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Image Denoising Based On Fast Noise Estimation Methods and Median Algorithm

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Abstract*—Impulse noise detection is a critical issue when re- moving impulse noise and impulse/Gaussian mixed noise. In this paper, we propose a new detection mechanism for universal noise and a universal noise-filtering framework based on the nonlocal means (NL-means). The operation is carried out in two stages, i.e., detection followed by filtering. For detection, first, we propose the robust outlyingness ratio (ROR) for measuring how impulse like each pixel is, and then all the pixels are divided into four clusters according to the ROR values. Second, different decision rules are used to detect the impulse noise based on the absolute deviation to the median in each cluster. In order to make the detection results more accurate and more robust, the from-coarse-to-fine strategy and the iterative framework are used. In addition, the detection procedure consists of two stages, i.e., the coarse and fine detection stages. For filtering, the NL-means are extended to the impulse noise by introducing a reference image. Then, a universal denoising framework is proposed by combining the new detection mechanism with the NL-means (ROR-NLM). Finally, extensive simulation results show that the proposed noise detector is su- perior to most existing detectors, and the ROR-NLM produces excellent results and outperforms most existing filters for different noise models. Unlike most of the other impulse noise filters, the proposed ROR-NLM also achieves high peak signal-to-noise ratio and great image quality by efficiently removing impulse/Gaussian mixed noise.

Index Terms*—Image denoising, impulse noise, mixed noise, noise detector, nonlocal means (NL-means).

I. INTRODUCTION

Digital images could be contaminated by noise during image acquisition and transmission due to malfunctioning pixel elements in the camera sensors, transmission errors, faulty memory locations, and timing errors in analog-to-digital con- version [1]. In addition, most noise added to images can be adequately represented by two models, namely, additive Gaussian noise and impulse noise. Little useful information can be acquired from the corrupted images without their being restored, and the corrupted images severely impede subsequent image processing operations such as image segmentation, object recognition, edge detection, and image analysis; hence, restoring the original image from the corrupted image is absolutely necessary.

Image denoising is one of the most fundamental, widely studied, and largely unsolved problems in digital image processing, and it has been studied for nearly half a century due to its important role as a preprocessing step in various image applications.

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Its objective is to recover the original image or the best estimation from noisy data while preserving image details. To this day, numerous and diverse denoising methods have been proposed to this end, and two outstanding reviews of state-of-the-art denoising algorithms can be found in [2] and [3].

Additive Gaussian noise is characterized by adding to each image pixel a value with a zero-mean Gaussian distribution, and it affects all pixels of the image. Such noise is usually introduced during image acquisition. The zero-mean distribution property allows such noise to be removed by average pixel values locally [1]. Recently, a number of nonlocal methods such as non- local means (NL-means) [4], K-SVD [5], and BM3D [6] have been developed, and these methods have shown great promise and obtained state-of-the-art results. This relatively new class of denoising methods originates from the NL-means [4]. Un- like previous denoising methods, which were developed under local regularity assumption, the NL-means exploits the correlation in the entire image. Basically, the NL-means filter estimates a noise-free intensity as a weighted average of all pixel intensities in the image, and the weights are proportional to the similarity between the local neighborhood of the pixel being processed and the local neighborhoods of the surrounding pixels. Therefore, these nonlocal methods are very powerful of pre- serving image details when denoising.

Impulse noise is characterized by replacing a portion of an image pixel with noise values, leaving the remainder un- changed. Such noise can be introduced due to acquisition or transmission errors [7]. Nonlinear filters have been developed for removing impulse noise. Among them, one of the most popular and robust nonlinear filters is the median filter [8] with good denoising power, simple implementation, and high computational efficiency, which exploits the rank-order information of pixel intensities within a filtering window and replaces the center pixel with the median. However, one difficulty with the median filter is that, in many cases, it removes desirable details. This is particularly a problem when the noise density is high. To obtain improved performance, various generalized and modified median-based filters have been proposed, such as the weighted median filter [9], the multistate median (MSM) filter [10], the center-weighted median filter [11], and the stack filter [12]. Nevertheless, they are still uniformly implemented across the image without considering whether the current pixel is noise free or not. As a result, this would inevitably alter the intensities and remove the image details contributed from uncorrupted pixels and cause image quality degradation. In order to deal with this problem, one solution is to introduce a noise-detection mechanism, prior to filtering, to identify the corrupted pixels and, meanwhile, leaving the uncorrupted pixels unaltered. By incorporating such noise-detection mechanism into the median filtering framework, the so-called switching median filter [13] is proposed, and it has been shown to be simple and yet more effective than uniformly applied median-based methods [8]–[12]. Next, over the years, better noise removal methods with different kinds of noise detectors have been proposed, such as MSM filter [14], tristate median (TRI) filter [15], adaptive center-weighted median (ACWM) filter [16], the pixel-wise median absolute deviation (PWMAD) filter [17], the adaptive switching median (ASWM) filter [18], a directional weighted median (DWM) filter [19], Luo-iterative median filter [20], the conditional signal-adaptive median (CSAM) filter [11], the rank-ordered logarithmic difference edge-preserving regularization filter (ROLD-EPR) [12], and so on.

For mixed noise, some filters have been also proposed [13]–[16]. The median-based signal-dependent rank-ordered mean filter can remove impulse noise rather effectively, but when applied to images with mixed noise, it often produces a visually disappointing output [15]. The trilateral filter [13] is a modification of the bilateral filter [17] with incorporated rank-order absolute difference (ROAD) statistics for impulse noise detection. It has been especially designed for uniform im- pulse and Gaussian noise removal. The ROAD value could be false provided that half of the pixels in the processing window are corrupted. The sorted quadrant median vector switching bilateral filter (SQMV-SBF) [14] is also a modification of the bilateral filter [17] with the incorporated SQMV for impulse noise detection. It removes the mixed noise by switching the bilateral filter between the Gaussian noise and the impulse noise depending upon the noise-detection results. The HDIR [16] filter is based on a Bayesian classification of the input pixels, and then it removes the mixed noise by the kernel regression framework. These methods also need a detection rule to classify the impulse noise and Gaussian noise.

As aforementioned, most of the impulse denoising and mixed denoising filters need a detection step before filtering. The main issue of these decision-based filters lies in building a decision rule, or a noise measure, that can discriminate the uncorrupted pixels from the corrupted pixels or impulse noise from the Gaussian noise as precisely as possible.

In this paper, we propose a new detector based on new statistics called robust outlyingness ratio (ROR), which is used to measure how much a pixel looks like an impulse noise. Based on the ROR, the pixels are divided into four different clusters. Then, different decision rules are adopted to detect the impulse noise in each cluster. During the detection process, the from- coarse-to-fine strategy is used. In addition, the detection process contains two stages, i.e., the coarse stage followed by the fine stage. Different thresholds are used in the two stages. Finally, the detection procedure is iteratively adopted. Furthermore, as aforementioned, the NL-means is very powerful for denoising Gaussian noise, but to the best of our knowledge, it is not yet extended to remove impulse noise. In this paper, the NL-means is extended to clean impulse noise, and then a universal noise removal framework is proposed by combining the NL-means with the new detection mechanism.

The rest of this paper is organized as follows. The new statistic ROR and detection mechanism are introduced in Section II. The extension of the NL-means for impulse noise and mixed noise is described in Section III. Extensive numerical experiments are presented in Section IV. Finally, a brief conclusion of this paper is presented in Section VI.

II. ROR FOR IMPULSE NOISE DETECTION

A. Noise Models

When an image is corrupted by impulse noise, only a por tion of the pixels are changed. To be precise $x_{i,j}$ and $y_{i,j}$ be the pixel values locate on (i,j) in the original and noisy images, respectively, and $[n_{\min}, n_{\max}]$ be the dynamic range of the allowed pixel values. Then, for an impulse model with noise probability or noise ratio p, we have

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

where $n_{i,j}$ is a noise value independent from $x_{i,j}$. There are two cases of noise distributions for impulse noise, namely, fixed-valued (also called salt-and-pepper) impulse noise and random- valued impulse noise. For fixed-valued impulse noise, the values of the corrupted pixels are equal to $n_{\min}$ or $n_{\max}$ with equal probability [18]. For random-valued impulse noise, however, the corrupted pixels are uniformly distributed between $n_{\min}$ and $n_{\max}$ [14]. For gray-level images with 8 bits per pixel (i.e., $n_{\min} = 0$ and $n_{\max} = 255$), the noise value $n_{i,j}$ of the first case corresponds to a fixed value of 0 or 255 with equal probability, whereas that of the second case corresponds to a random value uniformly distributed between 0 and 255. Cleaning random- valued impulse noise is far more difficult than removing fixed-valued noise because, in the latter case, the differences of the pixel values between a noisy pixel and its noise-free neighbors are often significant.

B. Motivation of the Noise-Detection Scheme

Two issues are involved in developing a decision process. First, a decision measure should be defined as a statistical parameter to capture and represent the local property of the region. Second, a mechanism to compute a threshold value should be determined. Existing impulse noise removal methods use many different techniques to determine whether a given pixel is an impulse one in this sense. These approaches vary in complexity from being relatively simple to highly complex. The most basic impulse detectors are based on two-state methods that attempt to definitively characterize each image pixel as either an impulse or an uncorrupted pixel. The underlying goal of these two-state methods is to find pixels that are significant outliers when com- pared to their neighbors. One of the simplest and most intuitive methods is to compare a pixel's intensity with the median in- density in its neighborhood, as shown in Fig.1, and then many modifications have been proposed in [14]–[16] and [19]. Other relative complex methods such as the ASWM [18], DWM [19], and CSAM [20] use more complex criteria to judge whether a pixel is an impulse one. However, whether the approach is simple or complex, each pixel is judged under the same decision rule without considering the underlying property of each pixel, i.e., how much impulse like each pixel is. Furthermore, these detectors are poor when the noise density is high. In fact, the level of how impulse like of each pixel is different. Some pixels look more like noisy pixels, and some do not look like noisy pixels. Theoretically and intuitively, for different levels, different decision rules should be adopted. In addition, this mechanism could get more accurate detection results and be more robust to the noise ratio. Hence, prior to making a decision, all pixels should be clustered based on the level of how impulse like. Then, in different clusters, adopt different decision rules. Therefore, how to measure the impulse like of the pixels is very important.

Otherwise, the impulse noise can be considered as an outlier in the image. In statistics, there are many methods for detecting outliers. Among them, a traditional measure of the outlyingness of an observation $y_{i,j}$ with respect to a sample is the ratio between its distance to the sample mean and the sample standard deviation (SD)

$t_i = (y_i - \bar{y})/s$ (2)

Observations with $|t_i| > 3$ are traditionally deemed as suspicious (the "three-sigma rule") based on the fact that they would be "very unlikely" under normality since $P(|y| \geq 3) = 0.003$ for a random variable y with a standard normal distribution. Due to the statistical properties of the image pixels, we can introduce the conception of t_i and the "three-sigma" rule to detect impulse noise.

In response to the aspects aforementioned, a new detection mechanism for impulse noise is proposed in this paper. More details will be shown in the next sections.

C. Definition of the ROR

In statistics, the value of t_i defined by (2) is used for measuring the outlying ness of an observation. In this paper, we introduce it to describe the level of how impulse like of each pixel. In (2), the traditional sample mean and SD are used. However, these two statistics are very sensitive to the outliers, as shown in *Example 1*. Furthermore, the traditional "three-sigma" rule has some drawbacks that deserve to be taken into account [20].

1) In a very large sample of "good" data, some observations will be declared suspicious and altered. More precisely, in a large normal sample, about 3 observations out of 1000 will have $|t_i| > 3$.
2) In very small samples, the rule is ineffective: it can be shown that

Fig. 1. (a) Original data of Lena marked with the black rectangle. (b) Noisy data with the pixel marked with the white ellipse in (a) replaced by an impulse noise (outlier).

For all possible data sample values, if $n \leq 10$, there always exists $|t_i| < 3$. When there are several outliers, their effects may interact in such a way that some of them remain unnoticed (an effect called "masking").

Example 1: Considering the following 25 observations from Lena, as shown in Fig. 1(a), sorted in ascending order: 42, 43, 44, 45, 45, 46, 47, 47, 47, 48, 49, 49, 49, 49, 50, 52, 53, 54, 54, 56, 56, 57, 57, 60. The sample mean and SD of these observations are $\bar{x} = 49.92$ and $s = 4.86$, respectively. If one observation is corrupted by an impulse noise, as shown in Fig. 1(b) (42, 43, 44, 45, 45, 46, 47, 47, 47, 48, 49, 49, 49, 49, 50, 52, 53, 54, 54, 56, 56, 57, 57, 60, 255), the sample mean and SD are $\bar{x} = 58.16$ and $s = 41.29$, respectively.

Since $\bar{x} = 58.16$ is larger than all but two of the data values, it is not among the bulk of the observations and, as such, does not represent a good estimate of the center of the data. While the sample mean $\bar{x} = 49.92$ of the original data dose provides a good estimation of the center of the data, as is clearly revealed in Fig. 2, the SD is over eight times smaller than it is with the outlier present.

To avoid these drawbacks caused by the sample mean and the sample SD, it is better to replace $\bar{y}$ and s in (2) by more robust statistics. Thankfully, the sample median and the normalized median absolute deviation (MADN) are robust versions respectively, in robust statistics [20], and the MADN is defined.

$$\text{MAD}(\mathbf{y}) = \text{Med}\{|\mathbf{y} - \text{Med}(\mathbf{y})|\}$$ (6)

$$\text{MADN}(\mathbf{y}) = \text{MAD}(\mathbf{y})/0.6457$$ (7)

Fig. 2. Sample mean and sample median of the data sets with or without impulse noise (outlier).

where the operation "Median" represents the median value of all the observations, the coefficient "0.6457" is the MAD of a standard normal random variable, and $\mathbf{y}$ is the vector representation of the data.

According to the analysis above, we define a new statistical parameter called ROR as

$$\text{ROR}(y_{i,j}) = |(y_{i,j} - \text{Med}(\mathbf{y}))/\text{MADN}(\mathbf{y})|$$ (3)

In what follows, we show how to calculate the ROR of each pixel in an image.

Let $y_{i,j}$ be the location of the pixel under consideration, and let (i,j)

$$\Omega_{\mathbf{y}}(N) = \{y_{i+k,j+l} : -N \leq l, k \leq N\}$$ (4)

be the set of points in a $(2N+1)\times(2N+1)$ neighborhood centered at $y_{i,j}$ for some positive integer N. Define Med $(\Omega_{\mathbf{y}}(N))$ as the median value of all pixels in $(\Omega_{\mathbf{y}}(N))$, i.e.,

$$\text{Med}(\Omega_{\mathbf{y}}(N)) = \text{Median}(\Omega_{\mathbf{y}}(N)).$$ (5)

Then, calculate median absolute deviations MAD $(\Omega_{\mathbf{y}}(N))$ and MADN $(\Omega_{\mathbf{y}}(N))$

$$\text{MAD}(\Omega_{\mathbf{y}}(N)) = \text{Med}\{|\Omega_{\mathbf{y}}(N) - \text{Med}(\Omega_{\mathbf{y}}(N))|\}$$ (6)

$$\text{MADN}(\Omega_{\mathbf{y}}(N)) = \text{MAD}(\Omega_{\mathbf{y}}(N))/0.6457.$$ (7)

Finally, the ROR of the pixel $y_{i,j}$ can be obtained as

$$\text{ROR}(y_{i,j}) = |(y_{i,j} - \text{Med}(\Omega_{\mathbf{y}}(N)))/\text{MADN}(\Omega_{\mathbf{y}}(N))|$$ (8)

Essentially, the ROR statistics provide a measure of how impulse like is a pixel to its neighbors. We do not directly use ROR to detect the outliers; we just use it to measure the outlying- ness of each pixel in the image.

TABLE I
NUMBER OF THE PIXELS IN EACH LEVEL OF LENA WITH DIFFERENT NOISE RATIOS ABOUT RANDOM-VALUED IMPULSE NOISE

Noise Ratio	The most like level ($ROR > 3$)	The second level ($2 < ROR \leq 3$)	The third level ($1 < ROR \leq 2$)	The fourth level ($0 \leq ROR \leq 1$)
Noise-free	2045	10059	41688	208352
10%	21305	7868	34056	198915
20%	39238	7093	26451	189362
30%	54517	8254	21260	178113
40%	62540	11590	20443	167571

D. Characteristics of our Method

Statistical parameter MAD is used in our method, and it has been utilized by ACWM [16]. In accordance with the principle of the ACWM and our method, the roles of MAD are different in these two methods. In ACWM, MAD is used to calculate the threshold for making the final decision, whereas MAD is applied to calculating the ROR used to divide the pixels into different clusters in our detection mechanism.

According to the description of our detection mechanism in Section II-D, the main characteristics of it can be simply sum- marized as follows.

- Hierarchical: The pixels in the image are divided into four clusters based on the value ROR, and they independently detect impulse noise in every cluster.
- Progressive: The from-coarse-to-fine strategy is adopted,

and the detection mechanism contains two stages, i.e., the coarse and fine stages. The detection results become more and more accurate.

- Iterative: The iterative framework is adopted by our

method.

- Anisotropic: The decision rule with different thresholds is used in different clusters. In contrast, the ACWM does not have these characteristics.

III. EXTENSION OF NL-MEANS

A. Main Review of NL-Means Algorithm

Let us consider the observation model about the Gaussian noise stands for the vector representation of the original image is the white Gaussian noise with zero mean and $\sigma^2\mathbf{I}$ variance, and it is the observed noisy image. The de-noised pixel $\hat{\mathbf{x}}(i)$ at image can be derived as the weighted average of all gray values in the image (indexed in set) where weights $w(i,j)$ express the amount of similarity between the neighborhoods of each pair of pixels involved in the computation

$$w(i,j) = \exp\left(-\left\|\mathbf{y}(N_i) \quad \mathbf{y}(N_j)\right\|_{2,a}^2 \Big/ h^2\right) \tag{9}$$

In the original NL-means, the weights are calculated among the neighborhoods of the pixels, and the all pixels in every neighborhood are used. However, if this method is directly used to the impulse noise, the weights would be wrong because the impulse noisy pixels are very different to their neighbors and do not contain any useful information unlike to the Gaussian noise. How to calculate the weights is the main problem when applying the NL-means to the impulse noise.

In order to deal with this problem, a reference image and the detection result are obtained, prior to using the NL-means, by the new detection mechanism. In addition, the stages of the NL-means to the impulse noise are shown in Fig. 3: first, using the new detection mechanism to obtain the final detection result and the reference image; and second, applying the NL-means to the pixels marked as noisy pixels according to the detection result, and then calculating the weights based on the reference image obtained in the detection mechanism.

B. Removing Mixed Gaussian Noise and Impulse Noise

The ROR-NLM filter can be easily extended to remove mixture of Gaussian and impulse noise. The ideal solution would be to locally vary parameters so that they are finely tuned to remove the precise amount and type of noise present in each section of the image. This solution, however, would require a deep statistical study of the ROR statistic for the automatic selection of parameters, and the best way to do this is not immediately clear.

A simpler yet still effective solution to restore an image cor- rupted by mixed noise is to apply the NL-means twice with two different values of h, i.e., once with a smaller value of h, to re- move the impulse noise, and another time with a larger value of h, to smoothen the remaining Gaussian noise, and the suit- able values are in the interval [5, 10]. A myriad of other op- tions is available for altering the parameters between filtering, but our simple approach produces visually appealing results and only requires changing one parameter.

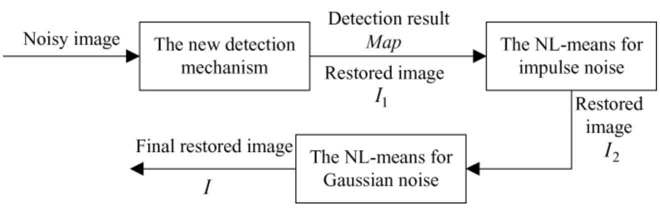

Fig. 3. Flowchart of the proposed image denoising algorithm for mixed noise.

IV. EXPERIMENTAL RESULTS

Simulations are carried out to verify the noise removing

Capability of the ROR-NLM filter, and the results are compared with several existing filters. Our method produces results superior to those of most methods in both visual image quality and quantitative measures. Simulations are made on several 512 8-bit grayscale standard test images with salt-and-pepper impulse noise, random-valued impulse noise, and mixed noise.

A. Implementations and Testing Procedures

The proposed ROR-NLM is implemented based upon the dataflow shown in Fig.3, with respect to impulse noise and mixed noise, respectively. Testing is divided into two parts, i.e., one for noise detection and the other for noise removal. In noise detection, the salt-and-pepper impulse noise and the random-valued impulse noise are both considered.

B. Comparison of Image Restoration

For the random-valued impulse noise, the ROLD-EPR and ROR-NLM show the best results in most of the images except for the Baboon when the noise ratio is 30%, whereas for the salt-and-pepper impulse noise, the ROR-NLM shows the best results in all the images. In Tables II and III, it is shown that our detection method is better than the ROLD-EPR, but some filtering results of the ROLD-EPR are better than those of our method, particularly for the complex images and the high noisy images such as Bridge and Baboon. It reveals that the edge-preserving regularization (EPR) [11] method is really an excellent approach for removing impulse noise.

In order to give a visual impression about the performances of the filters included in the comparison, the results of test images Pepper and Bridge are given in Fig. 4 for the random- valued impulse noise and the salt-and-pepper impulse noise, respectively. It shows that, for random-valued impulse noise, the most appealing visual result is produced by the ROLD-EPR and proposed ROR-NLM filter, and for salt-and-pepper impulse noise, the most appealing visual result is produced by the pro- posed ROR-NLM filter; almost all the impulse noise is removed, whereas most of the image details are well preserved.

TABLE II
COMPARISON OF RESTORATION RESULTS IN THE PSNR FOR IMAGES WITH MIXED NOISE (RANDOM-VALUED IMPULSE NOISE AND GAUSSIAN NOISE)

	Lena	Pepper
3×3 median	29.0387	28.7070
Trilateral [23]	31.1360	28.8911
SQMV-SBF[24]	29.6588	28.5459
ROR-NLM	**31.5780**	**30.0853**

TABLE III
COMPARISON OF RESTORATION RESULTS IN THE PSNR FOR IMAGES WITH MIXED NOISE (SALT-AND-PEPPER IMPULSE NOISE AND GAUSSIAN NOISE)

	Lena	Pepper
3×3 median	27.6177	27.4142
Trilateral [23]	30.9996	28.4562
SQMV-SBF[24]	30.5415	28.8348
ROR-NLM	**32.4500**	**30.4316**

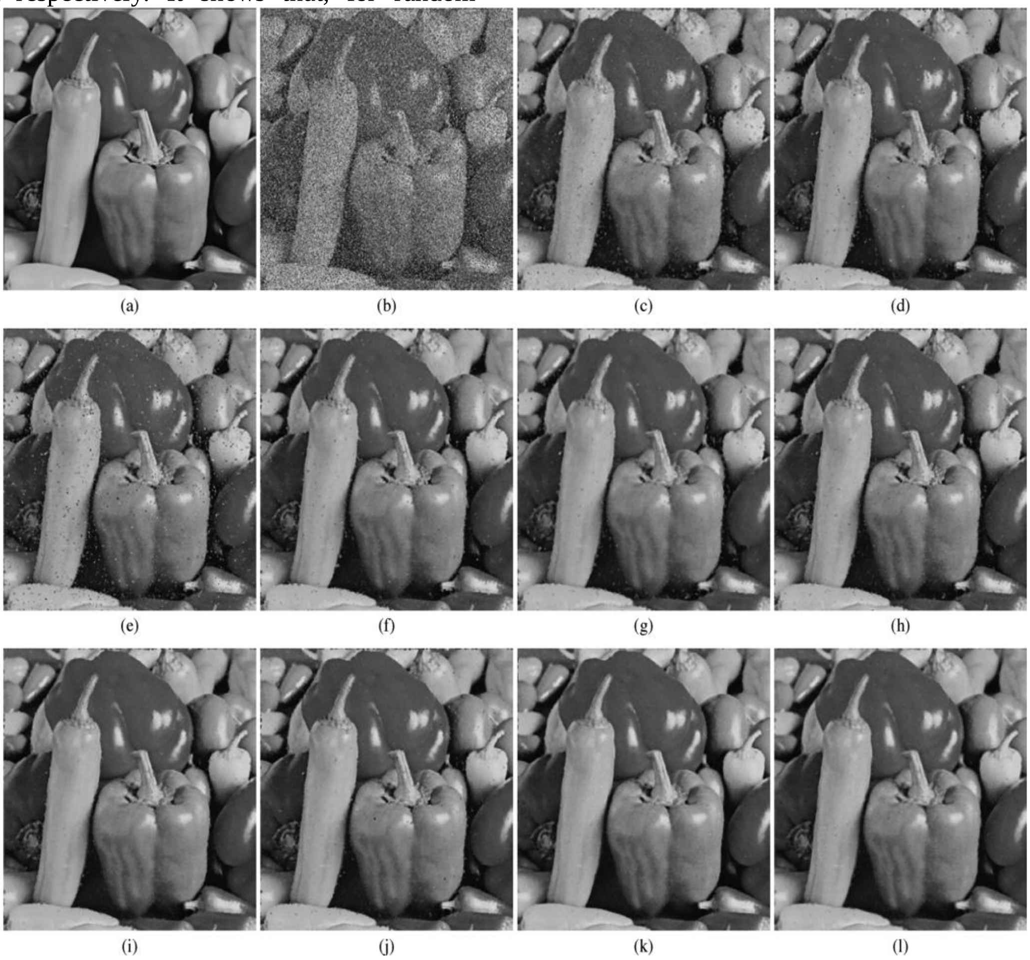

Fig. 4. Results of different filters included in comparison for test image Pepper with 50% of random-valued impulse noise. (a) Original image. (b) Noisy image.(c) SWM. (d) TRI. (e) MSM. (f) ACWM. (g) PWMAD. (h) Luo-iterative. (i) DWM. (j) ASWF. (k) ROLD-EPR. (l) Proposed ROR-NLM.

C. Snapshots and Experimental Results:

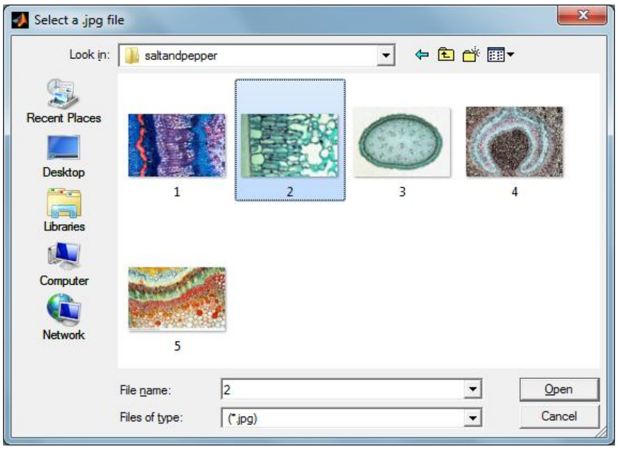

Fig. 5. Input noisy image

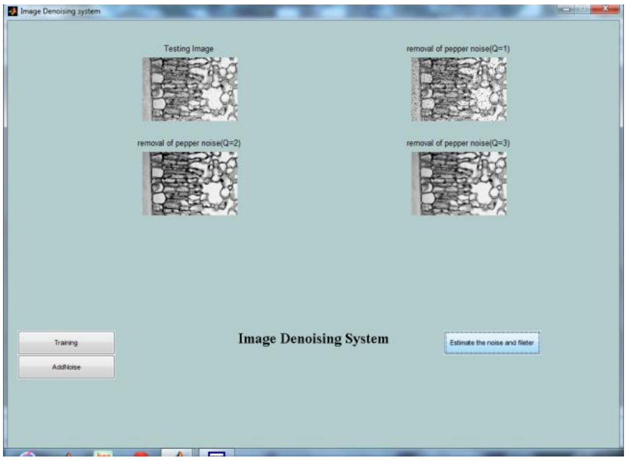

Fig. 6. Output noise-free image for image denoising method at various levels.

V. CONCLUSION

The main contribution of this paper can be summarized as follows: introduce new statistics ROR for describing the outlying- ness of the pixels and propose a new detection mechanism; extend the NL-means to the impulse noise; and obtain a universal noise removal framework with the proposed detection method and the NL-means.

The proposed approach can be adapted to various models such as salt-and-pepper impulse noise, random-valued impulse noise, and mixed noise by modifying some parameters in the algorithm. Extensive simulations reveal that the performance of the proposed algorithm is good.

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