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A detail-preserving random-valued impulse noise removal algorithm based on S-ROAD

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Abstract: In a random-valued impulse noise corrupted image, in order to remove impulse noise and, meanwhile, efficiently preserve image edges and details, a novel two-phase detail-preserving random-valued impulse noise removal algorithm is proposed. At the noise detecting phase, an image statistic called S-estimate based rank-ordered absolute difference (S-ROAD) is presented to distinguish image edge and detail pixels from impulse noise pixels in a noise corrupted image. By introducing S-estimate into ROAD statistic, the interference caused by the image edges and details in the ROAD statistic is eliminated. With the S-ROAD statistic, most of the noise pixels, including the noise at edges and details, can be distinguished. At the noise pixels filtering phase, a two-threshold iterative method is used to restore the identified noise pixels and the estimate precision is improved; thus, the image details can be efficiently preserved. Experimental results show that the proposed method provides a significant improvement over many existing filters in terms of both subjective and objective evaluations.

Key words: S-estimate; rank-ordered absolute difference; edges and details; impulse noise

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Impulse noise often corrupts an image seriously during acquisition and transmission. Generally, there are two types of impulse noise models: the fixed-valued impulse noise model and the random-valued impulse noise model. The gray-level value of the fixed-valued impulse noise is either minimal or maximal, while the gray-level value of the random-valued impulse noise is uniformly-distributed between minimal and maximal[1]. Comparatively, the former is easier to restore. This paper mainly focuses on the latter. The standard median (SM) filter is an efficient random-valued impulse noise removal technique which is widely used. However, as each pixel in the image is replaced by the median value in its neighborhood, the SM is prone to change lots of noise-free pixels and may damage some important information in the image.

In order to overcome this problem, many median-based filters have been proposed. The weight-based median filter and the switching-based median filter are two kinds of main types which are simple and effective, e. g. the weighted median (WM) filter[2], the center weighted median (CWM)[3] filter, the modified switching median (MSM) filter[4], the adaptive switching median (ASWM) filter[5], the adaptive center weighted median (ACWM) filter[6], the directional weighted median (DWM) filter[7], the pixel-wise MAD filter[8], the selective weighted median (SAWM) filter[9], and the contrast enhancement-based (CEF) filter[10]. However, these filters just simply use median values to restore the noisy pixels, which may blur image details when the image is highly corrupted.

The rank-ordered absolute difference statistics based trilateral filter (ROAD-TRIF)[11] and the rank-ordered logarithmic difference edge-preserving regularization (ROLD-EPR) filter[12] are good schemes to solve this problem. But improvement can still be made in these two areas: 1) The ROAD or ROLD cannot distinguish noise pixels from edges and details efficiently; 2) The EPR-based method is very complex. Aiming at these drawbacks, we propose an S-estimate[13] based ROAD statistic to improve the accuracy of noise detection, especially at edges and details. In order to reduce the computational complexity and preserve image details as much as possible, we introduce an efficient two-threshold iterative method at the filtering step. Finally, we give an efficient algorithm that combines the S-ROAD and the two-threshold median filter. Experimental results indicate that the proposed method provides a significant improvement over many existing impulse noise removal techniques.

1 Review of ROAD Statistic

The image statistic ROAD is proposed by Garnett et al. in Ref. [11]. It provides a measurement to judge how close a pixel value is to its n most similar neighbors. The basic idea underlying this statistic is that the unwanted impulses will vary greatly in intensity from most or all of their neighboring pixels.

Let $x_{i,j}$ and $y_{i,j}$ be the pixel values at (i, j) in the original image and the noisy image, respectively. The

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dynamic range of the image is $[L_{\min}, L_{\max}]$. If the noise ratio is p, then

$$y_{i,j} = \begin{cases} x_{i,j} \text{ with probability } 1-p \\ n_{i,j} \text{ with probability } p \end{cases} \tag{1}$$

where $n_{i,j}$ represents the gray-level value of the noisy pixel. Let Ω_N denote the set of coordinates in a local $(2N+1)\times(2N+1)$ window centered at $(0, 0)$, i. e.,

$$\Omega_N = \{(s,t) \mid -N \leqslant s, t \leqslant N\} \tag{2}$$

Let $W(i, j)$ be the local window and $y(i, j)$ be the central pixel in $W(i, j)$. The pixel value is $y_{i,j}$. $U_{i,j}$ denotes a set whose elements are the pixels in the $W(i, j)$ of the noisy image y.

$$U_{i,j} = \{y(i+s, j+t) \mid \forall (s,t) \in \Omega_N\} \tag{3}$$

Define d_{st} as the absolute differences between the gray-level values $y_{i+s, j+t}$ and $y_{i,j}$, i. e.,

$$d_{st}(y_{i,j}) = |y_{i+s,j+t} - y_{i,j}| \qquad \forall (s,t) \in \Omega_N \tag{4}$$

Sort d_{st} values in an increasing order, and let r_k be the k-th smallest one among them, then define

$$\mathrm{ROAD}_m(y_{i,j}) = \sum_{k=1}^{m} r_k(y_{i,j}) \qquad 2 \leqslant m \leqslant (2N-1)^2 - 2 \tag{5}$$

According to Refs. [11 - 12], we select a 3×3 size window and let $m = 5$ when the noise ratio is lower than 25%, and select a 5×5 size window and let $m = 13$ in other cases. By combining the ROAD with a priori threshold T, the impulses can be detected. A pixel $y_{i,j}$ is identified as noise if $\mathrm{ROAD}_m(y_{i,j}) > T$, and signal in other cases.

2 S-Estimate Based ROAD (S-ROAD) Statistic

2.1 Robust S-estimate of variance

The median of absolute deviation (MAD) is a well-known statistic as the variance estimate. Chen et al. [6] used the MAD for impulse noise suppression in the AC-WM filter. Crnojevic et al. [8] also used the modification of the MAD, the pixel-wise MAD, in the PWMAD filter. The MAD is a good estimate of variance, but it requires the calculation of location estimate, so it is only suitable when the underlying distribution is symmetric. But in the image regions where edges are presented, the signal can be hardly modeled by a symmetric distribution. Therefore, we need a robust estimator being able to work well both on symmetric and on asymmetric distributions. From Ref. [13], the S-estimate is an estimator with such a property. It is given as

$$S = \mathrm{med}_i\{\mathrm{med}_j \mid t_i - t_j \mid\} \tag{6}$$

where for each t_i, $i = 1, 2, \ldots, L$, the inner median of $\{|t_i - t_j|;\ j = 1, 2, \ldots, L\}$ is computed. This yields a new sample of L elements, and their median gives the final estimate S.

Let Ω_M denote the set of coordinates in a $(2M+1)\times(2M+1)$ window centered at $(0, 0)$, i. e.,

$$\Omega_M = \{(s_0, t_0) \mid -M \leqslant s_0, t_0 \leqslant M\} \tag{7}$$

Finally, in a noisy image, the S-estimate $S_M(y_{i,j})$ is computed as

$$S_M(y_{i,j}) = \mathrm{med}_{p,q}\{\mathrm{med}_{s_0,t_0}(|y_{i+p,j+q} - y_{i+s_0,j+t_0}|)\}$$
$$|p - s_0| + |q - t_0| \neq 0,\ \forall (s_0, t_0) \in \Omega_M, (p, q) \in \Omega_M \tag{8}$$

The S-estimate can present a good estimate of the local variance even in the highly corrupted noisy image. Fig. 1 shows the MAD estimate of variance and the S-estimate of variance for the image "Lena" corrupted by 50% random-valued impulse noise. The results show that the S-estimate not only presents image variance very well but also has a better anti-noise ability than the MAD.

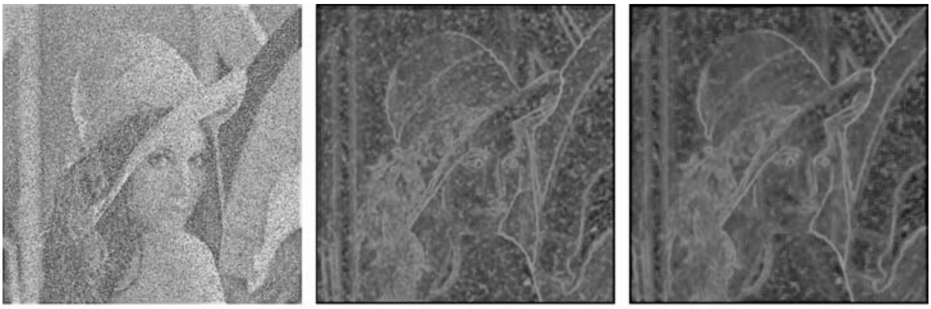

Fig. 1 Variance estimate for 50% random-valued impulse noise corrupted image "Lena". (a) Noisy image; (b) MAD estimate of variance; (c) S-estimate of variance

2.2 S-ROAD statistic

With the ROAD, we can identify most of the impulse noise except the impulses at or near the edges and the details in a noisy image, because edges and details in an image can cause some kinds of naturally large absolute differences d_{st}. If the edges and details are subtracted from the ROAD, a more accurate impulse noise detector can be generated. To this end, we propose the image statistic called the S-estimate based rank-ordered absolute difference (S-ROAD for short).

The S-ROAD is an improved statistic from the ROAD statistic. It is obtained by extracting the edges and details in the ROAD utilizing the S-estimate. The whole procedure can be described as extracting image edges and details by the S-estimate of variance first and utilizing the ROAD statistic amplifying the differences between noisy pixels and noise-free pixels afterwards.

$$d_{i,j}^{l} = \left| d_{i,j}^{l-1} - \alpha S_M(d_{i,j}^{l-2}) \right| \qquad l = 2, 3, 4, \ldots \tag{9}$$

$$d_{i,j}^{1} = \left| y_{i,j} - \mathrm{median}(y_{i+s_0, j+t_0}) \right| \qquad \forall (s_0, t_0) \in \Omega_M \tag{10}$$

$$d_{i,j}^{0} = y_{i,j} \tag{11}$$

where l is the number of iterations; α is a predefined parameter which is at interval (0, 1); $\boldsymbol{d}$ denotes the absolute deviation image; $\boldsymbol{d}^1$ is an absolute deviation image defined in Eq. (10), and $\boldsymbol{d}^0$ is a primary image absolute deviation image defined in Eq. (11). Then the S-ROAD statistic for the pixel $y_{i,j}$ is defined as

$$\text{S-ROAD}_m(y_{i,j}) = \text{ROAD}_m(d_{i,j}^{l}) \tag{12}$$

The iteration is used in our method. In each step, certain portions of edges and details are eliminated from the absolute deviation image, while the noise remains. Fig. 2 presents the whole course of this method. In Figs. 2(b) to (g), three iteration steps for image "Lena" corrupted by 30% random-valued impulse noise are presented, and in Figs. 2(h) and (i), the ROAD and S-ROAD statistics for the noise image are presented. Apparently, details fade away while noise remains. This reduces the probability of detecting image details as impulses.

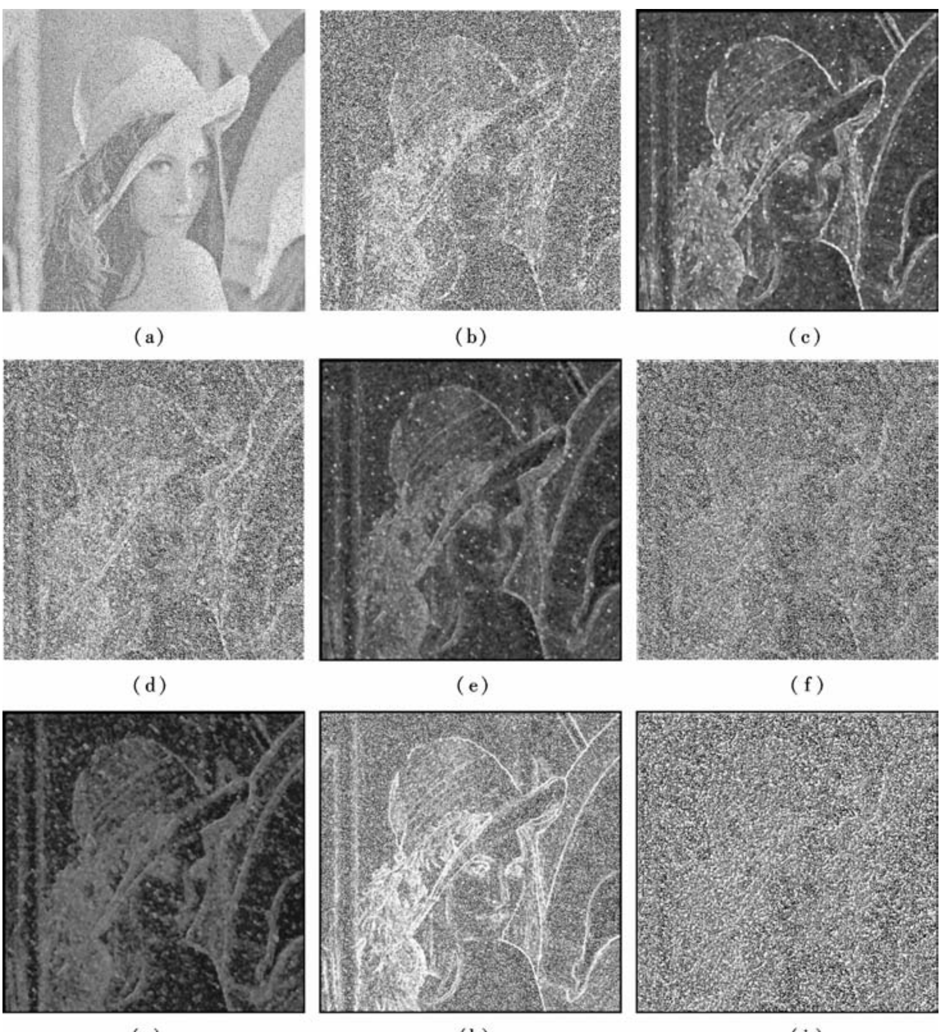

Fig. 2 Procedure of computing the S-ROAD statistic ($M = 5$). (a) Noise image; (b) $\boldsymbol{d}^1$; (c) $S_M(y)$; (d) $\boldsymbol{d}^2$; (e) $S_M(\boldsymbol{d}^1)$; (f) $\boldsymbol{d}^3$; (g) $S_M(\boldsymbol{d}^2)$; (h) ROAD; (i) S-ROAD

3 Proposed Noise Filter

In terms of the S-ROAD, we can classify image pixels in the noisy image into two parts: the outlier candidate set and the outlier-free set. A flag image δ, where the outlier and outlier-free are denoted as 1 and 0, respectively, is generated.

$$\delta(y_{i,j}) = \begin{cases} 1 & \text{S-ROAD}_M(y_{i,j}) \geq T_r \\ 0 & \text{S-ROAD}_M(y_{i,j}) < T_r \end{cases} \tag{13}$$

where T_r is a threshold to identify the impulse. If the pixel $y_{i,j}$ is identified as an impulse, it is replaced by median$(U'_{i,j})$. $U'_{i,j}$ is a subset of $U_{i,j}$ when the elements of $U_{i,j}$ satisfy

$$|U_{i,j} - \text{median}(U_{i,j})| \leqslant T_a \tag{14}$$

Generally, a noisy pixel (an impulse) is located near one of the two ends[14]. So, we use Eq. (14) to extract potential noise pixels to improve the accuracy of the noise pixels restoration. To determine the value of threshold T_a used in Eq. (14), the influence of T_a on filtering performance is studied. For this purpose, five grayscale images (8-bit, 512×512), "Lena", "Boat", "Goldhill", "Pepper" and "Baboon" are selected as the test images. By altering the value of the threshold T_a and using our filter to restore these test images contaminated by 20% and 40% impulsive noise, the average peak signal-to-noise ratio (PSNR) of the filtered images for each noise ratio is obtained. The results are shown in Fig. 3. From Fig. 3, we find that the PSNR values are not very sensitive to the values of T_a ranging from 80 to 100. So we select $T_a = 90$ (a 3×3 size window and a noise ratio lower than 25%) and $T_a = 80$ (a 5×5 size window and a noise ratio higher than 25%). In a 8-bit gray image median $(U'_{i,j})$ = median $(U_{i,j})$ when $T_a = 0$ or $T_a \geqslant 255$.

$$\text{PSNR} = 10\log_{10} \frac{255^2}{\sum_{i=1}^{M_0} \sum_{j=1}^{N_0} (r_{i,j} - x_{i,j})^2 / (M_0 N_0)} \tag{15}$$

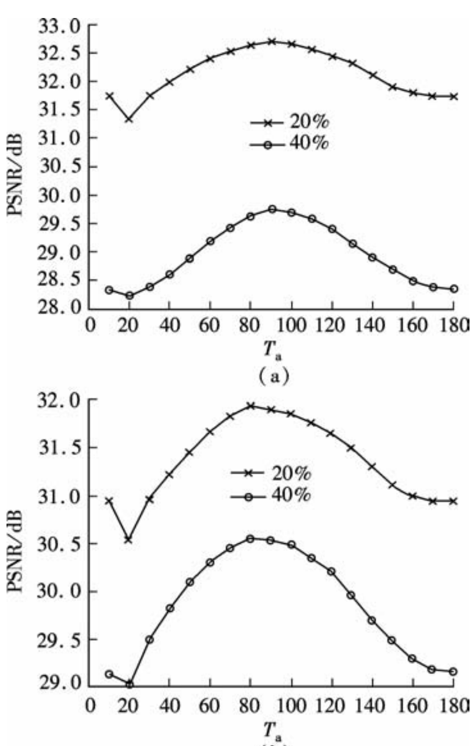

Fig. 3 Average PSNR values vs. threshold T_a operated on five 512×512 images corrupted random-valued impulse noise with densities of 20% and 40%. (a) 3×3 size window; (b) 5×5 size window

$$\text{MAE} = \frac{\sum_{i=1}^{M_0} \sum_{j=1}^{N_0} (r_{i,j} - x_{i,j})}{M_0 N_0} \tag{16}$$

where M_0 and N_0 are the image dimensions, and $r_{i,j}$ and $x_{i,j}$ are the restored images and the ideal noise-free pixels at position (i, j), respectively.

The algorithm steps are as follows:

1) Set $u = 0$, $\boldsymbol{r}^0 = \boldsymbol{y}$.

2) Compute the absolute deviation image $\boldsymbol{d}^l$ in an iterative manner (in this paper, $l = 3$ to 6).

3) In terms of the results obtained in Step 2), the S-ROAD$_m(\boldsymbol{r}^u)$ is generated (Eq. (12)).

4) If S-ROAD$_m$ $(r^u_{i,j}) > T_r$, replace $r^u_{i,j}$ with median $(U'_{i,j})$.

5) Stop the iteration until u is greater than $u_{\max}$, the maximum number of iterations. Otherwise set $u = u + 1$ and go to step 2).

The threshold T_r is important in noise detection. In order to find a suitable T_r, we select five test images with different texture features which are corrupted by 30%, 40%, 50% and 60% noise to do some experiments. The results are shown in Fig. 4. From Fig. 4, we choose T_r = 90 when the noise ratio is higher than 40%. In other cases, we select $T_r = 30$.

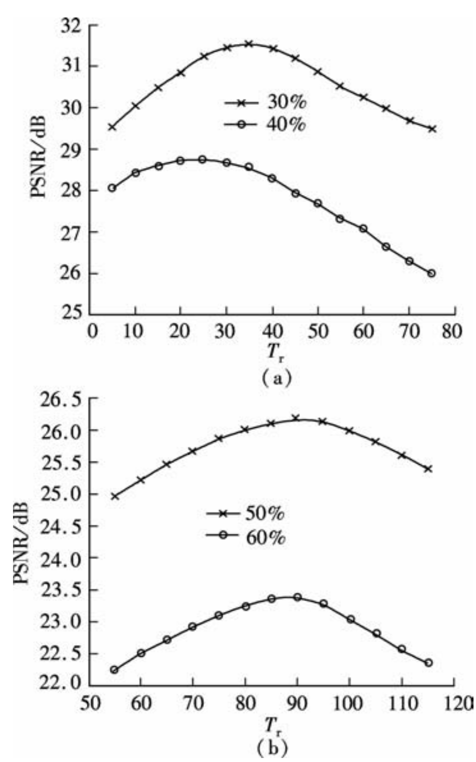

Fig. 4 Average PSNR values vs. threshold T_r operated on five 512×512 images corrupted random-valued impulse noise with noise ratios of 30% to 60%. (a) 30% and 40%; (b) 50% and 60%

Before filtering, we should determine another parameter α in Eq. (9). We test the restoration capability of our method by setting the parameter α from 0.1 to 0.9 with increments of 0.1. Six grayscale images (8-bit, 512 × 512), "Lena", "Boat", "Goldhill", "Bridge", "Pepper" and "Baboon", which are corrupted by 20% random valued impulse noise, are selected as the test images. The results are shown in Fig. 5. From the results, we find that the best α values are at intervals [0.4, 0.6]. For simplicity, we select the median value 0.5.

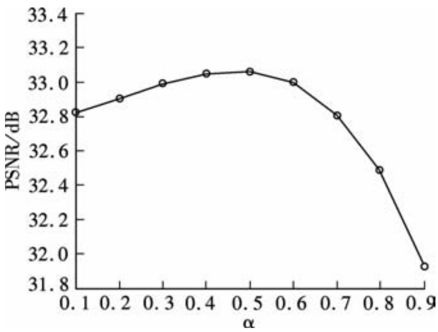

Fig. 5 Average PSNR values vs. parameter α operated on six 512 × 512 images corrupted random-valued impulse noise with a noise ratio of 20%

4 Numerical Experiments

In this section, the proposed algorithm is evaluated and compared with some other existing techniques. In our experiments, a group of 512 × 512 gray-scale images corrupted by random-valued impulse noise with various noise ratios are used. For performance comparison, the ACWM filter, the PWMAD filter, the ASWM filter, the DWM filter, the SAWM filter, the ROAD-TRIF filter, the ROLD-EPR filter and the CEF filter are simulated. The filtering window size of these compared filters is tuned to obtain the best restoration performance at various noise ratios.

4.1 Restoration performance measurements

The restoration performances are measured by the widely used PSNR and the mean absolute error (MAE) (Eq. (16)). The PSNR and MAE are given in Tab. 1. In the table we choose five different images corrupted by random-valued impulse with noise ratio of 30%. The results show that the proposed method performs better than other considered methods do for its larger PSNR values and smaller MAE. Besides, the performances of our method and other considered approaches for testing images "Pepper" and "Lena" in terms of the PSNR for random-valued impulse noise with different noise ratios are shown in Fig. 6. The curves also denote that our method performs better than other approaches do.

4.2 Noise detection performance measurements

Here, we compare our method with the PWMAD filter, the ASWM fiter, the DWM filter, the ROAD-TRIF filter, the ROLD-EPR filter and the CEF filter by the sum of the rate of miss detection (H_{miss}) and false detection (H_{false}) (SRMF). Tab. 2 lists the experimental results on the image "Lena" corrupted by noise from 10% to 60%. The results show that our method can distinguish more noisy pixels with fewer mistakes.

$$\text{SRMF} = \frac{H_{\text{miss}}}{H_{\text{all}}} + \frac{H_{\text{false}}}{H_{\text{all}}} \tag{17}$$

where H_{all} is the number of all noise pixels in the image.

Tab. 1 Comparison of restoration results in PSNR and MAE for images corrupted with 30% random-valued impulse noise

Filter	Method	Lena	Baboon	Goldhill	Boat	Pepper
ACWM	PSNR	31.75	22.80	29.93	29.03	30.72
	MAE	2.03	8.68	2.96	2.90	2.46
PWMAD	PSNR	30.02	20.75	28.44	27.58	29.03
	MAE	2.74	8.12	3.24	3.41	2.93
ASWM	PSNR	32.13	22.62	30.22	29.39	31.39
	MAE	1.98	8.64	2.80	2.75	2.09
DWM	PSNR	32.09	22.57	30.14	29.23	31.69
	MAE	2.31	10.26	3.30	3.37	2.40
SAWM	PSNR	29.21	20.45	26.76	28.94	28.74
	MAE	2.42	10.33	3.73	3.79	3.01
CEF	PSNR	32.35	22.84	30.31	29.52	32.08
	MAE	2.16	9.37	3.05	3.08	2.22
ROAD-TRIF	PSNR	32.22	22.93	30.25	29.68	32.45
	MAE	2.09	9.45	2.94	3.06	2.52
ROLD-EPR	PSNR	33.15	23.01	30.96	30.22	32.69
	MAE	1.75	7.43	2.79	2.75	2.16
Proposed	PSNR	33.70	23.85	31.68	31.08	33.64
	MAE	1.61	6.30	2.33	2.20	1.62

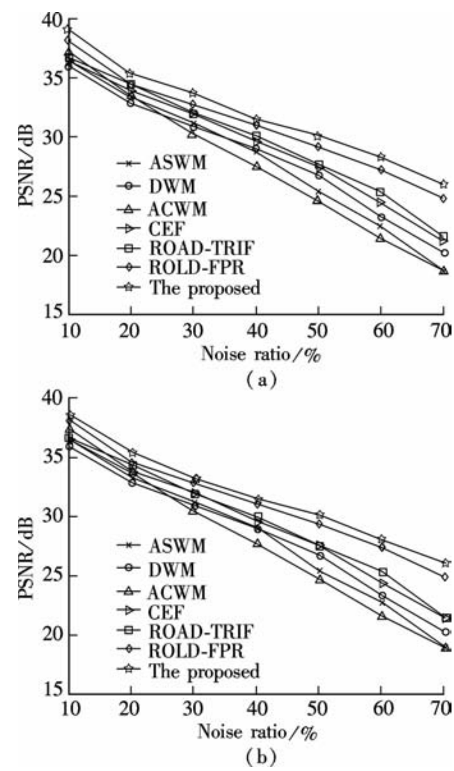

Fig. 6 Performance comparison of different approaches for restored images corrupted by random-valued impulse noise from 10% to 70%. (a) Lena; (b) Peppers

Tab. 2 Comparison of noise detector in SRMF with various ratios of impulse noise %

Filters	Noise ratio					
	10	20	30	40	50	60
PWMAD	20.3	16.1	15.2	14.1	12.8	11.1
ASWM	15.8	14.5	13.1	12.3	11.0	10.1
DWM	21.5	18.3	16.5	15.4	14.3	13.5
ROAD-TRIF	17.1	15.7	14.6	13.4	12.2	11.0
CEF	18.8	16.9	15.4	14.5	13.7	12.9
ROLD-EPR	16.1	14.6	12.8	11.3	10.6	9.8
Proposed	15.4	12.7	11.5	10.6	9.8	9.1

4.3 Visual performances

As the final illustration, we display the "Lena" image with 70% random-valued impulse noise restored by various methods in Fig. 7. Compared with other filters, the proposed method exhibits better visual performances.

5 Conclusion

We propose a detail-preserving random-valued impulse noise removing algorithm. The S-ROAD statistic is used as a noise detector. With the S-ROAD, we can distinguish more noisy pixels with fewer mistakes, even at edges and details. In order to reduce the calculation complexity, and, meanwhile, preserve image details as much as possible, we propose an efficient two-threshold iterative method at the filtering phase. Experimental results indicate that the proposed method provides a significant improvement over many existing impulse noise removal techniques both in a subjective aspect and an objective aspect.

Fig. 7 Results of different filters. (a) 70% noise corrupted image "Lena"; (b) ACWM filter; (c) PWMAD filter; (d) ASWM filter; (e) DWM filter; (f) SAWM filter; (g) CEF filter; (h) ROAD-TRIF; (i) Proposed method

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基于 S-ROAD 统计量的细节保护随机值脉冲噪声滤波算法

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摘要:在受随机值脉冲噪声干扰的图像中,为了去除图像中的脉冲噪声并有效地保护图像的边缘与细节,提出了一种新的两阶段细节保护随机值脉冲噪声滤波算法. 在噪声检测阶段,针对图像中边缘和细节像素难以和噪声像素有效区分的问题,提出了一种基于 S-估计的绝对级差统计量(S-ROAD). 通过引入 S-估计到 ROAD 统计量,消除了 ROAD 数据中由图像边缘和细节带来的干扰. 利用 S-ROAD 统计量,图像中的大部分噪声像素,包括位于图像边缘和细节处的噪声像素都可以被区分出来. 在图像滤波阶段,算法引入了双阈值迭代方法对确认出的噪声像素赋值,提高了对噪声像素的估值精度, 从而有效地保护了图像的细节. 无论是主观视觉评估还是客观数据评估,实验结果都表明了该算法优于现有的很多方法.

关键词:S-估计; 绝对级差; 边缘和细节; 脉冲噪声

中图分类号:TP391