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Removal of Random-Valued Impulse Noise by Using Texton

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Abstract-Images usually get contaminated with random-valued impulse noise (RVIN) at the time of compression, transmission and during encoding of images. The RVIN corrupts the pixels with any value in the dynamic range of pixels (for 8-bit image the dynamic range is 0 to 255). In the proposed method, a novel approach of dividing-sliding-window (DSW) into sub-windows (textons) for identification and removal of RVIN is presented. The pixels are identified as noisy pixels on the basis of four textons median values. Noisy pixels are replaced with the median value of texton having minimum absolute inner difference. Experiments have been done on the state-of-the-art images with standard RVIN methods shows that the proposed method outperforms over standard methods. DSW can preserve the fine edges and image details in better way.

Keywords-Dividing-Slidng-Window, Textons, Sliding Window, Minimum Absolute Inner Difference.

I. Introduction

The most important concern in the field of image processing is de-noising. Images are corrupted with any kind of noise can affect the processing especially in medical, weather forecasting and aviation system etc. Impulse noise often arises in digital images during compression, acquisition, decompression, transmission and electromagnetic interference. Impulse noise is categorized into two main categories, random-valued impulse noise (RVIN) that is difficult to remove due to randomness and salt-and-peppers (SNP) noise that is easy to remove due to predictability. In SNP noise, only least or most values in the dynamic range of pixels contaminate the image pixels. (In 8-bit image the dynamic range least value is 0 and most value is 255) [i]. The pixel recovery in RVIN is difficult as image pixels are contaminated with any intensity value (In 8-bit image the dynamic range is 0 to 255).

Median filter (MF) [ii] is commonly used in RVIN removal. The performance of MF is appropriate for flat regions. However, it replaces all pixels values either noisy or noise free. Due to it blurring effect is prominent in recovered images. When MF came across to high-density impulse noise, results are inappropriate. To overcome the problem of MF, an improved class of filters like Weighted Median Filter (WMF) [iii] and Centered Weighted Median (CWMF) [iv] filter are proposed. However, improved techniques also replace all image pixels uniformly. A new class of decision based filter is proposed that includes Adaptive Median filter (AMF) [v] and Adaptive Centered Weighted Median filter (ACWMF) [vi]. In AMF for each iteration a separate threshold is defined for every sliding strip and overcome the problem of median filter. ACWMF [vi] is adaptive filter and more weightage is assigned to central pixel for every sliding window. However Miss and false identification values are not satisfying. These filter overcome the problem MF. MF replaces all pixel values indifferently. AMF detects and replaces the noise pixel value. Accuracy depends upon detection procedure of AMF filters. An efficient procedure using Rank-Ordered Relative Difference (RORD) [vii] is proposed that preserves the edges using Rank-Ordered Absolute Difference (ROAD) [viii]. It compares the central pixel with sum of difference with central pixel and identify it noisy or noise less pixel. In [ix] Signal Dependent Rank-Ordered Mean (SDROM) [ix] is proposed. It operate on the pixels that are obtained by difference of input pixel and ROAD output in the sliding window. However it did not perform well for high-density impulse noise. Space Variant Median (SVM) [x] filter, Tri-state Median Filter (TSM) [xi] and Vector Directional Filter (VDF) [xii] are also proposed for the identification and removal of RVIN and not properly recovered the image details. A fuzzy based filter (FIDRM) [xiii] and fuzzy random filter (FRINRM) [xiv] are used for removal of RVIN. However uses fuzzy logic for enhancement of noisy pixels. ANN based detector [xv], Modified Progressive Switching Median (MPSM) filter [xvi] is mixture of PSM [xvii] and CWMF [iv] filter, Improved Adaptive Impulse Noise Suppression (IAINS) [xviii] and a fuzzy filter RUSSO [xix] often involved in miss and false identification of pixels. A New Method for Removal of RVIN using similar neighbors (SN) [xx] is based on four neighbors that could not differentiate if neighboring pixels are noisy. The removal of RVIN using local statistic (LS) [xxi] used small difference pixel in specified direction for noise removal. Results are not satisfactory if small difference among pixel is not available. Removal of RVIN using sparse representation [xxii] method used to remove impulse noise however computational complexity is increased for high density noise method. In [xxiii] a group sparse (GS) method is used for restoration of images corrupted with RVIN and de-noised in second step. They have used ROAD [viii] method for the identification of corrupted pixels. The sparse method is used for removal of noisy pixels. The group sparse method is extended sparse method that utilized the detection filter [xxiv] for removal of RVIN and self-similarity measure. However, it faces the problem of false detection and miss detection. Under high density noise, patches are prominent in de-noised image. In [xxv] advance filter utilized adaptive dual threshold for restoration of noisy pixels. However result under high density noise are not appropriate.

In [xxvi] restoration of pixel noisy pixel is performed using Khalimsky grid and in [xxvii] weber's law method, however restoration process is expensive. The Khalimsky grid method used 7x7 mask size and preserve image details finely. However, does not perform well for low density noise. The weber's law method has high computational cost for every window. In [xxviii]. shearlet-based approach is used to restore noisy image. This approach is better under low noise density and for high-density noise the visual results are not appropriate. Various types of noise are introduced in images during acquisition and compression like multiplicative noise and impulse noise. The following filter address impulse noise [xxix-xxxi]. The results of following filter regarding RVIN are not satisfactory. The proposed DSW method addresses the impulse noise properly and recover the edges properly and image details also. In [xxxii] filter is introduced that uses directional rank order absolute difference the results of proposed filter is satisfactory and the adaptive approach makes this effective. In [xxxiii] the sparse representation based filter is introduced. The detection process is based on sparse representation and to detect noisy pixel GRT is used and noisy pixel is compared with sparse estimation.

The proposed DSW method is based on sub-windows or textons [xxxiv] that has been used for image retrieval. The contribution in the proposed work is we have used the concept of textons for the identification and removal of RVIN and proposed a new texton. The identification noisy or noise free pixel is done on the bases of textons median value. Dual threshold is defined using texton median values. The removal of RVIN is based on the textons or sub-windows having least sum of inner difference. The noisy pixel is recovered by median of texton having least sum of inner difference. The proposed DSW method performance is better as compared with previous existing approaches in term of PSNR. The proposed method restores image details and preserves edges effectively.

The rest of paper is arranged in subsequent portion. In Section II, the proposed DSW methodology is discussed; the experimental results on DSW method are described and compared in section III. As a final point, the precise conclusion is furnished in section IV.

II. Proposed Methodology

The dividing-sliding-window (DSW) method has two stages. First one is identification of RVIN and second stage is the removal of RVIN. In section A., identification of RVIN using sub-windows (textons) median value is briefly discussed. Section B. describes the removal of RVIN using texton having minimum sum of absolute inner difference of pixels. The sub-windows (textons) concept is introduce by [xxxii] for image retrieval. The image enhancement and restoration is accomplished in spatial and frequency domain. The proposed work of image enhancement has been accomplished in spatial domain. In proposed DSW method the texton concept is adopted for the identification and removal of RVIN. Fig. 1 explain the proposed methodology of DSW method. The division of 3x3 window into four textons is explained in Fig. 2-6. Fig. 2 describes a 3x3 noisy image window and Fig. (3-6) describes the four textons that are moulded from Fig. 2. The central pixel value is kept intact. The orientations of textons are describes in equation 1, 2, 3 and 4. The Textons T1, T2, T3 and T4 are moulded using Fig. 3-6. Only highlighted part of Figures (3-6) are defining textons. The values belongs to these highlighted position are part of textons.

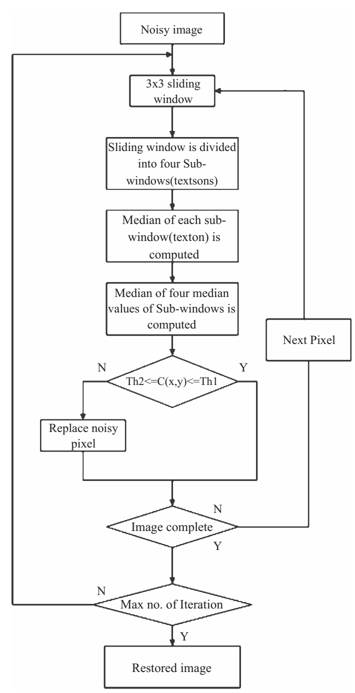


Fig. 1. is the flow diagram of proposed DSW method. Where C(x, y) is central values in the sliding windows and Th1 and Th2 are threshold value.

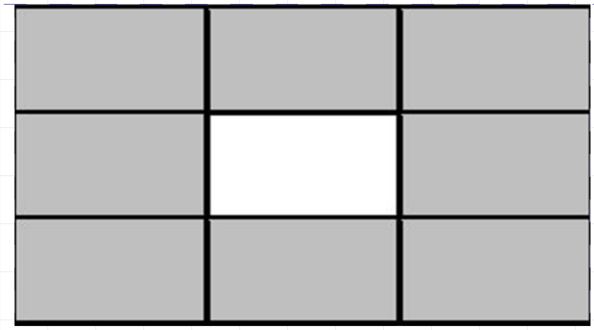


Fig. 2. Describe a 3x3 noisy image window / mask. White cell indicate that central pixel is not used in orientation of textons.

$$V = IR \quad \text{(A)}$$

$$T1 = \{N(1,1) \quad N(2,1) \quad N(3,1) \quad N(3,2) \quad (1)$$
$$T2 = \{N(31) \quad N(3,2) \quad N(3,3) \quad N(2,3) \quad (2)$$
$$T3 = \{N(3,3) \quad N(2,3) \quad N(1,3) \quad N(1,2) \quad (3)$$
$$T4 = \{N(1,3) \quad N(1,2) \quad N(1,1) \quad N(2,1) \quad (4)$$

The textons T1, T2, T3 and T4 are the main component of the algorithm. The four textons extraction diagram is shown in Fig. 3-6.

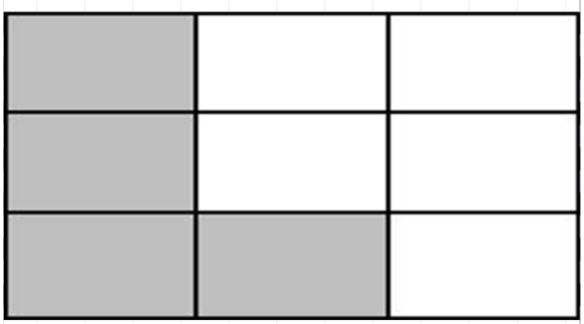


Fig. 3. describes the orientation of texton1 in a 3x3 mask. The highlighted part indicates texton1 pixel positions.

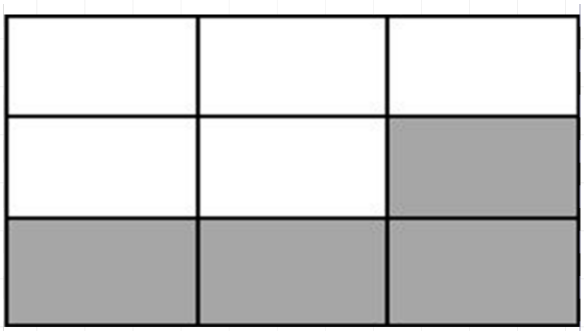


Fig. 4. describes the orientation of texton2 in a 3X3 mask. The highlighted part indicates the texton2 pixel position.

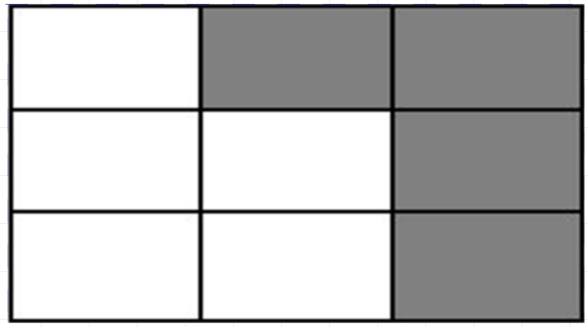


Fig. 5. describes the orientation of texton3 in 3x3 mask. The highlighted part indicates the pixel position of texton3.

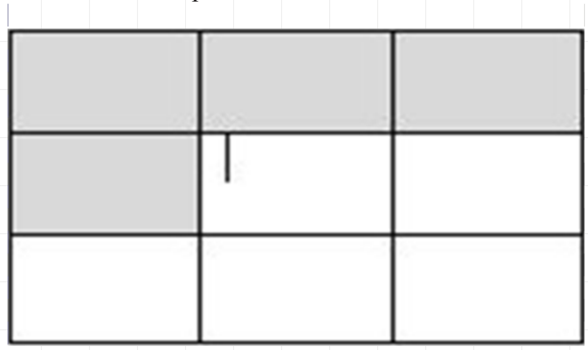


Fig. 6. describes the orientation of texton4 in 3x3 mask. The highlighted portion indicate the texton4 pixel position.

A. Identification of Random-valued Impulse Noise

In dividing-sliding-window (DSW) method, proposed procedure for identification of RVIN is described in the following steps. First the noisy image is divided into 3x3 sliding window. Then the 3x3 sliding window is divided into four sub-windows (textons) as shown in Fig. 2-6. The median of every sub-windows (textons) is computed. The four median of textons are obtained. The final median of the four textons median values is calculated and named as median of textons median value (MTM). In the MTM constant value is added and subtracted to define a dual threshold value. This threshold value decides the pixel value either noisy or remained intact from noise. If the pixel value is decided non-noisy remains the same. If it is noisy, restored in section B. of noise removal.

B. Removal of Random-Valued Impulse Noise

In dividing-sliding-window (DSW) method, the removal of RVIN is describes as follows. If the pixel is identified as noisy then it is replaced by using texton having least sum of absolute inner difference. Since 3x3 window is molded into four sub-windows (textons). For the removal of noise from pixels, the sum of absolute inner difference of every texton is determined. The texton having minimum sum of absolute inner difference of pixels is used for removal of noisy pixel value. The pixel declared as noisy is recovered with the texton median having least sum of absolute inner difference.

The whole process is explained using equation (5) of noisy image window contaminated with 20% RVIN. The identification and removal of noisy pixel value is explained by following example. First a 3x3 image strip is obtained from contaminated image. The whole process is performed for central pixel. In our case central pixel is 057. To decide it whether it is noisy or noise free pixel, if identified as noisy pixel the noise will be removed.

$$N = \begin{bmatrix} 162 & 230 & 161 \\ 162 & 057 & 161 \\ 162 & 162 & 009 \end{bmatrix} \quad (5)$$

Where N is noisy image window.

Then this 3x3 noisy image strip is divided into four sub-windows (textons) using equation (1), (2), (3) and (4) and replaced the position with correspondence values using equation (5).

$T1 = \{162 \quad 162 \quad 162 \quad 162\}$ (i)
$T2 = \{162 \quad 162 \quad 009 \quad 161\}$ (ii)
$T3 = \{009 \quad 161 \quad 161 \quad 230\}$ (iii)
$T4 = \{161 \quad 230 \quad 162 \quad 162\}$ (iv)

Then the median of each texton is computed. The median1, median2, median3 and median4 are median of texton1 (T1), texton2 (T2), texton3 (T3) and texton4 (T4).

median1=162, median2=162, median3=161, median4=162. Then final median of four textons median values (162, 162, 161, and 162) is computed named as median of textons median value (MTM). That is equal to 162.

$$MTM = 162 \quad \text{(v)}$$

Then threshold value is defined using MTM by adding and subtracting constant value in MTM. The constant value range is approximated from experiments. The constant values ranges from 15 to 30 are used in defining the threshold. The threshold value is computed in the following way.

$$Th1 = MTM + 30 \quad \text{(vi)}$$
$$Th2 = MTM - 30 \quad \text{(vii)}$$

If pixel value under experiment lies outside the dual threshold range then it is considered noisy. The threshold values are Th1=162+30 is 192 and Th2=162-30 is 132. So central pixel value is 57 that is under experiment (57) lies outside threshold range 132 to 192 is considered noisy. So the noisy pixel value is restored in noise removal phase.

In noise removal, the sum of absolute inner difference of every texton is calculated using equation 6, 7, 8 and 9

$$sid1 = |162-162|+|162-162|+|162-162| +|162-162|+|162-162|+|162-162|. \quad (6)$$

$$sid2 = |162-162|+|162-009|+|162-161| +|162-9|+|162-161|+|9-161|. \quad (7)$$

$$sid3 = |9-161|+|9-161|+|9-230| +|161-161|+|161-239|+|161-230|. \quad (8)$$

$$sid4 = |162-162|+|162-230|+|162-161| +|162-230|+|162-161|+|230-161|. \quad (9)$$

Where the |--| is used to compute absolute difference. The following sid1 (sum of absolute difference), sid2, sid3 and sid4 are absolute inner difference of texton1, texton2, texton3 and texton4. So the sid1 has least value among the four textons. So median of texton having minimum sum of absolute inner difference is used for noise removal. At last the contaminated image pixel is recovered. So sid1=0. So median of texton1 is used for noise removal. The median of texton1 is 162. So the corrupted pixel (57) is recovered by 162.

The proposed DSW algorithm is as follows.

Input=noisy image

1. The noisy image is converted into 3x3 image strips.

$$\mathrm{Im}age\_strip = \begin{bmatrix} 1,1 & 1,2 & 1,3 \\ 2,1 & 2,2 & 2,3 \\ 3,1 & 3,2 & 3,3 \end{bmatrix}$$

2. The 3x3 window mask is divided into four sub-windows (textons).

$T1 = \{N(1,1) \quad N(2,1) \quad N(3,1) \quad N(3,2)$ (11)
$T2 = \{N(31) \quad N(3,2) \quad N(3,3) \quad N(2,3)$ (12)
$T3 = \{N(3,3) \quad N(2,3) \quad N(1,3) \quad N(3,2)$ (13)
$T4 = \{N(2,1) \quad N(1,1) \quad N(1,2) \quad N(1,3)$ (14)

3. The median of every textons is computed.
   $Median\_of\_Texton = median \quad (T,2)$ (15)
   Where T represent texton.
4. Again the final median of four textons median is computed.
5. Decide the pixel value either noise free or contaminated with noise based on textons final median.
6. Replace the contaminated pixel value with textons median having least sum of absolute inner difference among pixels.

Output=restored image

III. Results and Evaluation Paremeter

In dataset contains standard test images "Lena", "Barbara", "Baboon" and "Pepper" etc. The well-known evaluation metric Peak Signal to Noise Ratio (PSNR) is used. The PSNR is calculated by Mean Square Error (MSE) that is average of difference of original image pixel and restored image pixel.

$$PSNR = 10\log 10\left(\frac{Max^2}{MSE}\right) \quad (10)$$

Where the max is maximum value in the dynamic range of grey level (255 for 8 bit image is Max). MSE equation is as follows.

$$MSE = \frac{1}{mxn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(O-R\right)^2 \quad (11)$$

Where original and recovered image are represented by O and R. Small m and small n are defining image dimensions.

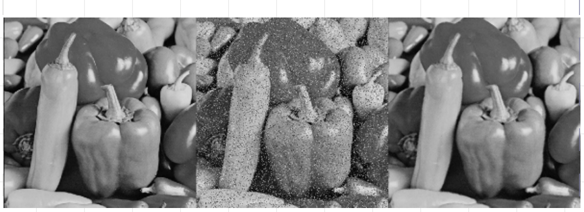
The Miss Detection (MD) refers to the noisy pixels that remain undetected during identification process. False Detection (FD) refers to noise free pixel that are considered noisy during identification process. The FD and MD are used as evaluation parameter. Lower the values of FD and MD refers to more accurate process.

A. Discussion and Comparison of results

The "Lena", "Peppers" and "Barbara" standard images are used for experimentation. The DSW and existing approaches results are in Table I, II and III.

TABLE I
PSNR Value of DSW and Previous Existing Method for Barbara Image.

Method	**Barbara**			
Noise%	10%	20%	30%	50%
MF	25.35	24.17	23.40	20.02
SDROM	25.89	25.74	24.65	22.42
Sparse	28.12	26.18	25.50	23.66
GS	31.57	30.34	28.25	25.25
Proposed	36.01	34.83	33.57	31.22



(a) (b) (c)

In Fig. 7, (a) is original image, (b) noisy image with noise density of 10% (c) is recovered image using DSW.

TABLE II
The PSNR Value of DSW Method and Previous Existing Methods for Lena Image.

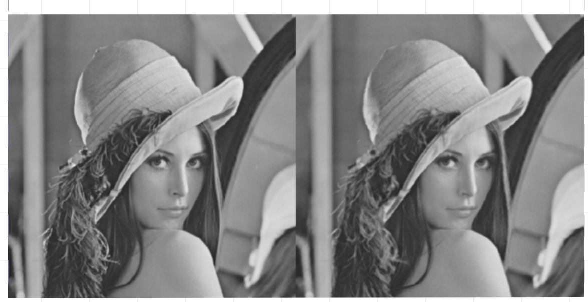
Method	**Lena**			
Noise%	10%	20%	30%	50%
MF	30.84	29.90	28.87	24.45
SDROM	34.29	33.55	31.06	26.01
Sparse	36.46	35.50	33.68	29.57
GS	37.12	36.12	34.37	30.92
Proposed	39.11	37.03	35.33	32.07

TABLE III
The Results of Proposed and Previous Method for Miss Detection and False Detection for Lena Image.

Method	**20%**		**40%**		**60%**	
	Miss	False	Miss	False	Miss	False
ACWM	12863	541	30881	796	569	98625
MPSM	8498	3649	24112	6321	59595	2115
SDROM	11178	1580	30337	4322	49504	12406
RUSSO	15490	1518	31596	3135	58192	10107
FIDRM	3868	11598	13286	14768	55725	12778
DWM	4210	9820	8969	9099	15589	10524
FRINRM	4104	11774	7341	30779	16790	24982
IAINS	12119	1045	12476	15459	17,511	30243
ANN	6186	6407	8104	12619	17511	10226
Proposed	4324	4338	7154	6914	6752	6323

Finally, In DSW the details of images are preserved finely. DSW method performance is better than the previous methods. Table I and II describes experimental evaluation of PNSR and previous existing method and Table III explain miss and false detection performance of DSW and previous methods.

PSNR results of different methods compared with the proposed method on standard test image Lena and Barbara.

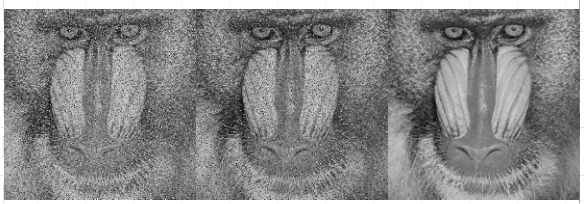


(a) (b)

In Fig. 8, (a) is Lena original image (b) is recovered image that is recovered from 30% Noise.

(a) (b) (c)

In Fig. 9, (a) is Barbara original image (b) is 20% noisy image (c) is recovered image.



(a) (b) (c)

In Fig. 10, (a) result after first iteration (b) is result after second iteration and (c) is results after third iteration of "Baboon" image contaminated with 30% noise.

The window size is determined from experiments, as it shows the least value of miss detection and false detection of pixels. The other window size like 5*5 and 7*7 often miss identify the noisy pixel value when noise % less and false identify the noise free pixel when noise % is high. Also the values SSIM and PSNR are also better.

The proposed DSW method preserve edges finely because the edge pixels are clearly identified as noise free in the noise identification process. DSW method does not consider edge pixels as noisy because mask is divided into sub-windows and edges pixel belongs to texton having more edge pixel values. There is no need to apply sharping filter after de-noising. As sharping filter is required after the de-noising process if edges are get blurred. The proposed method preserved edges clearly as depicted in Figures.

DSW method Miss and False detection results are compared on Lena image with the existing methods. The DSW method performance is for better previous existing method. DSW define the threshold in refined way using median values of four textons. And in the removal of noisy value the noise free texton is used. The values of Miss Detection (MD) and False Detection (FD) are satisfactory as compared with previous approaches. The values of MD and FD indicate that noise identification process is better as compared with previous approaches. The PSNR values indicates that the noise removal also better as compared with existing filter. Visual result of proposed DSD method are in Fig. 7, Fig. 8, Fig. 9 and Fig. 10. Visual results also indicates that the visual performance of DSD method are satisfactory. Visual result indicate that fine details of image are recovered. The proposed DSW method uses 3x3 window size which is determined from experiments. The proposed DSW method

IV. Conclusion

In this paper, a novel method of dividing-sliding-window (DSW) is proposed for the removal of RVIN. The proposed method uses four texton median values for noise identification. And the removal of RVIN using texton having minimum sum of absolute inner difference of pixels. The proposed and previous methods Peak Signal to Noise Ratio (PSNR) can be observed from Table I and Table II. The PSNR of proposed DSW method is better than the previous compared approaches. Table III shows that MD and FD values of proposed DSW and previous methods. The MD and FD values are better and shows that the identification process is improved. The Fig.7, Fig. 8, Fig.9 and Fig. 10 are presenting the visual results of the proposed DSW method. The proposed DSW method also preserves fine details of image and fine edges. The preserving of fine edges is due to DSW method fine identification of pixels either noise or noise free. The least values of miss and false detection supports the strong detection procedure of proposed DSW method. The need of sharpening filter is in case of blurred results. The DSW method preserve fine edges, so the need of sharpening filter is accommodated.

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