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Fuzzy based random valued Impulse noise suppression using optimal direction method

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ABSTRACT

This paper proposed new techniques based on fuzzy logic in optimal direction for suppression of random valued impulse noise in digital images. The deviation of the test pixel from its neighboring pixels present in the optimal direction shows its corruption level. According to how much a pixel is impulse-like, a fuzzy index is assigned to each and every pixel in the image. After the detection of impulsivity of each pixel, a non-local mean filter is employed for noise suppression. Extensive simulations are performed to prove that the proposed techniques give better visual quality and quantitative measurement than recent impulse noise suppression techniques.

Introduction

In general, digital images are frequently affected by impulse noise in the procedures of image acquisition and transmission. Therefor an image denoising step is highly required before use

the image for certain application. The image denoising steps not only efficiently remove the noise but also preserve the important details of the image. According to the distribution of noisy pixel values, impulse noise can be classified into two categories: salt & peppers impulse noise (SPIN) and random-valued impulse noise (RVIN). When an image is corrupted by salt & peppers noise, the noisy pixels attend a value equal to the maximum or minimum value of the image, whereas for Random value impulse noise, noisy pixel can take any value in the available dynamic range. So to develop an algorithm for removal of RVIN is more challenging than SPIN. In this paper we focus on removing the random-valued impulse noise from the noisy image.

Impulse noise denoising is one of the most widely studied and largely unsolved problems in digital image processing. Numbers of papers have been published with different innovative idea to recover the original image from the noisy image. The simple median filter [1] was once the most popular choice for removing the impulse noise from images because of its effectiveness and high computational efficiency. But, it performed filtering operation with all the pixels without distinguishing between noisy and nose free pixels and results in destroying important details and producing blotches in the filtered images. To solve this problem an impulse noise detector is required for detection of noisy pixels prior to filtering. Many such algorithms likes MSM[4], ACWMF[5], ASWMF[6], PWMAD[7], ADMAD[8],

ATBMF[9] and SDROM[10] have been proposed to allow only the noisy pixels for the filtering without disturbing the noise free pixels and maintain fine details of the image. In case of random valued impulse noise, the detection of an impulse is relatively more difficult in comparison with salt-and-pepper impulse noise. Hence the performance of these filters is satisfactory only for low noise density. To remove the RVIN more efficiently Dong and Xu proposed a directional weighted median (DWM)[11] filter which is applied recursively for 8 to 10 iterations to the noisy image to get the best result. This filter uses a new impulse detector, which is based on the differences between the current pixel and its neighbors aligned with four main directions. Even though it provides good result for high noise densities, the high computational overhead discourages for real time implementations. Recently a novel algorithm has been proposed called, standard deviation for obtaining the optimal direction in the removal of impulse noise (SDOOD) [12]. For detecting the central pixel whether it is noisy or noise-free pixel, a similarity parameter, i.e. normalized difference in optimal direction calculated by measuring the normalized distance between the tested pixel, and the pixels in the optimal direction. Then by using a proper threshold, it can decide whether the test pixel is a noisy or an original pixel. Also, more edge pixels can be detected if the accurate or optimal direction of the edge is determined. The noisy pixel that has small deviations with the pixels in the optimal direction is deemed an original pixel. In ENLM [13] GuangyuXu used the modified Rank ordered Absolute Difference calculation algorithm and named it as extremum compression rank order absolute difference (ECROAD) to distinguish between noisy and non-noisy pixels efficiently. Then the powerful Non local means (NLM) algorithm is applied to filter the noisy pixels.

In this paper a new filtering scheme based on Fuzzy based impulse detection using optimal direction method is proposed. The filter gives a fuzzy measure of each pixels indicating the

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corruption level depend upon its Absolute Difference in Optimal direction (ADOD) value. Then a modified fuzzy weighted Non Local means algorithm [14] is used restore the image. The fuzzy measure of each pixel helps the algorithm to define the contribution of neighborhood pixels for restoring a noisy pixel. The more a pixel is corrupted the less the pixel participates in image reconstruction.

The overall paper is organized as follows. Section-1 deals with introduction. Section-2 deals with noise model. Section-3 describes the proposed denoising work. Section-4 describes the performance measured used to show the efficacy of the proposed method. Section-5 discusses the simulation and results. Finally, Section-6 provides the concluding remarks.

Nose Model

Depending on the model used to characterize the noise, we can encounter impulse noise, Gaussian noise and many others. In this paper, we are giving more importance on impulse noise [1, 2, 3]. Impulse noises can be described by the following model:

$$x(i,j)=\begin{cases}\eta(i,j) \text{with probability} & p\\ y(i,j) \text{with probability} & 1-p\end{cases} \qquad (1)$$

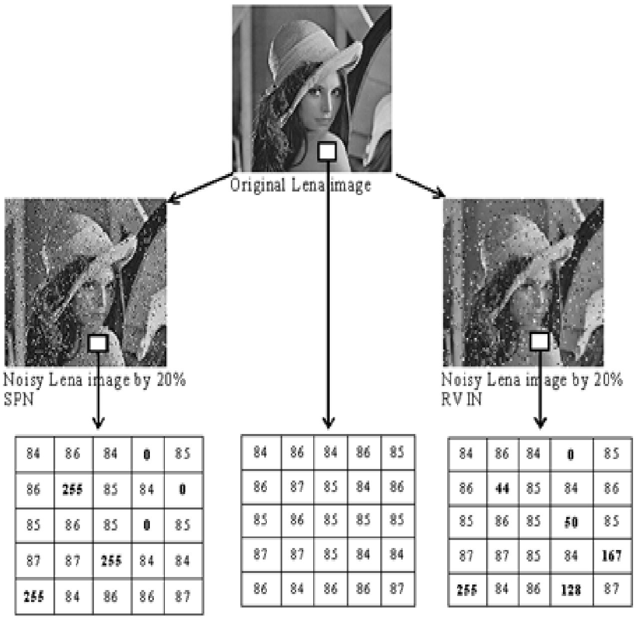

Figure 1:Original and noisy Lena image with SPN and RVIN

Where, x(i,j) denotes a noisy image pixel, y(i,j) denotes a noise free image pixel and η(i,j) denotes a noisy impulse at the location(i,j). Impulsive noise can be classified as salt-and-pepper noise (SPN) and random-valued impulse noise (RVIN)[1, 2, 3]. In salt-and-pepper noise, noisy pixels take either minimal or maximal values i.e. $\eta(i,j)\in\{L_{min},L_{max}\}$, and for random-valued impulse noise, noisy pixels take any value within the range minimal to maximal value i.e. $y(i,j)\in[L_{min},L_{max}]$ where, L_{min},L_{max} denote the lowest and the highest pixel luminance values within the dynamic range respectively so that it is a little bit difficult to remove random valued impulse noise rather than salt and pepper noise [3]. The preservation of image details faces difficulties due to the attenuation of noise. Figure-1 shows how an image corrupted by RVIN is different from an image corrupted by salt and pepper noise. In the case of SPN the pixel substitute in the form of noise may be either L_{min}=0or L_{max}=255for 8-bit images. Whereas in RVIN situation it may range from L_{min} to L_{max}. Cleaning such noise is far more difficult than cleaning fixed-valued impulse noise; the differences in gray levels between a noisy pixel and its noise-free neighbors are significant most of the time. In this letter, we focus on random valued impulse noise and schemes that are proposed to suppress them.

Proposed Technique

A novel method using fuzzy impulse noise detection technique followed by a non-local mean filter is designed for removal of random value impulse noise is presented here. The non-local means filtering method discussed in [15] is an efficient filtering for image denoising. It restores the noisy pixels by the weighted average of all similar pixels in the filtering window. Pixel similarity is defined in NLM as the Euclidean distance between image patches. Hence it can work effectively for suppression of Gaussian noise from image. But the simple NLM filter fails to remove impulse noise from image [16].As the impulse noisy pixels are very different from their neighbors and do not contain any useful information, taking the radiometric component of all neighboring pixels may not provide accurate weight for impulse noise removal [16]. However if the identity of each pixel is known before weight calculation, we can prohibit the unwanted pixels involvement and contribution of participate pixels in weight calculation. A fuzzy impulse detection technique based on Absolute Difference in Optimal direction (ADOD) [12]value is proposed here to do this task in two phase described below.

Fuzzy Impulse Detection

As the RVIN noise in a digital image can have any possible value in the available dynamic range, it is very hard to detect precisely the noisy pixel. To solve this problem a fuzzy index is assigned to each and every pixel in the image according to how impulse-like a pixel is.Here we calculated the Absolute Difference in Optimal Direction (ADOD) value of each pixel using optimal direction method discussed in [12] before filtering. Then the based on ADOD value of each pixel, a fuzzy index is assigned to each pixel which define its contribution in weight calculation.

The term ADODis Absolute difference between original pixel and other pixels in the optimal direction of the filtering window. As the similar pixels are present in the optimal direction, a test pixel can be identified as the original pixel if it has small deviations with the pixels in the optimal direction. Hence the ADOD can be taken as an important measure to distinguish between noisy and non-noisy pixel in the image. More edge pixels can be detected if the accurate or optimal direction of the edge is determined. The computation of ADOD is given in the following steps.

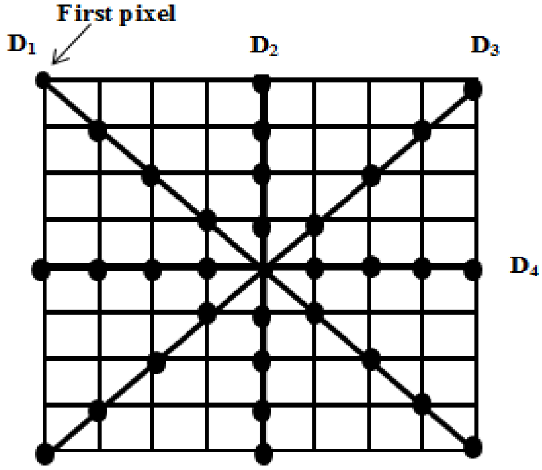

Figure 2: A 9×9window divided into four directions

Step 1: Consider a 9 x 9window and let the first pixel be denoted asx_{ij}. The total pixels in the window, except the central pixel $x_{i+(k+1)/2,\ j+(k+1)/2}$, are divided into four directions $D_d^{i,j'}$s, D=1:4 as shown in Figure 2. The pixelsin each direction are listed in terms of their coordinates as follows:

$$D_1^{0,0}=\{(0,0),(1,1),(3,3),(4,4),(5,5),(6,6),(7,7),(8,8)\}$$
$$D_2^{0,0}=\{(0,4),(1,4),(2,4),(3,4),(5,4),(6,4),(7,4),(8,4)\}$$
$$D_3^{0,0}=\{(0,2),(1,7),(2,6),(3,5),(5,3),(6,2),(7,1),(8,0)\}$$
$$D_4^{0,0}=\{(4,0),(4,1),(4,2),(4,3),(5,4),(6,4),(7,4),(8,4)\}$$

Step 2:Sort the pixels in each direction $D_d^{i,j}$ in ascending order so that the outlier pixels can be specified. The new vector $r_d^{i,j}$, d=1:4 that attained from the corresponding sorted direction $D_d^{i,j}$ is defined as;

$$r_d^{i,j}=\{x_{1,s}^d \mid x_{1,s}^d \in D_d^{i,j},\ s=1:(k-1),\ d=1:4,\ x_{1,\ s+1} \geq x_{1,\ s}\} \quad (\mathbf{2})$$

Step 3: The optimal direction D^{op} is attained by finding the vector $\tilde{r}_d^{i,j}$ that has minimum standard deviation σ:

$$D^{op}=\operatorname{argmin}_{\tilde{r}_d^{i,j}}\{\sigma_{\tilde{r}_d^{i,j}}\} \quad (\mathbf{3})$$

Here, $\sigma_{\tilde{r}_d^{i,j}}$ is the standard deviation of the pixels in the vector $\tilde{r}_d^{i,j}$. The D^{op} gives the optimum direction is the direction that has the most similar pixels.

Step 4: The ADOD for the central pixel $x_{i+(k+1)/2,\ j+(k+1)/2}$ is defined as,

$$ADOD=\sum_{s=2}^{k-2}\left|x_{1,s}^{op}-x_{\bar{ij}}\right| \quad (4)$$

where, $x_{1,s}^{op}$ is the pixel in the optimal direction.

As the ADOD value indicates the impulsivity of each pixel, i.e. higher ADOD value indicates that the pixel is corrupted whereas lower value means the pixel is the original one, we use this difference to define the fuzzy index in the following manner

$$\mu(x)=\begin{cases}0 & ADOD(x)>T_1\\ \dfrac{ADOD(x)-T_1}{T_2-T_1} & T_2\leq ADOD(x)\leq T_1\\ 1 & ADOD(x)<T_2\end{cases} \quad (5)$$

Where T_1 and T_2 are two predefined threshold.

The fuzzy index μ(x) ranges from the minimum value 0 to the maximum value 1 and indicates how contribution of a pixel is required for getting the restored value of noisy pixel in filtering operation. The value 1 denotes the pixel is noise free, and its information is fully required for image reconstruction. The fuzzy index 0 prohibits a pixel to participate in filtering.

Proposed fuzzy based Non Local means filtering

Here we combine the fuzzy index with the non-local means filtering to make it more efficient for random value impulse noise removal. The weight calculation is very much similar to the formula given in [14] and is defined for a test pixel $u(x)$at co-ordinate $x=x(x_1,x_2)$in a searching window $\mathbf{\Omega}_x(N)$of size $(2N+1)\times(2N+1)$ as;

$$\widehat{\omega}(x,y) =\mu(y).\exp\left(-\frac{\sum_{k\in\emptyset_m} f_a(k)\mu(x+k)\mu(y+k)|v(x+k)-v(y+k)|^2}{h^2}\right) \quad (6)$$

Where the weights $\widehat{\omega}(x,y)$ express the amount of similarity between each neighboring pixelv(y) with respect to the test or center pixel in the filtering window. The handf$_a$(k) represents the smoothing parameter and a centered symmetric Gaussian kernel with the standard deviation a respectively**.** The term $\emptyset_m$indicates the matching window used for calculation the pixels similarity by comparing the surrounding patches around the test pixels x and its neighbor's pixel at y in the searching window and defined as:

$$\emptyset_m\equiv\{k=(k_1,k_2)|-m\leq k_1,k_2\leq m\} \quad (7)$$

Where m is the size of the matching window.

Now the weighted average Non Local Means (NLM) filter used for calculation of the restored value $\hat{\boldsymbol{v}}_{\boldsymbol{R}}(\boldsymbol{x},\boldsymbol{y})$ of the corrupted pixels is defined as:

$$\hat{v}_R(x,y)=\frac{\sum_{y\in\Omega_x(N)}\widehat{\omega}(x,y)\,v(y)}{\sum_{y\in\Omega_x(N)}\widehat{\omega}(x,y)} \quad (8)$$

Performance Measures

One of the issues of denoising is the measure of the reconstruction error. The metrics used for performance comparison of different filters (existent and proposed) are defined below.

Peak Signal to Noise Ratio (PSNR)[2, 18]:

In statistics, the mean squared error or MSE of an estimator is one of many ways to quantify the amount by which an estimator differs from the true value of the quantity being estimated. The mean square error (MSE) is commonly used and given that original image V of size (M×N) pixels and as reconstructed image $\widehat{V}$, the MSE is defined as:

$$MSE=\frac{1}{M\times N}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(V_{i,j}-\widehat{V}_{i,j})^2 \quad (9)$$

MSE represents the power of noise or the difference between original and tested images. It estimates the quality of a reconstructed image with respect to an original image. Reconstructed images with higher PSNR are judged better. PSNR is the ratio between the maximum possible power of a signal and the power of noise. PSNR is usually expressed in terms of the logarithmic decibel. Given that original image V of size (M×N) pixels and as reconstructed image $\hat{V}$, the PSNR (dB) is defined as:

$$PSNR(dB)=10\log_{10}\left(\frac{255^2}{MSE}\right) \quad (10)$$

Where, 255 is the maximum possible amplitude for an 8-bit image. An improvement in the PSNR magnitude will increase the visual appearance of the image. PSNR is typically expressed in decibels (dB). For comparison with the noisy image, the greater the ratio, the easier it is to identify and subsequently isolate and eliminate the source of noise.

Structural Similarity Index Measures (SSIM) [17]

The Structural Similarity Index Measure (SSIM) [17] between the original image and restored image can be defined by,

$$SSIM=L(V,\widehat{V})*C(V,\widehat{V})*S(V,\widehat{V}) \quad (11)$$

where $L(X,\widehat{X})=(2\mu_V\mu_{\widehat{V}}+C_1)/(\mu_V^2+\mu_{\widehat{V}}^2+C_1)$

$C(V,\widehat{V})=(2\sigma_V\sigma_{\widehat{V}}+C_2)/(\sigma_V^2+\sigma_{\widehat{V}}^2+C_2)$

$S(V,\widehat{V})=(\sigma_{V\widehat{V}}+C_3)/(\sigma_V\sigma_{\widehat{V}}+C_3)$

$C_1=(K_1*G)^2,\ C_2=(K_2*G),\ \boldsymbol{C_3}=C_2/2$

$G=255,\ K_1,K_2\ll 1$

Where V, is the original Image, $\widehat{V}$is the restored image M × N is the size of the image, L is the luminance comparison, C is the contrast comparison, S is the structure comparison, μ is the mean and σ is the standard deviation of the image.

Simulation and Results

To validate the proposed scheme, simulation has been performed on standard images; only performance evaluation using images such as Lena, Peppers and Gold hill of size 512 × 512 are discussed here. The images are subjected to as low as 30% noise to as high as 60% noise.

Table 1: Comparative analysis of PSNR(dB) for various filters in Lena, Peppers and Gold hill images												
Methods / Noise	**% of RVIN**											
	Lena				**Peppers**				**Gold hill**			
	30%`	**40%**	**50%**	**60%**	**30%`**	**40%**	**50%**	**60%**	**30%`**	**40%**	**50%**	**60%**
SMF	28.05	24.57	21.04	18.54	27.19	23.63	20.61	17.95	26.67	23.49	20.69	18.31
MSM	30.66	26.86	23.67	20.60	30.22	26.57	23.26	20.38	29.52	26.25	23.49	20.40
ACWMF	31.95	28.80	25.75	22.23	31.28	28.15	24.97	21.59	30.17	27.81	25.03	21.96
PWMAD	28.19	23.95	20.56	17.83	27.66	23.58	20.09	17.41	27.15	23.55	20.27	17.68
ADMAD	28.17	24.06	20.66	17.89	27.42	23.78	20.25	17.56	27.35	23.69	20.36	17.67
ATBMF	32.45	29.37	25.74	22.13	31.99	28.52	25.17	21.48	30.45	28.07	25.13	21.76
SDROM	31.20	28.32	25.31	22.37	30.54	27.57	24.77	21.61	29.92	27.33	24.89	22.02
SDOOD	30.67	28.43	25.55	21.79	30.12	27.82	24.63	21.02	29.22	27.52	24.99	21.67
DWM	32.45	30.59	28.11	24.85	31.99	30.23	27.57	23.97	30.09	28.75	27.11	24.55
ENLM	31.50	30.31	29.20	27.48	31.44	30.44	29.15	27.24	28.78	28.01	27.27	25.98
PROPOSED	32.46	30.86	29.18	27.10	32.20	30.55	28.35	26.12	30.47	28.95	27.63	26.06

Table 2: Comparative analysis of SSIM for various filters in Lena, Peppers and Gold hill images												
Methods /Noise	**% of RVIN**											
	Lena				**Peppers**				**Gold hill**			
	30%`	**40%**	**50%**	**60%**	**30%`**	**40%**	**50%**	**60%**	**30%`**	**40%**	**50%**	**60%**
SMF	0.9762	0.9460	0.8756	0.7737	0.9777	0.9479	0.8910	0.7875	0.9699	0.9358	0.8735	0.7728
MSM	0.9871	0.9687	0.9336	0.8619	0.9891	0.9744	0.9434	0.8842	0.9847	0.9671	0.9364	0.8633
ACWMF	0.9905	0.9801	0.9593	0.9053	0.9915	0.9823	0.9624	0.9138	0.9869	0.9772	0.9559	0.9065
PWMAD	0.9772	0.9392	0.8666	0.7490	0.9803	0.9487	0.8822	0.7734	0.9735	0.9387	0.8671	0.7533
ADMAD	0.9773	0.9412	0.8709	0.7553	0.9793	0.9514	0.8873	0.7852	0.9750	0.9412	0.8711	0.7559
ATBMF	0.9915	0.9825	0.9588	0.9023	0.9928	0.9837	0.9638	0.9100	0.9877	0.9785	0.9565	0.8999
SDROM	0.9887	0.9779	0.9553	0.9102	0.9900	0.9799	0.9610	0.9161	0.9862	0.9747	0.9549	0.9102
SDOOD	0.9872	0.9784	0.9575	0.8961	0.9890	0.9810	0.9594	0.9021	0.9837	0.9758	0.9558	0.9017
DWM	0.9914	0.9867	0.9761	0.9476	0.9928	0.9890	0.9792	0.9496	0.9866	0.9815	0.9726	0.9479
ENLM	0.9894	0.9860	0.6685	0.9719	0.9919	0.9897	0.9859	0.9773	0.9819	0.9781	0.9737	0.9636
POPOSED	0.9915	0.9876	0.9815	0.9684	0.9932	0.9899	0.9830	0.9705	0.9878	0.9825	0.9759	0.9642

The proposed scheme as well as the recently suggested few well performing schemes like SMF, MSM, ACWMF, ASWMF, PWMAD, ADMAD, ATBMF, SDROM, SDOOD, DWM and ENLM are applied to the noisy images.

The simulation is carried out using MATLAB 7.0. The PSNR and SSIM are basically two Objective quality parameter through which performance measure and quality of restored image are evaluated to show the efficacy of the proposed scheme as compared to other standard and recently proposed schemes.

It has been observed experimentally that, when the threshold value of T_1 and T_2 are set to 320 and 100 respectively, the algorithm gives better result. For proper filtering the searching window [14] is taken as of size 15×15 and the pixel similarity is calculated in 7×7 matching window, i.e. $\boldsymbol{m}$ is set to a value 3 in equation (7). The standard deviation $\boldsymbol{a}$ of the Gaussian kernel and the smoothing parameter $\boldsymbol{h}$ is taken as 2 and 6 respectively.

The performance parameter values such as PSNR and SSIM obtained after applying the various filters are compared by varying the noise density from 30% to 60% are shown in Table-1 and Table-2 respectively. PSNR shows the noise ability of the proposed method in noise reduction whereas the parameter SSIM indicates how much similar is the restored image with the original image. It is easy to see that the proposed filter provides results with higher PSNR as well as SSIMvalues in all cases. In order to give a visual impression about the performances the restored Lena images at 60% noise density is shown in figure in Fig. 3.It is obvious that the proposed filter performs better than other.

Conclusion

In this paper a new restoration method is proposed to recovers images corrupted with RVIN effectively. To filter the impulse noise efficiently the method used the powerful non local means algorithm in a modified form by introducing the fuzzy weighted function into it. The fuzzy weighted function is derived from the ADOD value of the pixels in the image. The performance of the proposed scheme has been compared with many well-known techniques. The comparative performance analysis in general shows that the proposed scheme outperforms the existing schemes both in terms of noise reduction and retention of images details.

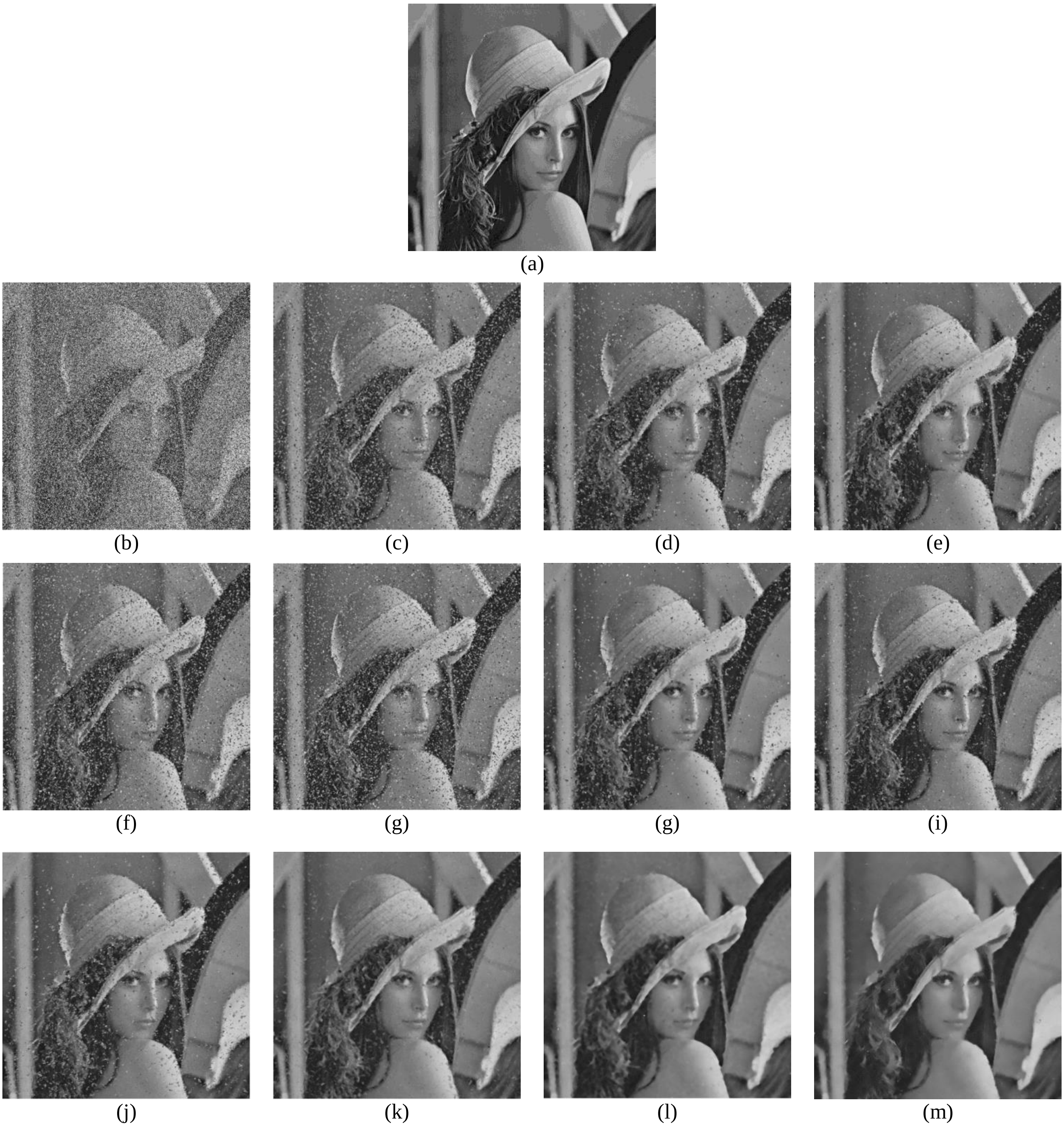

Figure 3: Results of different filters included in comparison for test image Bridge with 40% of random-valued impulse noise. (a) Original image. (b) Noisy image.(c) SMF. (d) MSM (e) ACWMF (f) PWMAD (g) ADMAD (h) ATBMF (i) SDROM (j) SDOOD (k) DWM (l) ENLM(m)Proposed method.

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