

Mixed noise removal for color images using quaternion representation

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Abstract: In order to effectively restore color noisy images with the mixture of Gaussian noise and impulse noise, a new algorithm is proposed using the quaternion-based holistic processing idea for color images. First, a color image is represented by a pure quaternion matrix. Secondly, according to the different characteristics of the Gaussian noise and the impulse noise, an algorithm based on quaternion directional vector order statistics is used to detect the impulse noise. Finally, the quaternion optimal weights non-local means filter (QOWNLMF) for Gaussian noise removal is improved for the mixed noise removal. The detected impulse noise pixels are not considered in the calculation of weights. Experimental results on five standard images demonstrate that the proposed algorithm performs better than the commonly used robust outlyingness ratio-nonlocal means (ROR-NLM) algorithm and the optimal weights mixed filter (OWMF).

Key words: color image denoising; Gaussian noise; impulse noise; mixed noise; quaternion

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Digital images are easily degraded by noise during acquisition, digitization and transmission. The influence factors include the quality of the sensor components and environmental conditions in image acquisition, the transmission channel interference in image transmission, and so on. However, in many cases, the digital image will be degraded by these factors at the same time. Consequently, the image will be corrupted by mixed noise^[1].

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In order to restore the color noise image with the mixture of Gaussian noise and impulse noise, many studies have been published during the last few decades. Among them, Xiong et al.^[2] proposed the robust outlyingness ratio-nonlocal means (ROR-NLM) algorithm. They utilized the robust outlyingness ratio algorithm to detect the impulse noise pixels, and then applied the non-local means filter twice to remove impulse noise and Gaussian noise, respectively. Lin et al.^[3] presented the sorted quadrant median vector switching bilateral filter (SQMV-SBF). This filter first took the median values of four small windows divided from the neighborhood window of current pixel to form a new vector, then detected the impulse noise from this vector after sorting, and finally removed the mixed noise by switching different types of bilateral filters, based on the detection results. Jin et al.^[4] proposed the optimal weights mixed filter (OWMF) based on the improved rand-ordered absolute differences algorithm and the optimal weighting filter for Gaussian noise. However, these works mainly focus on grayscale images. Although one can use these works to separately process each channel of color image, this approach fails to consider the entirety of the three channels and the inherent correlation among the three channels.

Since the 1990s, the algebra of quaternions has been extensively considered for color image processing by using the quaternion representation of color images. This representation encodes three channels of each pixel into three imaginary parts of a quaternion number. It can process a color image holistically as a vector field and handles the coupling between the color channels naturally^[5-8]. Based on this representation, many classical algorithms and tools for grayscale images have been effectively extended to color image processing, such as the Fourier transform, wavelet transform, neural networks, principal component analysis, the support vector machine, and so on.

For the color image noise removal, there are also some quaternion-based studies: for the impulse noise, such as the quaternion weighted vector median filter^[9], the switching vector median filter based on quaternion rotation^[10], the algorithm based on quaternion representation and a di-

rectional vector order-statistics^[5]; for the Gaussian noise, such as the quaternion optimal weights non-local means filter (QOWNLMF)^[6]; for the Poisson noise, such as quaternion weighted mean filter^[7]. However, the quaternion-based work for mixed noise removal has not yet been reported in the literature so far. In this paper, a new quaternion-based algorithm for color image mixed noise removal is proposed by combining the impulse noise detection algorithm shown in Ref. [5] with an improved algorithm of QOWNLMF^[6].

1 Some Preliminaries

1.1 Quaternions and quaternion representation of color images

Quaternions were introduced in 1843 by the mathematician Hamilton. The basic form of a quaternion is given by

$$q = a + bi + cj + dk \quad a, b, c, d \in \mathbf{R} \quad (1)$$

where i, j, k are three imaginary units, which satisfy the following rules:

$$\begin{aligned} i^2 = j^2 = k^2 = -1, \quad ij = -ji = k, \quad jk = -kj = i \\ ki = -ik = j \end{aligned} \quad (2)$$

When $a = 0$, q is called a pure quaternion. The modulus and conjugate of the quaternion q are, respectively, defined as

$$\|q\| = \sqrt{a^2 + b^2 + c^2 + d^2}, \quad \bar{q} = a - bi - cj - dk \quad (3)$$

Using the quaternion representation of color images, a color image $f(x)$ can be represented as

$$f(x) = f_R(x)i + f_G(x)j + f_B(x)k \quad (4)$$

where $f_R(x)$, $f_G(x)$, $f_B(x)$ represent the red, green, and blue channels of the pixel x , respectively.

1.2 Color image impulsive noise removal based on quaternion representation and directional vector order-statistics^[5]

The commonly used impulse noise model can be described as

$$g(y) = \begin{cases} \eta(y) & p \\ f(y) & 1-p \end{cases} \quad 0 \leq p \leq 1, y \in \Omega \quad (5)$$

where $f(y)$, $g(y)$ and $\eta(y)$ are the original pixel value, the observed noisy one and the impulse noise at a pixel y , respectively; p is the density of impulse noise; Ω is the image definition domain.

Jin et al.^[5] proposed an algorithm based on quaternion representation and a directional vector order statistics algorithm. The detailed steps of their algorithm are as follows.

1) Select the pixels lying in the four directions (0° , 45° , 90° , and 135°) of the 5×5 neighborhood centered at the current pixel q and denote them as $h_i (i = 1, 2, 3, 4)$.

2) Count the number of similar pixels in the four in directions h_i , denoted as $\text{card}(h_i)$, and mark the direction

with the greatest number of similar pixels as h^* .

3) Determine the impulse noise pixel and remove it using the following equation:

$$q = \begin{cases} q & \text{if } \text{card}(h^*) \geq m \text{ and } \|q - q_{\text{VM}, h^*}\| < T_{\text{pre}} \\ q_{\text{VMF}} & \text{otherwise (impulse noise)} \end{cases} \quad (6)$$

where m and T_{pre} are the predefined thresholds; $\|\cdot\|$ is the modulus of quaternion defined in Eq.(3); q_{VMF} represents the vector median of the 5×5 neighborhood of the pixel q .

1.3 Color image Gaussian noise removal based on quaternion representation and QOWNLMF^[6]

The commonly used Gaussian noise corruption is modeled as

$$g(y) = f(y) + \sigma(y) \quad y \in \Omega \quad (7)$$

where $\sigma(y)$ is the noise perturbation at pixel y . Moreover, $\sigma(y)$ are independent and identically distributed Gaussian random variables with zero mean and σ standard deviation.

The basic idea of optimal weights non-local means filter is to estimate the unknown original image $f(x)$ by a weighted average of noise image $g(y)$.

$$\tilde{f}_{h,w}(x) = \sum_{y \in U_{x,h}} w(y) g(y) \quad (8)$$

where $\tilde{f}_{h,w}(x)$ represents the restored image; $U_{x,h}$ is a searching window with center x and width $2h + 1$; the weights $w(y)$ satisfy

$$w(y) \geq 0, \quad \sum_{y \in U_{x,h}} w(y) = 1 \quad (9)$$

Chen et al.^[6] first used the quaternion mean square error (QMSE) to quantify the difference between the restored quaternion value $\tilde{f}_{h,w}(x)$ and the unknown original one $f(x)$. After that, using the method of Lagrange multipliers, they obtained the optimal weights minimizing a tight upper bound of the QMSE under the constraints (9). The weights are given by

$$w_{\rho_{f,x}}(y) = \frac{K_{\text{tr}} \left(\frac{\rho_{f,x}(y)}{a} \right)}{\sum_{z \in U_{x,h}} K_{\text{tr}} \left(\frac{\rho_{f,x}(z)}{a} \right)} \quad y \in U_{x,h} \quad (10)$$

Here, some related variables are defined as follows:

1) $\rho_{f,x}(y)$ is calculated by

$$\rho_{f,x}(y) = (d(g_{y,\eta}, g_{x,\eta}) - \sqrt{2}\sigma)^+ \quad (11)$$

where $(\cdot)^+$ represents the positive part of a real number as

$$b^+ = \begin{cases} b & b > 0 \\ 0 & \text{otherwise} \end{cases} \quad (12)$$

$\sigma = \sqrt{\sigma_R^2 + \sigma_G^2 + \sigma_B^2}$, σ_R , σ_G and σ_B are the standard deviation values of the three channels of a color image; $d(g_{y,\eta}, g_{x,\eta})$ is the distance between two similarity windows $g_{y,\eta} = (g(y + \Delta))_{\|\Delta\| \leq \eta}$ and $g_{x,\eta} = (g(x + \Delta))_{\|\Delta\| \leq \eta}$, which is given by

$$d(g_{y,\eta}, g_{x,\eta}) = \frac{\sqrt{\sum_{\|\Delta\|_\infty \leq \eta} [k(\Delta)(g(y + \Delta) - g(x + \Delta))]^2}}{\sqrt{\sum_{\|\Delta\|_\infty \leq \eta} [k(\Delta)]^2}} \quad (13)$$

where $\|\Delta\|_\infty = \max(|\Delta_1|, |\Delta_2|)$ if $\Delta = \{\Delta_1, \Delta_2\}$, and $k(\Delta)$ is defined by

$$k(\Delta) = \begin{cases} \sum_{m=\|\Delta\|_\infty}^{\eta} \frac{1}{(2m+1)^2} & y \neq x \\ \sum_{m=1}^{\eta} \frac{1}{(2m+1)^2} & y = x \end{cases} \quad \|\Delta\|_\infty \leq \eta \quad (14)$$

2) The bandwidth a is the unique solution of the equation $\sum_{y \in U_{x,h}} \rho_{f,x}(y)(a - \rho_{f,x}(y))^+ = \sigma^2$. It can be calculated as explained in remark 1 of Ref. [4].

3) K_{tr} is the usual triangular kernel given by $K_{tr}(r) = (1 - |r|)^+$.

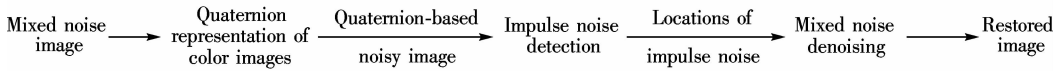


Fig. 1 Flowchart of the proposed mixed noise removal algorithm

Let $g(y)$ be the noise image. The main steps of the proposed algorithm are as follows:

1) Quaternion representation of color images. Since the quaternion representation of a color image given in Eq. (4) can process the color image holistically and consider the relationship among three channels, it is used to represent $g(y)$.

2) Impulse noise detection. By traversing the image $g(y)$, the algorithm described in Section 1.2 is used to detect impulse noise pixels.

3) Mixed noise denoising. By traversing the image $g(y)$ again, the filter QOWNLMF presented in Section 1.3 for Gaussian noise removal is improved for mixed noise removal.

The improved measures and their reasons are as follows:

1) Since the impulse noise pixels do not contain the useful information for restoring the image, only the impulse-free pixels in a current window were considered in the QOWNLMF proposed by Chen et al. [6] to remove mixed noise. Therefore, the improved QOWNLMF for mixed noise removal is as follows:

$$\tilde{f}_{h,w}(x) = \sum_{y \in U_{x,h}, y \notin S} w(y) g(y) \quad (16)$$

where S is the detected noisy pixel set; $w(y)$ are the weights given in Eq. (10) updated by

$$d(g_{y,\eta}, g_{x,\eta}) = \frac{\sqrt{\sum_{\substack{\|\Delta\|_\infty \leq \eta \\ x+\Delta \notin S, y+\Delta \notin S}} [k(\Delta)(g(y + \Delta) - g(x + \Delta))]^2}}{\sqrt{\sum_{\substack{\|\Delta\|_\infty \leq \eta \\ x+\Delta \notin S, y+\Delta \notin S}} [k(\Delta)]^2}} \quad (17)$$

Substituting the weights given in Eq. (10) into Eq. (8), Chen et al. [6] proposed the QOWNLMF to remove Gaussian noise in color images.

2 Proposed Algorithm

The commonly used mixed noise with the mixture of Gaussian noise and impulse noise can be modeled as

$$g(y) = \begin{cases} \eta(y) & p \\ f(y) + \sigma(y) & 1 - p \end{cases} \quad (15)$$

where $0 \leq p \leq 1, y \in \Omega$.

Since the quaternion-based approaches are more appreciated than the component-wise methods in color image processing, the proposed algorithm combines the two quaternion-based algorithms described in Section 1. The impulse noise pixels are detected before the mixed noise removal. The flowchart of the proposed algorithm is given in Fig. 1.

2) With the increase in the density of impulse noise, fewer and fewer pixels are available in a similarity window and a search window with the fixed size since only non-impulsive noise pixels are considered. This leads to the low quality of restored image. Therefore, we propose to adaptively adjust the size of the search window according to the density of impulse noise instead of the size of the similarity window. The reasons are as follows: on the one hand, it is difficult to adjust both windows at the same time; on the other hand, Chen et al. [6] pointed out that “the pixel values in the similarity window are only used to obtain the weights of the pixel values in the search window. Therefore, the search window plays a more important role than the similarity window.”

3 Experimental Results

In order to evaluate the performance of the proposed algorithm, five color standard images with size 256×256 shown in Fig. 2 are considered. They are added to the mixed noises with different degrees: the standard deviation of Gaussian noise varies with 12, 14, 16, 18 and 20; the density of impulse noise varies with 2%, 4%, 6%, 8% and 10%. Then, these noisy test images are restored by the proposed algorithm.

During the implementation of the proposed algorithm, two thresholds in the impulse noise detection stage are set as $T_{ol} = 48$ and $m = 3$; the similarity window size is 11×11 ; the search window size is adaptive with the density of impulse noise under the consideration of the speed and the denoising efficiency. They are given in Tab. 1.

We compare the proposed algorithm with two recent algorithms mentioned in the introduction section, the ROR-

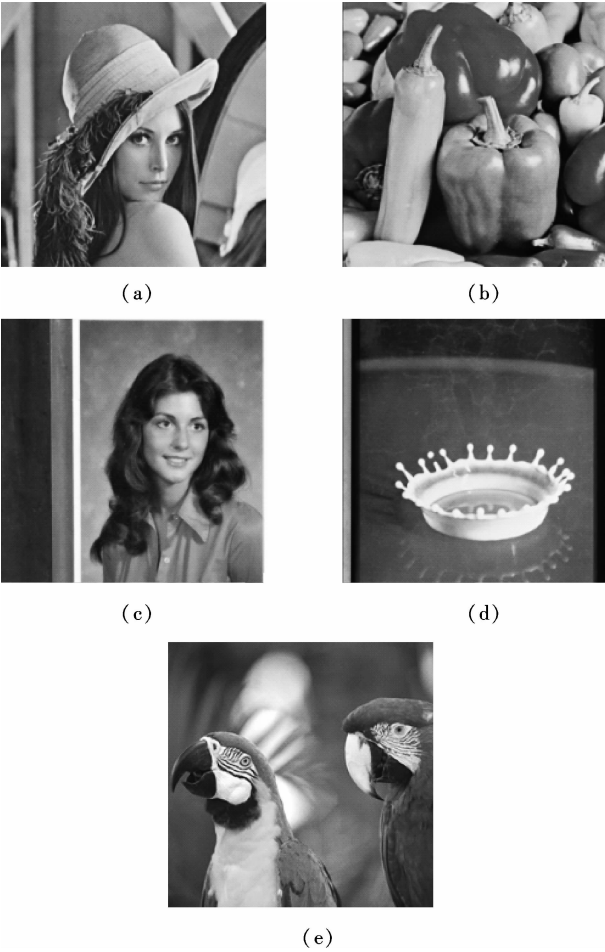


Fig. 2 Five color standard images with size 256×256 . (a) Lena; (b) Peppers; (c) Girl; (d) Milkdrop; (e) Parrots

Tab. 1 Size of the similarity window size and the search window size for different densities of impulse noise

Noise ratios/%	[0, 4)	[4, 8)	[8, 14)	[14, +∞)
Similarity window size	11×11	11×11	11×11	11×11
Search window size	15×15	17×17	19×19	21×21

NLM algorithm^[2] and the OWMF algorithm^[4]. The commonly-used PSNR (peak signal-to-noise) is used to measure the quality of the restored image. Tab. 2 shows the PSNR values of three algorithms for five test images affected by various degrees of mixed noise. In addition, Fig. 3 provides the difference of the average PSNR values between the proposed algorithm and the compared algorithms. The average PSNR values correspond to five test images. It can be observed from Tab. 2 and Fig. 3 that the proposed algorithm is superior to both of the two compared algorithms. All of the difference values between the proposed algorithm and the ROR-NLM are greater than 1 and those between the proposed algorithm and the OWMF are greater than 0.5. The main reason is that the proposed algorithm is a quaternion-based algorithm, which processes a color image holistically and considers the inherent correlation among the three channels of a color image.

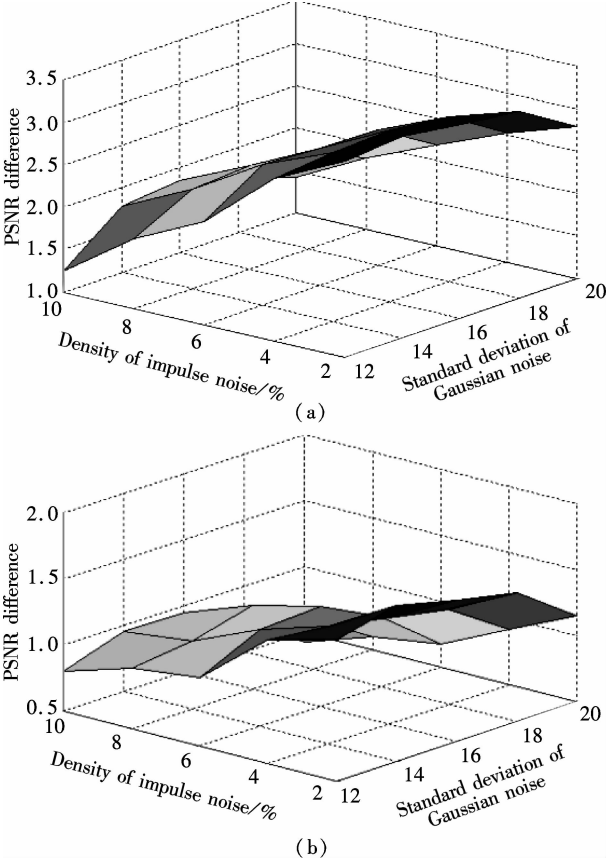


Fig. 3 Differences of the PSNR values between the proposed algorithm and compared algorithm for different noise degrees. (a) Proposed algorithm and ROR-NLM; (b) Proposed algorithm and OWMF

In order to visually illustrate performance, the restored images for noisy images shown in Fig. 4 and their corresponding error images of three compared algorithms are given in Fig. 5 and Fig. 6. In Fig. 4, σ is the standard deviation of Gaussian noise, p is the density of impulse noise. These results show that, for both Fig. 4 (a) with the relative low level noise and Fig. 4 (b) with the heavy one, the performance of the proposed algorithm is better than that of the other two compared algorithms. The proposed algorithm can retain more texture details than the other two compared algorithms, especially for the marked area in Fig. 5 and Fig. 6.

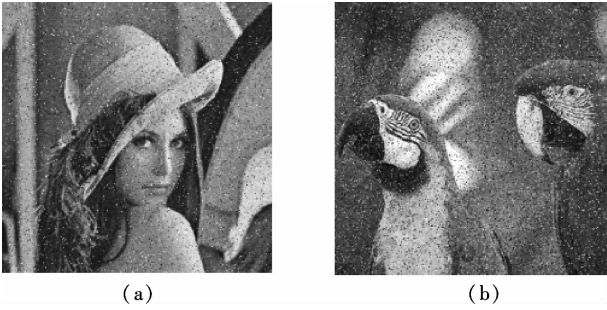
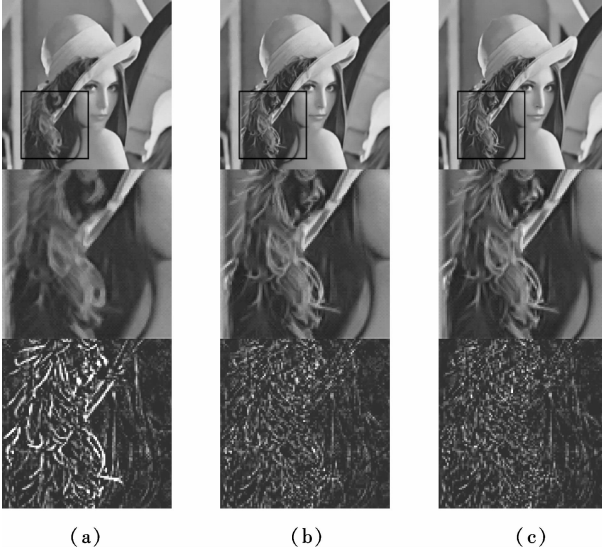
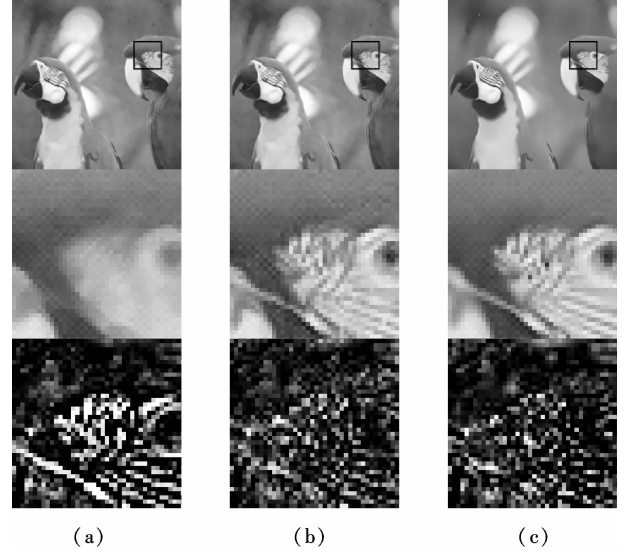


Fig. 4 Two noisy images corrupted by a mixed noise with different noise levels. (a) $\sigma = 12$, $p = 2\%$, PSNR = 20.825 1; (b) $\sigma = 20$, $p = 10\%$, PSNR = 14.425 2

Tab.2 PSNR values of three algorithms for five color images with varying degrees of mixed noise

Images		$p=2\%$			$p=4\%$			$p=6\%$			$p=8\%$			$p=10\%$		
		ROR-NLM	OWMF	Proposed	ROR-NLM	OWMF	Proposed	ROR-NLM	OWMF	Proposed	ROR-NLM	OWMF	Proposed	ROR-NLM	OWMF	Proposed
Fig. 2 (a)	$\sigma=12$	31.245 5	33.292 7	33.958 6	31.076 3	32.890 4	33.376 5	30.884 2	32.407 2	32.775 4	30.730 4	31.650 1	31.888 5	30.653 4	31.109 8	31.654 4
	$\sigma=14$	30.854 6	32.478 4	33.268 3	30.691 3	32.193 3	32.818 8	30.486 2	31.729 8	32.335 0	30.223 3	31.291 2	31.782 0	30.053 5	30.678 8	31.056 9
	$\sigma=16$	30.234 1	31.846 0	32.696 2	29.949 0	31.554 0	32.151 1	29.679 8	31.036 2	31.593 8	29.419 8	30.167 9	31.112 8	29.136 5	30.117 1	30.532 2
	$\sigma=18$	29.571 9	31.183 3	32.051 5	29.258 3	30.988	31.647 7	29.005 2	30.641 8	31.092 6	28.835 9	30.139 8	30.426 3	28.583 7	29.569 9	29.947 6
	$\sigma=20$	29.284 3	30.711 5	31.373 0	28.905 7	30.396	30.870 9	28.679 8	30.038 7	30.417 6	28.362 2	29.555 4	29.893 6	28.161 2	29.177 6	29.305 7
Fig. 2 (b)	$\sigma=12$	30.482 4	32.068 3	33.338 4	30.244 8	31.595 0	32.685 0	29.925 2	30.979 7	31.969 7	29.692 8	30.485 4	31.287 0	29.331 1	29.817 4	30.566 0
	$\sigma=14$	29.607 9	31.212 8	32.567 4	29.475 6	30.924 5	32.049 9	29.145 7	30.485 8	31.646 4	28.978 0	30.015 8	30.779 1	28.666 6	29.363 4	30.275 2
	$\sigma=16$	28.954 4	30.757 2	31.971 9	28.713 1	30.486 4	31.487 5	28.584 4	30.042 7	30.995 0	28.478 6	29.639 2	30.292 0	27.918 5	29.044 6	29.638 7
	$\sigma=18$	28.519 9	30.293 7	31.307 3	28.302 1	29.941 5	30.597 3	28.016 9	29.610 5	30.156 6	27.904 6	29.065 9	29.819 6	27.821 6	28.535 2	29.300 5
	$\sigma=20$	28.174 9	29.814 0	30.373 4	27.955 2	29.455 3	29.987 4	27.711 3	28.999 4	29.198 6	27.511 6	28.705 1	28.829 2	27.281 0	28.143 6	28.147 1
Fig. 2 (c)	$\sigma=12$	30.748 3	31.211 4	34.580 6	30.566 1	31.144 2	34.296 8	30.312 1	30.784 7	32.710 1	30.188 4	30.588 9	32.744 7	29.998 5	30.058 2	31.251 5
	$\sigma=14$	29.893 7	30.824 8	34.204 2	29.650 6	30.657 3	33.568 8	29.334 6	30.481 3	32.020 6	29.281 8	30.184 2	31.817 8	29.199 5	29.861 2	31.054 3
	$\sigma=16$	29.529 4	30.491 4	33.427 2	29.341 3	30.429 4	32.870 4	29.157 3	30.004 9	31.734 6	28.977 8	29.781 5	31.211 7	28.864 8	29.553 5	30.637 9
	$\sigma=18$	29.173 8	30.157 3	32.716 0	28.833 0	29.969 6	32.032 2	28.613 9	29.744 1	31.424 5	28.410 8	29.479	30.719 0	28.243 1	29.110 7	29.616 1
	$\sigma=20$	28.938 7	29.880 8	31.917 8	28.733 4	29.637 3	30.965 4	28.420 9	29.362 1	30.272 3	28.296 4	29.009 4	29.592 6	28.098 7	28.591 9	28.864 9
Fig. 2 (d)	$\sigma=12$	31.806 7	34.100 4	35.484 5	31.684 6	33.340 1	34.878 3	31.472 3	32.759 5	33.710 2	31.123 6	32.130 6	33.030 2	30.920 1	31.451 6	32.300 6
	$\sigma=14$	31.078 6	33.334 5	34.918 2	30.824 6	32.814 2	34.107 0	30.511 9	32.258 9	33.961 8	30.205 1	31.507 0	32.693 6	29.901 2	30.895 4	32.018 3
	$\sigma=16$	30.563 0	32.701 9	34.249 5	30.218 7	32.283 8	33.748 3	29.997 9	31.611 8	33.292 9	29.757 7	30.948 3	32.564 9	29.581 3	30.328 4	31.679 7
	$\sigma=18$	30.109 1	32.082 3	33.725 0	29.849 5	31.698 9	33.197 7	29.624 2	31.244 9	32.574 1	29.444 6	30.727 2	31.529 0	29.165 8	30.027 6	30.801 7
	$\sigma=20$	29.545 7	31.705 3	33.026 0	29.239 5	31.185 3	32.429 4	28.900 8	30.771 7	31.769 4	28.773 3	30.209 7	30.973 4	28.576 5	29.740 5	30.420 3
Fig. 2 (e)	$\sigma=12$	30.105 8	32.504 4	33.635 3	29.857 9	31.947 3	32.838 4	29.599 5	31.270 9	32.133 1	29.350 7	30.596 3	31.291 7	29.068 6	29.810 2	30.461 5
	$\sigma=14$	29.510 8	31.650 4	32.922 7	29.289 8	31.345 6	32.346 7	28.960 9	30.634 1	31.793 8	28.678 8	30.205 6	31.182 1	28.312 5	29.483 5	30.636 6
	$\sigma=16$	28.969 5	31.085 2	32.374 2	28.613 6	30.713 6	31.725 7	28.427 7	29.985 6	31.341 9	28.210 6	29.755 7	30.798 8	27.920 2	28.883 1	30.183 5
	$\sigma=18$	28.254 3	30.603 2	31.884 5	27.947 8	30.254 4	31.443 5	27.794 3	29.701 9	30.841 7	27.566 5	29.023 1	30.304 3	27.328 2	28.547 2	29.699 2
	$\sigma=20$	28.096 7	30.136 8	31.333 6	27.603 1	29.805 3	30.818 2	27.269 5	29.371 8	30.254 2	26.950 3	28.646 6	29.809 0	26.798 2	28.221 8	29.271 8

**Fig.5** Restored images of Fig.4(a) and five times magnified error images using different algorithms. (a) ROR-NLM (PSNR = 31.245 5); (b) OWMF (PSNR = 33.292 7); (c) Proposed algorithm (PSNR = 33.958 6)**Fig.6** Restored images of Fig.4(b) and five times magnified error images using different algorithms. (a) ROR-NLM (PSNR = 26.798 2); (b) OWMF (PSNR = 28.221 8); (c) Proposed algorithm (PSNR = 29.271 8)

algorithm and OWMF filter.

4 Conclusion

In this paper, a new denoising algorithm, which removes the mixture of Gaussian noise and impulse noise for color images, is proposed. The proposed algorithm based on quaternion representation deals with a color image in a holistic manner and considers the correlation between the color channels sufficiently. For mixed noise removal, the proposed algorithm improves the QOWNLMF and then combines the improved QOWNLMF with the existing quaternion-based impulse noise detection algorithm. Experimental results show that the proposed algorithm performs better than the commonly used ROR-NLM

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基于四元数表示的彩色图像混合噪声去噪

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摘要:为了能够更加有效地恢复受混合高斯和脉冲噪声污染的彩色图像,采用基于四元数的彩色图像整体处理方案,提出了一种彩色图像混合噪声去噪算法.首先,通过一个纯四元数矩阵表征一幅彩色图像;然后,根据高斯噪声和脉冲噪声的不同特性,采用基于四元数方向矢量排序统计的算法检测脉冲噪声位置;最后,将针对高斯噪声的基于四元数最优权值的非局部均值滤波器进行改进以应用于混合噪声图像去噪,在权值计算时不考虑已被检测出的脉冲噪声点.对5幅标准图像的实验结果表明,所提算法的去噪效果优于目前常用的 ROR-NLM(robust outlyingness ratio-nonlocal means)算法和最优权值混合滤波器.

关键词:彩色图像去噪;高斯噪声;脉冲噪声;混合噪声;四元数

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