Improved Neighborhood Based Switching Filter for Protecting the Thin Curves in Arbitrary Direction in Color Images

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SUMMARY Although the classical vector median filter (VMF) has been widely used to suppress the impulse noise in the color image, many thin color curve pixels aligned in arbitrary directions are usually removed out as impulse noise. This serious problem can be solved by the proposed method that can protect the thin curves in arbitrary direction in color image and remove out the impulse noise at the same time. Firstly, samples in the 3x3 filter window are considered to preliminarily detect whether the center pixel is corrupted by impulse noise or not. Then, samples outside a 5x5 filter window are conditionally and partly considered to accurately distinguish the impulse noise and the noise-free pixel. At last, based on the previous outputs, samples on the processed positions in a 3x3 filter window are chosen as the samples of VMF operation to suppress the impulse noise. Extensive experimental results indicate that the proposed algorithm can be used to remove the impulse noise of color image while protecting the thin curves in arbitrary directions.

key words: impulse noise, color image, thin curve, arbitrary direction

1. Introduction

Images are often corrupted by the impulse noise due to a noisy sensor or channel transmission error [1]. Since subsequent image processing, such as edge detection, image segmentation, and object tracking, might get worse if the input image contains impulse noise, it is important to suppress the impulse noise in the whole image. For the fixed-valued impulse noise, a noisy value takes the value of 0 or 255, while in the random-valued impulse noise, noisy intensity is uniformly distributed within the range of [0, 255] [2]. Usually, since the random-valued impulse noise is considered a more realistic model of impulse noise in the real word, this work is mainly designed to suppress the random-valued impulse noise.

For color image noise filtering methods [3–23], since vector based method considers the inherent correlations between each color channel, many classical vector filters are proposed to protect the chromaticity in suppressing impulse noise. Classical vector based methods, including the vector median filter (VMF) [15], the basic vector directional filter (BVDF) [16], and the directional distance filter (DDF) [17] are realized through ordering vectors in a sliding filter window. However, since these classical filters are implemented uniformly across the whole image, they tend to modify both the impulse noise and the noise-free pixels. Therefore, switching based algorithms, such as the adaptive vector median filter (AVMF) [18], the fast peer group filter (FPGF) [19], the switching vector median filter (SVMF) [20], the switching non-local vector median filter (SNVMF) [22], the fuzzy weighted non-local means filter (FWMNMF) [23], use the measured value on each pixel to detect whether the center pixel is corrupted by impulse noise: if it is found to be noise, then it is replaced; otherwise unchanged. In particular, the fuzzy weighted non-local means filter (FWMNLW) is an extension of the non-local means filter and can be used to remove a mixture of Gaussian noise and impulse noise.

Directional operators, based from normal filtering windows, have been widely used as noise detection mechanism of many switching filters. For example: FPGF detects the impulse noise by counting the pixels which have similar vector distance between the center pixel and its eight neighboring positions, while SVMF detects the impulse noise by comparing the color distance between the center pixel and other samples in each directional operator. However, since they do not usually fully consider each pixel in a 5 × 5 filtering window, filtering performance on detail preservation may not be fully satisfied while removing the impulse noise. In one word, almost none of the above mentioned filters can distinguish the arbitrary direction thin lines and impulse noise.

This paper designed a new switching based mechanism to avoid the drawback of the conventional directional operators. Firstly, samples in the 3x3 filter window are preliminarily considered to detect whether the center pixel is corrupted by impulse noise or not. Then, samples outside a 5 × 5 filter window are conditionally considered to accurately detect the impulse noise. At last, based on the previous outputs, samples on the processed positions in a 3 × 3 filter window are chosen as the samples of VMF operation to suppress the impulse noise. Extensive experimental results indicate that the proposed algorithm can be used to remove the impulse noise of color image while protecting the thin curves in arbitrary directions. The outline of this paper is described as follows: Firstly, some special algorithms are reviewed in Sect. 2. Secondly, the proposed method is introduced in Sect. 3. Then, simulation results between the proposed method and other compared methods are shown in Sect. 4. Finally, the conclusions are drawn in Sect. 5.
2. Direction Operator Based Noise Detection Algorithms

Let \( \{(i, j) | 1 \leq i \leq H, 1 \leq j \leq W \} \) be the pixel coordinate of an RGB image, where \( H \) and \( W \) denote the image height and width. At each location \((i, j)\), let \( \Omega_{W}^i \) denote the filter window of size \((2N+1) \times (2N+1)\), i.e., \( \Omega_{W}^i = \{x_{i,j} : -N \leq s - i, t - j \leq N\} \). Figure 1 shows four conventional directional operators by the angle of 0, 45, 90 and 135 degree, respectively. Let \( K_p \), \( p = 1, 2, 3, 4 \) denote the pixels aligned in each direction operator.

\[
\begin{align*}
K_1 &= \{x_{i,j-2}, x_{i,j-1}, x_{i,j}, x_{i,j+1}, x_{i,j+2}\} \\
K_2 &= \{x_{i+2,j-2}, x_{i+1,j-1}, x_{i,j}, x_{i-1,j+1}, x_{i-2,j+2}\} \\
K_3 &= \{x_{i-2,j}, x_{i,j-1}, x_{i,j}, x_{i+1,j}, x_{i+2,j}\} \\
K_4 &= \{x_{i-2,j-2}, x_{i-1,j-1}, x_{i,j}, x_{i+1,j+1}, x_{i+2,j+2}\} \\
\end{align*}
\]

The above directional operators have been used by many switching based algorithms to detect whether the center pixel is corrupted by impulse noise. For examples of FPGF filter and SVMF filter in the later discussion.

2.1 Reviewing the Noise Detection Mechanism of FPGF

FPGF takes pixel \( x_{i,j} \) and \( x_{s,j} \) close to each other if their color distance \( \|x_{i,j} - x_{s,j}\|_2 \) is less than a set threshold. When \( x_{i,j} \) is uncorrupted by impulse noise, many close pixels can be found in its eight neighbor positions. On the other hand, \( \Omega_{W}^i \) includes few close pixels when \( x_{i,j} \) is corrupted by impulse noise. Therefore, if the number of close pixels of \( x_{i,j} \) in \( \Omega_{W}^i \) is large, FPGF detects \( x_{i,j} \) as noise free. However, not all of the noise-free pixels have many close samples in its eight neighboring positions of \( \Omega_{W}^i \). For the detail pixel examples of Fig. 2 (a) and Fig. 2 (b), since both the center pixels have only two close pixels in their eight neighboring positions, \( x_{i,j} \) are both error detected as impulse noise. This means that the FPGF has some drawback in protecting the noise-free pixel.

2.2 Reviewing the Noise Detection Mechanism of SVMF

According to Eq. (1), for convenience, let the five pixels samples in \( K_p \) be \( x \{x_{(p,1)}, x_{(p,2)}, x_{(p,3)}, x_{(p,4)}\} \). For the current pixel and the samples in each operator, the average color distance can be obtained as:

\[
\text{LineDiff}(K_p) = \frac{1}{4} \sum_{l=1}^{4} \text{ColorDiff}(x_{i,j}, x_{(p,l)})
\]

where ColorDiff\((x_{i,j}, x_{(p,l)})\) is the color distance between two pixels in CIELAB space. The noise detector of SVMF compares the minimum value of directional operators, i.e., \( \min[\text{LineDiff}(K_p)] \): \( p = 1, 2, 3, 4 \), with a threshold. If the minimum average value is less than a set threshold, \( x_{i,j} \) will be detected as noise free. However, since all direction operators do not consider \( \{x_{i-2,j-1}, x_{i-2,j+1}, x_{i-1,j+2}, x_{i+1,j-2}, x_{i+1,j+2}, x_{i+2,j-1}, x_{i+2,j+1}, x_{i-1,j-2}\} \) if these unconsidered pixels have vital influence to the noise detection performance, the noise detection results may not be fully satisfied. According to Eq. (2), for the detail example of Fig. 2 (a) and Fig. 2 (b), \( K_2 \) and \( K_3 \) can obtain the minimum color vector distance respectively. Seen from samples of \( K_2 \) in Fig. 2 (a) and samples of \( K_3 \) in Fig. 2 (b), since both operators have two small and two big color distance with \( x_{i,j} \), the average color distance will be still large to make \( x_{i,j} \) both error detected as impulse noise. This also means that SVMF has some drawback in protecting the noise-free pixel.

3. Algorithm about the Proposed Method

3.1 New Defined Filtering Window

Usually, many switching based algorithms use the original samples in a filtering window to detect the impulse noise, if pixels in the processed positions are noise, they will badly affect the filtering performance. Instead, due to that the

![Fig. 1](image1)

![Fig. 2](image2)
noise. Therefore, we define a new filtering window \( \tilde{\Omega}_{i,j}^2 \) respectively.

The noisy pixels in the half part of the window at the proposed position can be replaced by their filtering results. Then, we can lessen their bad effects in detecting impulse noise. Therefore, we define a new filtering window \( \tilde{\Omega}_{i,j}^2 \) in Fig. 3(b) by combing the processed positions and the later filtered positions in \( \Omega_{i,j}^2 \). Compared with \( \Omega_{i,j}^2 \) in Fig. 3(a),
\[
\{ x_{i-1,j-1}; x_{i-1,j}; x_{i-1,j+1}; x_{i-1,j+2}; x_{i-1,j+3}; x_{i-1,j+4}; x_{i-1,j+5}; x_{i-1,j+6}; x_{i-1,j+7}; x_{i-1,j+8} \}
\]

have been filtered as
\[
\{ y_{i-2,j-1}; y_{i-2,j}; y_{i-2,j+1}; y_{i-2,j+2}; y_{i-2,j+3}; y_{i-2,j+4}; y_{i-2,j+5}; y_{i-2,j+6}; y_{i-2,j+7}; y_{i-2,j+8} \}.
\]

Seen from Fig. 3(b), let \( \tilde{\Omega}_{i,j}^1 \), with the blue background, denote the eight neighbors of \( x_{i,j} \), and let \( \tilde{\Omega}_{i,j}^2 \), with dotted line background, denote the outside pixels of \( \tilde{\Omega}_{i,j}^2 \) as follows:
\[
\tilde{\Omega}_{i,j}^1 = \left\{ y_{i-1,j-1}; y_{i-1,j}; y_{i-1,j+1}; y_{i-1,j+2}; y_{i-1,j+3}; y_{i-1,j+4}; y_{i-1,j+5}; y_{i-1,j+6}; y_{i-1,j+7}; y_{i-1,j+8} \right\}
\]
\[
\tilde{\Omega}_{i,j}^2 = \left\{ y_{i-2,j-1}; y_{i-2,j}; y_{i-2,j+1}; y_{i-2,j+2}; y_{i-2,j+3}; y_{i-2,j+4}; y_{i-2,j+5}; y_{i-2,j+6}; y_{i-2,j+7}; y_{i-2,j+8} \right\}
\]

For eight samples in \( \tilde{\Omega}_{i,j}^1 \), clockwise from \( y_{i-1,j-1} \) to \( y_{i-1,j+8} \) around \( x_{i,j} \), let \( W_{i,j}^n \), \( n = 1, 2, 3, 4, 5, 6, 7, 8 \) denote its neighbors in \( \tilde{\Omega}_{i,j}^2 \). Figure 4(a) to 4(h) show the structure of \( W_{i,j}^1 \), \( W_{i,j}^2 \), \( W_{i,j}^3 \), \( W_{i,j}^4 \), \( W_{i,j}^5 \), \( W_{i,j}^6 \), \( W_{i,j}^7 \), and \( W_{i,j}^8 \) respectively.

\[
W_{i,j}^1 = \left\{ y_{i-1,j-1}; y_{i-1,j}; y_{i-1,j+1}; y_{i-1,j+2}; y_{i-1,j+3}; y_{i-1,j+4}; y_{i-1,j+5}; y_{i-1,j+6}; y_{i-1,j+7}; y_{i-1,j+8} \right\}
\]
\[
W_{i,j}^2 = \left\{ y_{i-2,j-1}; y_{i-2,j}; y_{i-2,j+1}; y_{i-2,j+2}; y_{i-2,j+3}; y_{i-2,j+4}; y_{i-2,j+5}; y_{i-2,j+6}; y_{i-2,j+7}; y_{i-2,j+8} \right\}
\]
\[
W_{i,j}^3 = \left\{ y_{i-1,j-1}; y_{i-1,j+1}; y_{i-1,j+2}; y_{i-1,j+3}; y_{i-1,j+4}; y_{i-1,j+5}; y_{i-1,j+6}; y_{i-1,j+7}; y_{i-1,j+8} \right\}
\]
\[
W_{i,j}^4 = \left\{ y_{i-2,j+1}; y_{i-2,j+2}; y_{i-2,j+3}; y_{i-2,j+4}; y_{i-2,j+5}; y_{i-2,j+6}; y_{i-2,j+7}; y_{i-2,j+8} \right\}
\]
\[
W_{i,j}^5 = \left\{ y_{i-1,j-1}; y_{i-1,j+1}; y_{i-1,j+2}; y_{i-1,j+3}; y_{i-1,j+4}; y_{i-1,j+5}; y_{i-1,j+6}; y_{i-1,j+7}; y_{i-1,j+8} \right\}
\]
\[
W_{i,j}^6 = \left\{ x_{i,j-1}; x_{i,j+1}; x_{i,j+2}; x_{i,j+3}; x_{i,j+4}; x_{i,j+5}; x_{i,j+6}; x_{i,j+7}; x_{i,j+8} \right\}
\]
\[
W_{i,j}^7 = \left\{ y_{i-1,j-1}; y_{i-1,j+1}; y_{i-1,j+2}; y_{i-1,j+3}; y_{i-1,j+4}; y_{i-1,j+5}; y_{i-1,j+6}; y_{i-1,j+7}; y_{i-1,j+8} \right\}
\]
\[
W_{i,j}^8 = \left\{ x_{i,j-1}; x_{i,j+1}; x_{i,j+2}; x_{i,j+3}; x_{i,j+4}; x_{i,j+5}; x_{i,j+6}; x_{i,j+7}; x_{i,j+8} \right\}
\]

### 3.2 Noise Detection Mechanism

Similar to FPGA, pixel \( x_{i,j} \) and \( x_{s,t} \) can be seen close to each other if their color distance \( ||x_{i,j} - x_{s,t}||_2 \) are less than the set threshold \( d \). Main steps of the proposed noise detection are described as follows:

**Step1:** Considering the close pixels of \( x_{i,j} \) in \( \tilde{\Omega}_{i,j}^1 \) first. A conclusion can be drawn that \( x_{i,j} \) is corrupted by impulse noise if none of the close samples can be found in \( \tilde{\Omega}_{i,j}^1 \).

Otherwise, the existence of close pixels in \( W_{i,j}^n \) should be
the propose method if \( x_{i+1,j} \) is a close pixel;

(7). Figure 4 (g) shows that positions of \((i + 2, j - 1)\) and 
\((i + 1, j - 2)\), marked green background, are considered by
the propose method if \( x_{i+1,j-1} \) is a close pixel;

(8). Figure 4 (h) shows that positions of \((i + 1, j - 2)\) and 
\((i - 1, j - 2)\), marked green background, are considered by
the propose method if \( y_{i-1,j} \) is a close pixel;

Considering a general pixel, if the pixels on these un-
considered positions, marked green background, have vital
relation to \( x_{i,j} \), better noise detection results can be obtained
by proposed method:

1. Considering the example in Fig. 2 (a), \( y_{i-1,j+1} \) and \( x_{i+1,j-1} \) are two close pixels of \( x_{i,j} \) in \( \Omega_{i,j} \). \( y_{i-1,j+1} \) is the close pixel of \( y_{i-1,j} \) in \( W_{i,j}^{4} \), while \( x_{i+1,j-2} \) is the close pixel of \( x_{i+1,j-1} \) in \( W_{i,j}^{5} \). both conclusions making \( x_{i,j} \) recognized as noise free
according to Eq. (6), detecting the detail information as noise
free better when compared with the FPGF and SVMF in Sect. 2.

2. Considering the example in Fig. 2 (b), \( y_{i-1,j-1} \) and \( x_{i+1,j+1} \) are two close pixels of \( x_{i,j} \) in \( \Omega_{i,j} \). \( y_{i-1,j-2} \) is the close pixel of
\( y_{i-1,j-1} \) in \( W_{i,j}^{1} \), while \( x_{i+1,j+2} \) is the close pixel of \( x_{i+1,j+1} \) in \( W_{i,j}^{5} \). both conclusions making \( x_{i,j} \) recognized as noise
free according to Eq. (6), detecting the detail information as noise
free better when compared with the FPGF and SVMF in Sect. 2.

3.3 Noise Cancelation Method

Many switching based filters use the VMF operation directly on
the samples of \( \Omega_{i,j} \) to obtain the noise suppression result
\( V_{i,j}^{VMF} \).

\[
V_{i,j}^{VMF} = VMF(\Omega_{i,j}^{1})
= \arg \min \left\{ \sum_{p=1}^{1} \sum_{q=1}^{1} ||x_{i+p,j+q} - x_{i,j}||_{2} \right\}
\]  

(7)

where \( || \bullet ||_{2} \) denotes the \( L_{2} \) norm between two color vec-
tors and \( VMF \) denotes operation of obtaining vector median
from a set of samples in the filtering window. However, noise
cancelation result is not always perfect if too many noisy
pixels exist in the filtering window. To eliminate the
negative efforts of noisy pixels in obtaining noise cancela-
tion results, only noise free pixels are used as the samples of
noise cancelation result. This procedure ensures that noise
cancelation result will not be affected by the noise. In \( \Omega_{i,j}^{1} \),
since \( \{x_{i-1,j-1}, x_{i-1,j}, x_{i-1,j+1}, x_{i-1,j+1}\} \) have been processed as \( \{y_{i-1,j-1}, y_{i-1,j}, y_{i-1,j+1}, y_{i-1,j+1}\} \) when obtaining the noise cancela-
tion result, similar to the noise cancelation mechanism of
many switching based methods, we use \( \Omega_{i,j}^{1} \), including the previous outputs \( \{y_{i-1,j-1}, y_{i-1,j}, y_{i-1,j+1}, y_{i-1,j+1}\} \) and the later processed pixels \( \{x_{i,j+1}, x_{i+1,j-1}, x_{i+1,j}, x_{i+1,j+1}\} \), as the samples of VMF operation to obtain the noise cancelation result:

\[
m_{i,j} = VMF(\Omega_{i,j}^{1}) = VMF \left\{ y_{i-1,j-1}, y_{i-1,j}, y_{i-1,j+1}, 
\{y_{i-1,j-1}, y_{i-1,j}, y_{i-1,j+1}, y_{i-1,j+1}\} \right\}
\]

(8)
From above all, the output of the proposed switching based filter \( y_{i,j} \) is given as following:

\[
y_{i,j} = x_{i,j} \times \alpha_{i,j} + (1 - \alpha_{i,j}) \times m_{i,j}
\]

(9)

where \( \alpha_{i,j} \), valued 1 for noise-free pixel and valued 0 for noisy pixel respectively, is the noise detection result, and \( m_{i,j} \) is the noise cancelation result.

4. Simulation and Performance Analysis

4.1 Experiment Background

Background 1: Impulse noise model

Impulse noise model is described in Eq. (10), where \( \{x_R, x_G, x_B\} \) is the noise-free color vector, \( o_t \), \( t = 1, 2, 3 \) are the impulse noise, and \( p_t \), \( t = 1, 2, 3 \) are the degree of impulse noise contamination [2].

\[
x^n = \begin{cases} 
\{o_1, x_G, x_R\} & \text{with probability } p_1p \\
\{x_R, o_2, x_B\} & \text{with probability } p_2p \\
\{x_R, x_G, o_3\} & \text{with probability } p_3p \\
\{o_1, o_2, o_3\} & \text{with probability } p(1 - p_1 - p_2 - p_3) 
\end{cases}
\]

where \( o_1 \), \( t = 1, 2, 3 \) of the fixed-valued impulse noise is 0 or 255, while \( o_1 \), \( t = 1, 2, 3 \) of the random-valued impulse noise is uniformly distributed in the range of \([0, 255]\).

Background 2: Testing images and methods

Figure 5 shows four standard images, sized 512 × 512, will be experimented throughout the whole paper [25]. The experimental results of the proposed filter were compared with many methods, including the VMF (3 × 3 filter window), the BVDF (3 × 3 filter window), the SVMF (ToI = 65), the FPGF (\( d = 45, m = 3 \)). To set the close condition between two color pixels in this proposed filter, parameter \( d \) in Eq. (6) is tuned to 40. That is to say that, if the color distance between two pixels is no more than 40, these two pixels can be seen close to each other in RGB color space.

4.2 The First Experiment

Since the most important part of proposed method is the noise detection mechanism, we use the “true-positive”, the “true-negative”, the “false-negative” and the “false-positive” four aspects to evaluate the noise detection performance about the proposed method in the first experiment. The “true-positive” and the “true-negative” are defined as the result about detecting the uncorrupted pixels as noise-free and detecting the corrupted pixels as impulse noise. The “false-positive” and “false-negative” are defined as the result about detecting the corrupted pixel as noise-free and detecting the uncorrupted pixels as impulse noise. Both the “true-positive” and the “true-negative” are the correct noise detection results, while the other “false-positive” and “false-negative” are wrong noise detection results. Usually, the bigger correct noise detection result and the smaller wrong noise detection result are desirable for each switching based method. Figure 6 shows the noise detection results about the proposed method and some compared switching based filters on the “Baboon” image corrupted by random-valued impulse noise with the ratio of 5%. Figure 6(a) to Fig. 6(f) are the original image and a noise-corrupted image, respectively. Figure 6(c) to Fig. 6(e) are the noise detection results for the AVMF, FPGF, SVMF and the proposed method. In these figures, both the “true-positive” and the “true-negative” detection results are illustrated by the gray (valued 100) pixels. The “false-positive” and the “false-negative” detection results are illustrated by the black pixels (valued 0) and the white (valued 255) pixels, respectively. Seen from Fig. 6(c) to Fig. 6(f), since Fig. 6(f) contains the most gray pixels, we can see that the proposed method can give the best performance in the “true-positive” and the “true-negative” detection result. Similarly, science Fig. 6(f) contains the least black pixels, we also can see that the proposed method can give the best performance in the “false-positive” detection result. For the white pixels in Fig. 6(c) to Fig. 6(f), Fig. 6(f) also contains fewer white pixels, especially than Fig. 6(c) and Fig. 6(e), obtaining better performance than the AVMF and FPGF methods in the “false-negative” detection result. From above all, only the proposed method can give the best “true-positive” and “true-negative” noise detection results by the most gray pixels, together with the best “false-positive” and the “false-negative” detection results illustrated by the fewest black and white pixels, respectively.

4.3 The Second Experiment

The second experiment evaluates the quantitative evaluation performance in terms of the mean squared error (MSE)
values and the structural similarity (SSIM) values [27]. Usually, both a smaller MSE value and a higher SSIM value indicate that the similarity between the original image and the output image is higher, and the quality of the output is better. Tables 1 and 2 list the MSE and the SSIM values of the proposed filter and the VMF, BVDF, FPGF, SVMF, SNVMF, FWNMF methods on the testing images, corrupted by the random-valued impulse noise with the corruption ratio of $p = 3\%$, $5\%$ and $7\%$. For the classical methods of VMF and BVDF, the proposed filter has much better performance. Therefore, we can say that our algorithm could achieve the best quantitative performance among these classical filters in smaller MSE values and bigger SSIM values. Compared with the FPGF, SVMF, SNVMF and FWNMF methods, the proposed method can give a comparable performance in MSE and SSIM values, but better in images that contains a large amount of detailed information, such as the “Parrots” and “Baboon” images.

### 4.4 The Third Experiment

The third experiment compares the visual restoration performance of the proposed algorithm with many other several existing filters including the VMF, BVDF, AVMF, FPGF, SVMF, FWNMF, FWNLW methods. As shown in Fig. 7 (a), the Lena image is corrupted by 10\% random-valued impulse noise. Figure 7 (b) and Fig. 7 (c) are the restoration results of the VMF and the BVDF filters respectively, not only including some spots and artifacts in the output image, but also producing an obvious blur in the entire image. Figure 7 (d) to Fig. 7 (g) are the noise suppression performance of the AVMF, FPGF, SVMF, and FWNLW methods, respectively. Compared with the classical filters, although the detail preservation performance is improved, impulse noise suppression performance are not satisfied, especially in Fig. 7 (f). However, seen from Fig. 7 (h), only the proposed filter can give the best subjective visual quality of restored image with the most noise suppression and detail preservation.

| Table 1 | MSE performance for the testing images corrupted by 3\%, 5\% and 7\% random-valued impulse noise |
| --- | --- |
| Filter | Lena | Baboon |
| | 3\% | 5\% | 7\% | 3\% | 5\% | 7\% |
| VMF | 42.9 | 44.7 | 46.9 | 72.1 | 75.6 | 80.3 |
| BVDF | 44.1 | 46.3 | 47.5 | 75.6 | 77.4 | 82.3 |
| AVMF | 39.3 | 39.8 | 41.9 | 65.3 | 69.3 | 73.6 |
| FPGF | 36.2 | 37.8 | 39.3 | 60.8 | 63.8 | 67.8 |
| SVMF | 24.3 | 25.6 | 26.9 | 40.8 | 46.9 | 46.9 |
| SNVMF | 23.5 | 24.9 | 25.8 | 39.5 | 42.6 | 44.7 |
| FWNMF | 21.8 | 23.2 | 24.6 | 36.6 | 39.5 | 42.6 |
| Proposed | 20.3 | 22.1 | 23.9 | 34.2 | 37.9 | 40.3 |

| Table 2 | SSIM performance for the testing images corrupted by 3\%, 5\%, and 7\% random-valued impulse noise |
| --- | --- |
| Filter | Lena | Baboon |
| | 3\% | 5\% | 7\% | 3\% | 5\% | 7\% |
| VMF | 0.925 | 0.922 | 0.919 | 0.842 | 0.843 | 0.841 |
| BVDF | 0.911 | 0.896 | 0.893 | 0.829 | 0.819 | 0.817 |
| AVMF | 0.926 | 0.918 | 0.915 | 0.831 | 0.847 | 0.844 |
| FPGF | 0.936 | 0.929 | 0.925 | 0.852 | 0.849 | 0.846 |
| SVMF | 0.943 | 0.939 | 0.935 | 0.858 | 0.856 | 0.853 |
| SNVMF | 0.956 | 0.953 | 0.951 | 0.871 | 0.869 | 0.867 |
| FWNMF | 0.958 | 0.955 | 0.952 | 0.872 | 0.871 | 0.865 |
| Proposed | 0.969 | 0.961 | 0.953 | 0.882 | 0.876 | 0.869 |

| Filter | Parrots | Peppers |
| --- | --- |
| | 3\% | 5\% | 7\% | 3\% | 5\% | 7\% |
| VMF | 0.935 | 0.932 | 0.931 | 0.962 | 0.959 | 0.956 |
| BVDF | 0.922 | 0.905 | 0.902 | 0.947 | 0.945 | 0.939 |
| AVMF | 0.941 | 0.936 | 0.941 | 0.969 | 0.966 | 0.963 |
| FPGF | 0.949 | 0.939 | 0.937 | 0.973 | 0.971 | 0.967 |
| SVMF | 0.953 | 0.949 | 0.947 | 0.975 | 0.972 | 0.968 |
| SNVMF | 0.966 | 0.963 | 0.958 | 0.979 | 0.977 | 0.975 |
| FWNMF | 0.971 | 0.965 | 0.964 | 0.985 | 0.981 | 0.976 |
| Proposed | 0.991 | 0.987 | 0.981 | 0.995 | 0.992 | 0.989 |

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![Fig. 6 Noise detection error images for “Baboon” tested image. The gray pixels show both “true-positive” and “true-negative” noise detection results. The white and black pixels are “false-negative” and “false-positive” noise detection results, respectively: (a) original image; (b) input image; (c) AVMF; (d) FPGF; (e) SVMF; (f) proposed.](image-url)
4.5 The Fourth Experiment

Different from the third experiment, this experiment mainly compares the performance of the proposed algorithm with other methods in protecting the detailed information of arbitrary directions. As shown in Fig. 8(a), the original image Peppers is contaminated by 10% random-valued impulsive noise and attached several thin lines, including the straight line by the direction angle of 0, 45, 90, 135 degrees, and a circular representing thin lines in arbitrary directions. Seen from Fig. 8(b) and Fig. 8(c), although these classical filters (VMF and BVDF) can suppress the noise well, the attached straight lines and the circular are almost completely removed out. For the filtered performance of the AVMF in Fig. 8(d), the FPGF in Fig. 8(e), the FWNLW in Fig. 8(g), their performances are similar to that of VMF and BVDF, with the attached lines suppressed as impulse noise. For the filtered result of SVMF in Fig. 8(f), although the square and its two diagonals could be protected as noise free, most
Fig. 9 Visual restoration performance of different methods on the real image: (a) image of a small car with the car logo of Mazda; (b) car logo; (c) VMF; (d) BVDF; (e) proposed

Fig. 10 Visual restoration performance of different methods on the real image: (a) image of a small car with the car logo of Benz; (b) car logo; (c) VMF; (d) BVDF; (e) proposed

information of the circular is removed out as noise. Therefore, compared Fig. 8 (h) with Fig. 8 (b) to Fig. 8 (g), we can see that only our algorithm works best amongst these compared classical and switching filters in protecting the lines of arbitrary directions.

4.6 The Final Experiment

The final experiments examine the performance of our algorithm on the real images which is different from the simulated impulse noise in characteristics and statistical properties. The real images are captured by the automatic driving vehicle monitoring equipment of China national intelligent transportation comprehensive test base. Figure 9 (a) and Fig. 10 (a) are the captured images of small cars with the car logo of Mazda and Benz respectively. Figure 9 (c) to Fig. 9 (e) and Fig. 10 (c) to Fig. 10 (e) show the filtered images of our algorithm and the compared methods. Detailed visual inspection of the restoration results in Fig. 9 (e) and Fig. 10 (e) reveal that our algorithm can provide an excellent trade-off between the noise attenuation and detail preservation. Unlike our algorithm, owning to the excessive smoothing, the VMF (Fig. 9 (c) and Fig. 10 (c)) and BVDF (Fig. 9 (d) and Fig. 10 (d)) blur the edges and remove fine details.

5. Conclusion

A new switching based method is introduced in this paper to suppress the impulse noise while protecting the detail information from the corrupted image. Firstly, samples in the 3x3 filter window are considered to preliminarily detect whether the center pixel is corrupted by impulse noise or not. Then, samples outside a 5x5 filter window are conditionally and partly considered to accurately distinguish the impulse noise and the edge pixel. At last, based on the previous outputs, samples on the processed positions in a 3x3 filter window are chosen as the samples of VMF operation to suppress the impulse noise. Extensive experimental results indicate that the proposed algorithm can be used to remove the impulse noise of color image while protecting the thin curves in arbitrary directions. Specially, the proposed method can be used to improve the detail protection ability about the automatic driving vehicle test and monitoring equipment.
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