A quaternion-based switching filter for colour image denoising

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ABSTRACT

An improved quaternion switching filter for colour image denoising is presented. It proposes a RGB colour image as a pure quaternion form and measures differences between two colour pixels with the quaternion-based distance. Further, in noise-detection, a two-stage detection method is proposed to determine whether the current pixel is noise or not. The noisy pixels are replaced by the vector median filter (VMF) output and the noise-free ones are unchanged. Finally, we combine the advantages of quaternion-based switching filter and non-local means filter to remove mixture noise. By comparing the performance and computing time processing different images, the proposed method has superior performance which not only provides the best noise suppression results but also yields better image quality compared to other widely used filters.

1. Introduction

Images are often contaminated by noise during acquisition, transmission, and storage, and which will significantly degrade the quality and accuracy of image processing. Therefore, it is of vital importance to restore the corruptions in the image before performing any subsequent procedures.

The method based on order statistics filters is used widely, which exploit the rank order information of the pixels in a filtering window. Such as vector median filter (VFM) [1], basic vector directional filter (BVDF) [2] and directional distance filter (DDF) [3]. Meanwhile, various modified vector median filters, such as the weighted median (WM) filter [4] and the fuzzy-rule-based median (FM) filter [5], have also been developed. The disadvantage of above vector median filters is that all pixels in colour image are treated equally. When pixels are noise-free, it will blur image details. And which results in undesirable distortions and also causes loss of valuable information from the image data.

To avoid the damage of noise-free pixels, some published papers suggested switching strategies. Adaptive vector median filter (AVMF) [6], fast peer group filter (FPGF) [7] and vector lower–upper–middle smoother (VLUM) [8,9] are widely used for impulse noise removal by certain switching scheme. Based on these switching vector filters, many researchers have done a great number of studies, and which are classified as: (1) improving noise detection: noise detection by combining edge detection [9], noise detection based on cellular automata (CA) [10,11] and noise detection based on histogram [12,13] etc. (2) improving filtering algorithm: adapted switching vector filters [14–16], iterated switching filters [17] and switching filters based on fuzzy or optimization theory [18–20] etc. for
example, a system using particle swarm optimization, and support vector regression is presented to design a median-type filter with a 2-level impulse detector for image enhancement [21]. It proposes an adaptive fuzzy inference system based impulse detection method for the restoration of images [22,23]. An efficient approach to detect the impulse noise from the corrupted image using feed forward neural network (FFNN) is presented [24]. (3) Improving algorithm based on colour transform: vector filter by CIELAB colour transform [25] and improving filter by using Quaternion theory to transform [26,27] etc.

To improve the filtering results, this paper has proposed a RGB colour image as a pure quaternion form. We use the quaternion-based distance to measures differences between two colour pixels. It can discriminate pixels exactly. And then, an efficient two-stage impulse detector is presented. The noisy pixels are replaced by using VMF and the noise-free ones are unchanged. Finally, to remove Gaussian noise, we combine quaternion-based switching filter (QSF) and non-local means (NLM) filter. It is demonstrated that the proposed filter performs impressively in noise suppression and edge preservation.

The remaining work is arranged as follows. In Section 2, we briefly review related works. Section 3 states basic principles for the proposed method. In Section 4, the experimental results and performance comparisons between the proposed method and other filtering techniques are reported. Finally, conclusions are drawn in Section 5.

2. Related works

Quaternion was discovered by Hamilton in 1843 [28]. A quaternion \( q \) is a four-dimensional number, which consists of one real part and three imaginary parts. And it is usually represented in the following algebraic form (Eq. (1)).

\[
q = a + bi + cj + dk
\]

where \( a, b, c, \) and \( d \) are real coefficients. And \( i, j, \) and \( k \) are complex operators that satisfy the following rules (Eq. (2)).

\[
\begin{align*}
\hat{i}^2 &= \hat{j}^2 = \hat{k}^2 = \hat{ij} = \hat{ji} = 1 \\
\hat{ij} &= \hat{k}, \hat{k}i = \hat{i}, \hat{ki} = \hat{j} \\
\hat{ji} &= -\hat{k}, \hat{k}j = -\hat{i}, \hat{ik} = -\hat{j}
\end{align*}
\]

The modulus and conjugate of quaternion \( q \) are defined respectively as follows (Eq. (3)).

\[
|q| = \sqrt{a^2 + b^2 + c^2 + d^2}, \quad q^* = a - bi - cj - dk
\]

A colour RGB image is commonly represented as a two-dimensional array \( H \times W \times 3 \), where every pixel is a three-component vector of integer values in the interval \([0, 255]\). It can be represented as the pure quaternion form (Eq. (4)).

\[
q_{x,y} = r_{x,y} + g_{x,y}j + b_{x,y}k
\]

To analyze the properties of the quaternion representation of a colour image, a unit pure quaternion is defined as \( \mu = (i + j + k)/\sqrt{3} \). Any unit quaternion \( U \) can be represented as \( U = |U|e^{i\theta} = \cos \theta + \mu \sin \theta \). It defines the quaternion unit transform of a colour pixel \( q_{x,y} \) as follows (Eq. (5)).

\[
Y = Uq_{x,y}U^* = [\cos \theta + \mu \sin \theta]q_{x,y}[\cos \theta - \mu \sin \theta]
\]

\[
= (r_{x,y} + g_{x,y}j + b_{x,y}k) \cos 2\theta + \frac{2}{\sqrt{3}} q_{x,y} + b_{x,y}k \sin 2\theta
\]

\[
+ \frac{1}{\sqrt{3}} [(b_{x,y} - g_{x,y})i + (r_{x,y} - b_{x,y})j + (g_{x,y} - r_{x,y})k] \sin 2\theta
\]

\[
= Y_{RGB} + Y_{Y} + Y_{\mu}
\]

(5)

When \( \theta = \pi/4 \), we define \( T \) in following Eq. (6).

\[
T = U_{\theta = \pi/4} = \frac{1}{\sqrt{2}} + \frac{1}{\sqrt{2}i} (i + j + k)
\]

(6)

According to Eq. (5), from the papers [26,29], they define the quaternion unit transform of a colour pixel \( q_{x,y} \) as follows (Eq. (7)).

\[
Y_{x,y} = Tq_{x,y}^* - \frac{r + g + b}{3} (i + j + k) + \frac{1}{\sqrt{3}} [(b - g)i + (r - b)y + (g - r)k]
\]

(7)

And the conjugate of \( Y_{x,y} \) is \( Y_{x,y}^* \) (Eq. (8)).

\[
Y_{x,y}^* = T^*q_{x,y} = \frac{r + g + b}{3} (i + j + k) - \frac{1}{\sqrt{3}} [(b - g)i + (r - b)y + (g - r)k]
\]

(8)

The difference between \( Y_{x,y} \) and \( Y_{x,y}^* \) is defined as Eq. (9).

\[
Y_{x,y} - Y_{x,y}^* = Tq_{x,y}^* - T^*q_{x,y} = \frac{2}{\sqrt{3}} [(b - g)i + (r - b)y + (g - r)k]
\]

(9)

According to the paper [26], it calculates the colour pixel differences between the central pixel and other two neighbouring pixels in four directions of 0°, 45°, 90° and 135° based on quaternion distance. If the current pixel is corrupted by impulse noise, all four values will turn significantly larger. Therefore it sets a threshold \( T \) to determine whether the pixel is noisy or not. If the colour pixel difference \( V = \min \{V_i, i = 1, 2, 3, 4\} \) exceeds the value of \( T \), the central pixel is determined as noisy and replaced by the VMF output. Otherwise the central pixel is deemed as noise-free and kept unchanged. We define it as QSVF1 which can be represented as follows (Eq. (10)).

\[
Y_{\text{QSVF1}} = \begin{cases} 
Y_{\text{VMF}}, & \text{if } V > T \\
Y_{\text{QSVF1}}, & \text{otherwise}
\end{cases}
\]

(10)

3. Description of the proposed method

3.1. Quaternion-based distance of colour image

From the relate work, the pure quaternion form of colour pixel is \( q_{x,y} \). Given the colour pixels \( q_1 = r_1i + g_1j + b_1k \) and \( q_2 = r_2i + g_2j + b_2k \), we can obtain the difference of colour pixels (Eq. (11)). Quaternion \( d(q_1, q_2) \) represents the colour pixel difference between \( q_1 \) and \( q_2 \).

\[
d(q_1, q_2) = (Tq_1^* - T^*q_1) - (Tq_2^* - T^*q_2)
\]

(11)

When the intensity values of \( q_1 \) and \( q_2 \) are similar, \( |d(q_1, q_2)| \) approaches zero. When the intensity values of \( q_1 \) and \( q_2 \) are large, \( |d(q_1, q_2)| \) is large. The proposed
method employs quaternion-based distance to detect whether the central pixel in a filtering window is noisy or not.

3.2. The process of noise detection

The purpose for the noise-detection is detecting the central pixel of filter window whether it is corrupted or not. Hence, the noise-detection can be strongly regarded as a classification problem. Given \( f_k(x,y) \) is the current pixel that locates at position \( (x,y) \) in the image. \( \{f_k(x-L,y-L), \ldots, f_k(x,y), \ldots, f_k(x+L,y+L)\} \) represents the input sample in the \( (2L+1) \times (2L+1) \) sliding window. \( N \) is the total count of the pixels of sliding window. \( \{R_{1k}, R_{2k}, \ldots, R_{(N+1)/2k}, \ldots, R_{Nk}\} \) is the result of rank-order in the sliding window. Since a larger window size leads to a longer execute time, we use a \( 3 \times 3 \) window as a filtering window \( (N = 9, L = 1) \). In the filtering window, we calculate the colour pixel differences between the central pixel and other neighbouring pixels by using quaternion-based distance.

In FPGF, the pixels are divided into two sets in the sliding window. The first one consists of the pixels similar to the central pixel of the window. And the other one is composed of those pixels, which diverge greatly from the central pixel. Only when the pixel count is less than \( m \), \( f_k(x,y) \) is filtered which can be used for the detection of pixels corrupted by impulse noise \[17\]. We get the pixel count \( \text{Count}(f_k(x,y), d) \) (Eq. (12)) where distance \( d \) is less than a certain threshold \( T \) according to the idea of FPGF.

\[
\text{Count}(f_k(x,y), d) < m
\]  

(12)

where \( d \) is the quaternion-based distance between certain pixel and \( f_k(x,y) \) in the \( 3 \times 3 \) sliding window. \( m \) is a certain pixel count (in the paper, \( m = 4 \)).
Fig. 3. Performance evaluation: (a) “autumn” original image (b) “autumn” image with 10% impulsive noise (c) the output of VMF (d) the output of AVMF (e) the output of FPGF (f) the output of VLUM (g) the output of QSVF1 (h) the proposed output.

<table>
<thead>
<tr>
<th>Noise algorithms</th>
<th>3% Impulsive noise</th>
<th>10% Impulsive noise</th>
<th>15% Impulsive noise</th>
<th>30% Impulsive noise</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PSNR</td>
<td>NMSE</td>
<td>MSE</td>
<td>Time (s)</td>
</tr>
<tr>
<td>VMF</td>
<td>33.0947</td>
<td>0.0025</td>
<td>31.8867</td>
<td>1.500913</td>
</tr>
<tr>
<td>AVMF</td>
<td>37.4372</td>
<td>9.0501e-004</td>
<td>11.7318</td>
<td>5.536067</td>
</tr>
<tr>
<td>FPGF</td>
<td>37.0843</td>
<td>9.8161e-004</td>
<td>12.7247</td>
<td>0.872019</td>
</tr>
<tr>
<td>VLUM</td>
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<td>6.9461e-004</td>
<td>9.0043</td>
<td>1.515048</td>
</tr>
<tr>
<td>QSVF1</td>
<td>40.8182</td>
<td>4.1999e-004</td>
<td>5.3860</td>
<td>0.671212</td>
</tr>
<tr>
<td>The proposed</td>
<td>41.0500</td>
<td>3.9342e-004</td>
<td>5.1060</td>
<td>1.729837</td>
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</tbody>
</table>

Table 1
Comparison of performance using “onion” image corrupted by impulsive noise.

<table>
<thead>
<tr>
<th>Noise algorithms</th>
<th>3% Impulsive noise</th>
<th>10% Impulsive noise</th>
<th>15% Impulsive noise</th>
<th>30% Impulsive noise</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PSNR</td>
<td>NMSE</td>
<td>MSE</td>
<td>Time (s)</td>
</tr>
<tr>
<td>VMF</td>
<td>26.5164</td>
<td>0.0112</td>
<td>145.0247</td>
<td>1.133718</td>
</tr>
<tr>
<td>FPGF</td>
<td>29.0119</td>
<td>0.0061</td>
<td>79.6466</td>
<td>1.851262</td>
</tr>
<tr>
<td>VLUM</td>
<td>29.6431</td>
<td>0.0054</td>
<td>70.5938</td>
<td>1.016972</td>
</tr>
<tr>
<td>QSVF1</td>
<td>31.7479</td>
<td>0.0034</td>
<td>43.4802</td>
<td>3.614137</td>
</tr>
<tr>
<td>The proposed</td>
<td>32.9553</td>
<td>9.7572e-004</td>
<td>32.9268</td>
<td>2.808692</td>
</tr>
</tbody>
</table>

Table 2
Comparison of performance using “hestain” image corrupted by impulsive noise.
classify the central pixel of filter window. The threshold is

\[
\text{Count}(\cdot) = \begin{cases} 
1, & \text{if } 1 < \text{Count}(\cdot) < 7, \\
8, & \text{if } \text{Count}(\cdot) = 8, \\
0, & \text{otherwise}, 
\end{cases}
\]

According to the idea of FPGF, first we judge whether pixels are noise or not according to following rules.

(1) When \(\text{Count}(\cdot) = 0\) or \(\text{Count}(\cdot) = 1\), the pixel is noise.
(2) When \(\text{Count}(\cdot) = 8\) or \(\text{Count}(\cdot) = 7\), the pixel is flat area.
(3) When \(1 < \text{Count}(\cdot) < 7\), the pixel is a candidate.

The above pixels-detection requires the threshold to classify the central pixel of filter window. The threshold is manually determined in a trial-and-error fashion \((T = 50)\). For a candidate, we continue to use the idea of AVMF to judge whether they are noisy or not (Eq. (13)).

\[
\frac{1}{r} \sum_{m=1}^{r} |R_{mk} - f_k(x, y)| \geq T
\]

From Eq. (13), \(1/r \sum_{m=1}^{r} R_{mk}\) is the mean of \(r\) pixels previous to \(R_k\) in the \([R_{1k}, R_{2k}, \ldots, R_{(N+1)/2k}, \ldots, R_{Nk}]\). \(1/r \sum_{m=1}^{r} |R_{mk} - f_k(x, y)|\) is quaternion-based distance between two colour vectors. The idea of AVMF employs the comparison between mean of \(r\) pixels and current pixel to judge impulse noise. When distance is larger than the threshold \(T\), the current pixel is regarded as a noise pixel. When distance is smaller than the threshold \(T\), the current pixel is regarded as a noise-free pixel.

### 3.3. The process of filtering

Let \(Y_{\text{proposed}}\) denote the output of the proposed filter on the current central pixel \(f_{(N+1)/2}\). Since the samples positioned before the current pixel \(f_{(N+1)/2}\) have been processed when considering \(f_{(N+1)/2}\), the filter window can determine the following pixels (Eq. (14)).

\[
\Omega^* = \{Y_{\text{proposed}} \quad Y_{\text{proposed}} \quad \cdots \quad Y_{\text{proposed}} \quad Y_{\text{proposed}} \quad f_{(N+1)/2} \quad f_{(N+1)/2} \quad \cdots \quad f_N\}
\]

If a filtering method can preserve image details well while effectively removing noise, then we can use the filtered results as much as possible to produce its output. Based on the considerations, the VMF will use the pixels in \(\Omega^*\) rather than the original to restore the detected noisy pixels.

\[
Y_{\text{QSF}} = \begin{cases} 
Y_{\text{VMF}}, & \text{noise – pixels} \\
f_k(x, y), & \text{Otherwise} 
\end{cases}
\]

Through two-stage noise detection. All noisy pixels are replaced by VMF, while noise-free pixels will be kept unchanged (Eq. (15)).
PSNR = 10 \log \frac{3 \times 255^2}{1/HW \sum_{x=1}^{W} \sum_{y=1}^{W} (Y(x,y) - \hat{Y}(x,y))^2} \tag{16}

NMSE = \frac{\sum_{x=1}^{W} \sum_{y=1}^{W} ||Y(x,y) - \hat{Y}(x,y)||_2^2}{\sum_{x=1}^{W} \sum_{y=1}^{W} ||Y(x,y)||_2^2} \tag{17}

MSE = \frac{1}{3HW} \sum_{x=1}^{W} \sum_{y=1}^{W} ||Y(x,y) - \hat{Y}(x,y)||_2^2 \tag{18}

\( (x,y) \) characterizes the sample position. \( \hat{Y}(x,y) \) is the original, desired image. And \( Y(x,y) \) represents the output of the filter image. The symbol \( \|\cdot\|_2 \) denotes the \( L_2 \) (Euclidean) norm.

4. Experiments and results

We choose some colour images obtained in actual experiments to assess the performance of our algorithm. The execute time (in seconds) is measured on a desktop personal computer with 2.0 GHz CPU and 1.0 G RAM by using Matlab7.0. In order to evaluate both the noise suppression and detail preservation capabilities of the proposed filter, the peak signal-to-noise ratio (PSNR), the normalized mean square error (NMSE) and the mean square error (MSE) are used to measure the distortion between two colour images. These criteria are defined as follows (Eqs. (16)–(18)).

For comparison, the performance in term of VMF, AVMF, FPGF (The threshold value is set for 50), VLUM (The threshold value is 50) and QSVF1 are also tested. All thresholds are manually determined in a trial-and-error fashion. And filters operate on

\[ 3 \times 3 \]

filtering window. The test images were corrupted with impulse noise with different noise densities, ranging from 3% to 30%.

In order to explore the visual quality, we give the restored images for various denoising methods. In Fig. 1, we add 15% impulse noise to “onion” image (198 × 135). Fig. 1(a) is “onion” original image. The visual effect of VLUM is worse, and it has more noise. VMF has produced more blurring image, because all pixels are filtered. In Fig. 2, we add 30% impulse noise to “hestain” image (303 × 207). From Fig. 2, we can see that Fig. 2(c)–(f) cannot remove impulse noise effectively. In Fig. 3, we add 10% impulse noise to “autumn” image (345 × 206).

Fig. 3(a) is “autumn” original image. Fig. 3(b) is image with impulse noise. It is easily observed from Figs. 1 to 3 that the classical filters VMF provide the most smoothed images in which image details have been heavily blurred, especially for the “tree” details in Fig. 3(c). The results of AVMF, FPGF and VLUM have more noise in Fig. 3(d)–(f). The results for performance comparison in terms of PSNR, NMSE, MSE and execute time are shown in Tables 1–3.

By summarizing and analysing the numerical results listed in Tables 1–3, some conclusions can be drawn. In the classical VMF, the value of PNSR is smaller, for example, in Table 3, the value of PNSR is 27.6538 under 3% impulse noise. The value of NMSE and MSE is larger; it is 0.0062 and 111.6096 respectively under 3% impulse noise. It blurs image details severely. VLUM has a better performance than the classical solutions at low noise density. For example, in Table 1, the value of PNSR is 38.5863, larger than that of AVMF and FPGF under 3% impulse noise. But when the impulse noise arrives at 30%, VLUM has dramatically dropped. And the value of PNSR is 20.0848, smaller...
than that of VMF. AVMF and FPGF can provide better performance than VLUM at high noise density. But their performances significantly drop with increasing noise density from 3% to 30%. AVMF has a longer computational time than other methods, as shown in Table 1, the computational time exceeds 5 s at different noise density. QSVF1 has faster running time and better performance. The proposed method significantly outperforms all the other filters. In Tables 1 and 2, the value of PNSR exceeds 40 for using our proposed method. In Table 3, the value of PNSR is 35.9588 under 3% impulse noise for our method, meanwhile, the NMSE and MSE are smallest. Although the computational time is longer than QSVF1, it is acceptable. In Fig. 4, it gives filtering results in PSNR (dB) of the various filters operating on the images. When the density of impulse noise is increased, VLUM has worse performance than VMF. QSF has best performance under lower noise or higher noise.

According to Eq. (18), MSE can describe the average error difference between the original and filtered image obtained from different methods. Fig. 5 gives the filtering results in MSE. Fig. 5(a) is the filtering result in MSE for "onion" image. Fig. 5(b) is the filtering result for "hestain" image. Fig. 5(c) is the filtering result for "autumn" image. According to Fig. 5, when the density of noise gets to 15%, the MSE value is increasing sharply for VLUM. It represents that the error difference of VLUM is increasing sharply. The MSE value of the proposed method is smallest, and it shows that the error difference between the desired image and the proposed method is smallest, especially for Fig. 5(a) and (b).

We also evaluate the accuracy of the proposed switching mechanisms using false detection (FDT) rate. \( n0(x, y) \) is the mark matrix that use the binary 1 to represent noise pixels. \( \text{noise}(x, y) \) is the mark matrix that use the binary 1 to represent simulated noise. The sum of difference between \( n0(x, y) \) and \( \text{noise}(x, y) \) is the number of false detection pixels. According to Eq. (19), Table 4 shows the FDT rate of impulse noise detection using "hestain" image. The proposed method has a lower FDT value, especially with 30% impulse noise.

\[
\text{FDP} = \frac{\sum_{x=1}^{H} \sum_{y=1}^{W} n0(x, y) - \text{noise}(x, y)}{H \times W} \times 100 \tag{19}
\]

In short, our proposed method has superior performance, which not only provides the best impulse noise suppression results but also yields better image quality compared to the other filters.

### 4.2. Mixture noise

Due to totally different image degrading mechanisms brought out by Gaussian noise and impulse noise. For Gaussian noise, some popular methods have been proposed. For example, the non-local means (NLM) method was proposed by Buades et al. [30]. The bilateral filter (BILF) is presented which is a non-linear filter that extends the concept of Gaussian filter [31]. To verify the efficiency of our method, we also compare our method and NLM, BILF with mixture noise. To remove noise effectively, we combined QSF and NLM, which is called as QSNLM. In Fig. 6, We add mixture noise with 15% impulse noise and Gaussian noise of mean 0 and variance 0.01 to original image. Fig. 6(a) is the "football" original image. We give labelled region to compare. Fig. 6(b) is noise image, and the labelled region does not have any details. In Fig. 6(c), the result of NLM has severely blocking artefacts, and the labelled region is blurred. In Fig. 6(d), the result of BILF can protect details, but the visual effect is bad. Our method is...
Table 5
Comparison of performance using “football” image corrupted by mixture noise.

<table>
<thead>
<tr>
<th>Noise algorithms</th>
<th>3% Impulsive noise + Gaussian noise of variance 0.01</th>
<th>3% Impulsive noise + Gaussian noise of variance 0.03</th>
<th>3% Impulsive noise + Gaussian noise of variance 0.05</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>PSNR</td>
<td>MSE</td>
<td>NMSE</td>
</tr>
<tr>
<td>NML</td>
<td>26.4755</td>
<td>146.3975</td>
<td>0.0180</td>
</tr>
<tr>
<td>BILF</td>
<td>26.9987</td>
<td>129.7806</td>
<td>0.0159</td>
</tr>
<tr>
<td>The proposed</td>
<td>27.3007</td>
<td>121.0630</td>
<td>0.0149</td>
</tr>
<tr>
<td></td>
<td>26.9584</td>
<td>121.0630</td>
<td>0.0149</td>
</tr>
<tr>
<td>NML</td>
<td>24.1500</td>
<td>250.0814</td>
<td>0.0307</td>
</tr>
<tr>
<td>BILF</td>
<td>26.0266</td>
<td>162.3393</td>
<td>0.0199</td>
</tr>
<tr>
<td>The proposed</td>
<td>26.9584</td>
<td>121.0630</td>
<td>0.0149</td>
</tr>
<tr>
<td></td>
<td>26.9584</td>
<td>121.0630</td>
<td>0.0149</td>
</tr>
<tr>
<td>NML</td>
<td>22.5418</td>
<td>362.1598</td>
<td>0.0445</td>
</tr>
<tr>
<td>BILF</td>
<td>25.3580</td>
<td>189.3564</td>
<td>0.0233</td>
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<tr>
<td>The proposed</td>
<td>26.6162</td>
<td>141.7285</td>
<td>0.0174</td>
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a compromise between denoising and retaining details. Table 5 compares the performance using “football” image corrupted by mixture noise. For NLM, It can mainly remove Gaussian noise effectively. When we add mixture noise to images, the performance of NLM is dropped dramatically. From Table 5, for Gaussian noise of variance 0.01, when the density of impulse noise is 3%, the value of NLM’s PNSR is 26.4755. When the density of impulse noise is 15%, the value of NLM’s PNSR is 22.5418. Our method has higher PNSR, and lower MSE and NMSE. Fig. 7 is filtering results in PSNR (dB) of the various filters operating on the images. In Fig. 7(a), we fixed the density of impulse noise for 3%. With increasing Gaussian noise, the performance of NLM is better than BILF.QSNLM has a great progress. And the performance of QSNLM is best. In Fig. 7(b), we fixed the variance of Gaussian noise for 0.01. With increasing Gaussian noise, NLM has a drop significantly.

5. Conclusions

This paper presents a novel quaternion switching filter for suppression of noise in colour images. The proposed method identifies the difference between two colour pixels based on the quaternion unit transform. In noise-detection, we design a two-stage noise detection method to determine the noise pixels with higher accuracy and efficiency. To remove mixture noise effectively, we combine QSF and NLM. The extensive experimental results have shown that the proposed method can overcome some of disadvantages of existing methods and significantly outperforms other commonly used filtering solutions in both noise suppression and detail preservation.

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