smoothed out by the proposed weight algorithm in Eq. (7). When the center of filter window is noise-free, \( m_x \) is small according to Eq. (2) and weights between its neighbors \( \omega(x, y) : y \in \Omega_{i,j}^{(N)} \) can be described as following:

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noise-free, noise-free pixels in some neighbor positions will be weighted heavily by their corresponding large radiometric weights, and noise pixels in the other neighbor positions will be weighted lightly by their corresponding small impulsive weights. Therefore, noise-free pixel can be protected very well by the proposed weight algorithm in Eq. (7).

3. Simulation Experiments

In the whole experiment, the performances on suppressing noise and preserving details are evaluated in terms of two quantitative criteria: the peak signal to noise ratio (PSNR) in the units (dB):

$$\text{PSNR} = 10 \log_{10} \frac{255^2}{\frac{1}{HW} \sum_{i} \sum_{j} [s_{i,j} - o_{i,j}]^2},$$

and the mean absolute error (MAE):

$$\text{MAE} = \frac{1}{HW} \sum_{i} \sum_{j} |s_{i,j} - o_{i,j}|.$$

where $s_{i,j}$ and $o_{i,j}$ in Eqs. (9) and (10) are the original noise-free pixel value the output value of the proposed method, respectively; $H$ and $W$ are the image height and width, respectively.

In this section, the whole experiment is tested through various $512 \times 512$ standard images (Lena, Lake, Peppers, Boat, Man, Bridge, Baboon), corrupted by the random-valued impulse noise with ratios from 20% to 50%, and the proposed method is compared with several other nonlinear filters, such as the median (MED) filter [5], the new switching median (NSM) filter [14], the pixel wise median absolute deviation (PWMAD) filter [16], and Trilateral filter [19]. The primary difficulty associated with the proposed approach is the selection of the thresholds. From simulations conducted on a broad variety of images, it can be observed that the $\sigma_R$ in Eq. (5), the $\sigma_I$ in Eq. (4), and the $\sigma_J$ in Eq. (8) can be taken as 40, 50 and 50 respectively as the simulation parameters. However, in the future work, other methods are explored to automatically choose the control parameters $\sigma_R$, $\sigma_I$ and $\sigma_J$ locally.

| Table 1 | PSNR and MAE values about the proposed filter and the compared methods for the standard images corrupted by 20% random-valued impulse noise. |
|---------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Lena    | Lake | Pepper | Boat | Man | Bridge | Baboon |
| PSNR    | MED  | 32.51  | 27.95 | 31.06 | 28.49 | 29.47 | 25.17 | 23.99 |
|         | PWMAD | 32.13  | 26.94 | 31.27 | 27.26 | 28.62 | 24.17 | 23.12 |
|         | ACWM  | 33.77  | 28.71 | 31.86 | 28.89 | 30.01 | 25.51 | 24.31 |
|         | NSM   | 32.47  | 29.07 | 31.78 | 29.41 | 30.26 | 26.67 | 25.71 |
|         | Trilateral | 33.36 | 28.28 | 31.86 | 28.21 | 26.99 | 26.64 | 23.51 |
|         | Proposed | 34.11 | 30.12 | 32.14 | 29.75 | 30.52 | 27.21 | 26.14 |
| MAE     | MED  | 2.91   | 5.65  | 3.71  | 5.23  | 4.31  | 8.34  | 10.02 |
|         | PWMAD | 3.25   | 6.56  | 3.87  | 6.17  | 5.16  | 10.05 | 11.76 |
|         | ACWM  | 2.63   | 3.54  | 2.96  | 3.28  | 2.66  | 6.21  | 7.75  |
|         | NSM   | 2.64   | 2.88  | 2.84  | 2.61  | 2.27  | 4.21  | 5.06  |
|         | Trilateral | 3.26 | 3.11  | 3.07  | 2.87  | 2.98  | 4.44  | 5.23  |
|         | Proposed | 2.45 | 2.51  | 2.61  | 2.37  | 2.01  | 4.01  | 4.77  |

| Table 2 | PSNR and MAE values about the proposed filter and the compared methods for the standard images corrupted by 40% random-valued impulse noise. |
|---------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Lena    | Lake | Pepper | Boat | Man | Bridge | Baboon |
| PSNR    | MED  | 32.52  | 27.94 | 31.06 | 28.49 | 29.47 | 25.17 | 23.99 |
|         | PWMAD | 32.13  | 26.94 | 31.27 | 27.26 | 28.62 | 24.17 | 23.12 |
|         | ACWM  | 33.77  | 28.71 | 31.86 | 28.89 | 30.01 | 25.51 | 24.31 |
|         | NSM   | 32.47  | 29.07 | 31.78 | 29.41 | 30.26 | 26.67 | 25.71 |
|         | Trilateral | 33.36 | 28.28 | 31.86 | 28.21 | 26.99 | 26.64 | 23.51 |
|         | Proposed | 34.11 | 30.12 | 32.14 | 29.75 | 30.52 | 27.21 | 26.14 |
| MAE     | MED  | 2.91   | 5.65  | 3.71  | 5.23  | 4.31  | 8.34  | 10.02 |
|         | PWMAD | 3.25   | 6.56  | 3.87  | 6.17  | 5.16  | 10.05 | 11.76 |
|         | ACWM  | 2.63   | 3.54  | 2.96  | 3.28  | 2.66  | 6.21  | 7.75  |
|         | NSM   | 2.64   | 2.88  | 2.84  | 2.61  | 2.27  | 4.21  | 5.06  |
|         | Trilateral | 3.26 | 3.11  | 3.07  | 2.87  | 2.98  | 4.44  | 5.23  |
|         | Proposed | 2.45 | 2.51  | 2.61  | 2.37  | 2.01  | 4.01  | 4.77  |

| Table 3 | PSNR and MAE values about the proposed filter and the compared methods for the standard images corrupted by 50% random-valued impulse noise. |
|---------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Lena    | Lake | Pepper | Boat | Man | Bridge | Baboon |
| PSNR    | MED  | 32.51  | 27.95 | 31.06 | 28.49 | 29.47 | 25.17 | 23.99 |
|         | PWMAD | 32.13  | 26.94 | 31.27 | 27.26 | 28.62 | 24.17 | 23.12 |
|         | ACWM  | 33.77  | 28.71 | 31.86 | 28.89 | 30.01 | 25.51 | 24.31 |
|         | NSM   | 32.47  | 29.07 | 31.78 | 29.41 | 30.26 | 26.67 | 25.71 |
|         | Trilateral | 33.36 | 28.28 | 31.86 | 28.21 | 26.99 | 26.64 | 23.51 |
|         | Proposed | 34.11 | 30.12 | 32.14 | 29.75 | 30.52 | 27.21 | 26.14 |
| MAE     | MED  | 2.91   | 5.65  | 3.71  | 5.23  | 4.31  | 8.34  | 10.02 |
|         | PWMAD | 3.25   | 6.56  | 3.87  | 6.17  | 5.16  | 10.05 | 11.76 |
|         | ACWM  | 2.63   | 3.54  | 2.96  | 3.28  | 2.66  | 6.21  | 7.75  |
|         | NSM   | 2.64   | 2.88  | 2.84  | 2.61  | 2.27  | 4.21  | 5.06  |
|         | Trilateral | 3.26 | 3.11  | 3.07  | 2.87  | 2.98  | 4.44  | 5.23  |
|         | Proposed | 2.45 | 2.51  | 2.61  | 2.37  | 2.01  | 4.01  | 4.77  |
3.1 Quantity Comparison

In order to show the better quantitative performance of the proposed algorithm, Tables 1 to 3 list the PSNR and the MAE results of the proposed algorithm and the compared methods on the test images, corrupted by the random-valued impulse noise with ratios of $p = 20\%$, $40\%$, and $50\%$, respectively.

Seen from Table 1, the proposed filter can work better than the classical filter in terms of MAE and PSNR values when the noise corruption is low. However, when the noise corruption is high in Tables 2 to 3, the proposed filter can still give much better restoration results than the classical filter. Therefore, the proposed filter can work better than the classical filter in the quantitative aspects no matter how high the noise corruption is. Compared with other existing filters, although they can give the comparable restoration results as the proposed filter when noise corruption is low in Table 1, the proposed filter can give much better performance on both PSNR and MAE values when the noise corruption is high in Tables 2 to 3.

![Fig. 4](image1.png)  ![Fig. 5](image2.png)

**Fig. 4** Visual restoration results of the proposed method and the compared filters on standard testing image: (a) original image Peppers; (b) corrupted image with 40\% random-valued impulse noise; (c) MED with MAE = 7.31; (d) PWMAD with MAE = 5.31; (e) ACWM with MAE = 5.86; (f) NSM with MAE = 5.81; (g) Trilateral with MAE = 4.94; (h) proposed algorithm with MAE = 4.71.

**Fig. 5** Visual restoration results of the proposed method and the compared filters on standard testing image: (a) original image Boat; (b) corrupted image with 60\% random-valued impulse noise; (c) MED with MAE = 11.76; (d) PWMAD with MAE = 9.29; (e) ACWM with MAE = 10.54; (f) NSM with MAE = 10.48; (g) Trilateral with MAE = 8.19; (h) proposed algorithm with MAE = 7.97.
3.2 Quality Comparison

Figures 4 and 5 compare the qualitative restoration performances about the proposed algorithm and the compared algorithms for the images Peppers and Boat, corrupted by the random-valued impulse noise with $p = 40\%$ and $60\%$. Seen from these filtered figures, the proposed algorithm outputs the best visual quality with fewest spots and has the best details preservation by the smallest MAE values results. Therefore, the proposed algorithm can give best performance among these compared filters in terms of the qualitative aspects.

As shown in Fig. 6, we use two real images, obtained from the Kodak company, to compare the proposed algorithm with other methods on visual restoration performance. Figures 7 and 8 give their qualitative restoration performances for the random-valued impulse noise with corruption of $40\%$ and $60\%$. We can get the same visual restorations as that on the standard testing images. Therefore, the proposed algorithm can achieve the satisfied visual restorations among these compared methods no matter whether on the standard testing images or on the real images.

4. Conclusions

The radiometric based method is improved to suppress the impulse noise while protecting the noise-free pixel from the corrupted image. Firstly, a new method is introduced to design impulsive weight by measuring how impulsive a pixel is. Then, the impulsive weight is combined with the radiometric weight to evaluate both the noise and the noise-free pixel in the whole corrupted image. Experimental results on the standard and real images show that the proposed filter can perform much better than many classical and existing filters in terms of the quantitative and qualitative aspects.

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Fig. 6 Two real images obtained from the Kodak company: (a) Balloons; (b) Bleed hearts.

Fig. 7 Visual restoration results of the proposed algorithm and compared filters on the real image: (a) original image Bleed hearts; (b) corrupted image with 40\% random-valued impulse noise; filtered images by (c) MED; (d) PWMAD; (e) ACWM; (f) NSM; (g) Trilateral; (h) proposed algorithm.
Fig. 8 Visual restoration results of the proposed algorithm and compared filters on the real image: (a) original image Balloons; (b) corrupted image with 60% random-valued impulse noise; filtered images by (c) MED; (d) PWMAD; (e) ACWM; (f) NSM; (g) Trilateral; (h) proposed algorithm.

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