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High-Density Impulse Noise Reduction From Colour Images Using Combined Adaptive Vector Median Filter And Weighted Mean Filter

T Kosalai[1], Dr. N. Sugitha[2], J P Jayan[3]

[1]Noorul Islam Centre for Higher Education, Kumaracoil, Kanyakumari Dist., India

[2]Associate Professor, Department of IT, Noorul Islam Centre for Higher Education, Kumaracoil, Kanyakumari, India

[3]HOD, Department of Software Engineering, Noorul Islam Centre for Higher Education, Kumaracoil, Kanyakumari Dist., India

[1]tkosalai5@gmail.com [2]sugi_vi@yahoo.com [3]jeyanjp@gmail.com

ABSTRACT

Image processing is carried out to improve and upgrade the quality of a noisy image. The images usually get different kinds of noises in process of receiving, coding and transmission. Denoising can be done by numerous methods like neighbourhood operations, arithmetic operations, Transforms etc. In this work, high-density impulse noise reduction on colour images can be performed by the combined effect of adaptive vector median filter (VMF) and weighted mean filter. In the proposed filtering scheme, the corrupted and good pixels are classified based on the non-causal linear prediction error (NCLPE). For a corrupted pixel, the adaptive VMF is processed on the picture element where the window size is adapted based on the availability of good pixels. Whereas, a non-noisy pixel is substituted with the weighted mean of the good pixels of the processing window. The tests have been carried out on a big database for different classes of images, and the performance is measured in terms of peak signal-to-noise ratio, mean squared error and structural similarity. It is observed that the proposed filter outperforms some of the existing noise reduction methods of impulse noise at low density as well as at high-density.

Keywords : Denoising, VMF, WMF, Mean square error, Peak Signal to Noise Ratio, Structural Similarity Index Measure.

I. INTRODUCTION

An image is a pictorial representation of a thing that has been in any form. The term image refers to a 2-D function f(x,y), here x and y represent the plane coordinates, and the value of f at any point (x,y) is proportional to the intensity of the image at the coordinates. If x,y and the values of f are finite and disconnected quantities, then the image is a digital image. A digital image is created using a limited number of components called pixels, each has a specific position and value [1].

Processing of an image is a technique to achieve some jobs on an image, with the purpose of getting an improved image or to extract some valuable data from that image. It is a form of signal processing in which input is an image and the result may be in a picture form or attributes/features related with that image. One of the basic tasks in image processing is recovering a clean image from its corrupted version. The two types of methods used for image processing are analog and digital image processing. The prior image processing can be done by the hard copies like printouts and photographs.

Image noise is an unwanted consequence of image acquisition that conceals the desired facts and it is a unsystematic deviation of brightness or color information. The original meaning of "noise" was "unwanted signal"; By analogy, unwanted electrical fluctuations are also called "noise" [2]. The process of reducing noise from a signal or an image is called noise reduction. Noise can be random or white noise.

In digital images, noise occurs during the image acquisition time or broadcasting time. Then the performance of imaging sensors is affected by various aspects, such as the surrounding situations while acquiring the image and the quality of the sensing elements themselves. At the time of image acquisition with a charge coupled device [CCD], the light level and sensor temperature are the main reasons affecting the quantity of noise in the output image. Then the noise of an input image is the result of errors in the image acquirement process that result is the pixel value of the image does not reflect the true intensities of real picture, over to noise, the image is represented as grainy rough, molted or snowy appearance. The extent of image noise can differ from gradual speaks on a digital picture to optical radio astronomical images that are complex noise. The second fact in the form of noise is the transmission of data in the image is corrupted due to intrusion in the channel used for transferring it. For example, an image transferred using a wireless network might be degraded as an effect of lightning or other atmosphere trouble [3].

II. RELATED WORK

Smolka, et al., [2004] proposed the problem of impulsive noise reduction in multichannel images. The processing of color image data as vector fields is ideal because of the connection that exists among the picture channels, and that the nonlinear vector processing of colour images is the best approach to clean-up noise. Since VMF has the drawback of swapping excessively numerous non-noisy image pixels. It is improved in this innovative nonlinear filtering approach which uses the association among the image channels. The advantages are Adaptive filtering techniques that can be generalized to multidimensional signals and the computational Complexity is Low. The restrictions are speedy and consistent and reduction of impulses is needed with minimum image quality degradation [4].

Jin and Li, [2007] presents a different clarification for impulse noise recognition in color images. The suggested description is a switching vector filter and that filter evaluates the color variation of pixels inside the CIELAB color space using four directional operators. According to the consequence of the evaluation, the impulse recognition component can become aware of corrupted pixels, which are changed within the filtering component using particular strong estimate. Then makes use of strong vector median operations in the spotted noisy positions to eliminate impulse noises and hold the original configuration content. However the drawback is image corrupted rate is larger [5].

Laskar, R.H., et al., [2009] introduces a vector median filter that consists of a different method aimed at the recognition of impulses in color pictures prior to additional processing operations. The suggested filter has been verified for pictures degraded through salt and pepper noise model. The two sided fixed impulses recognition technique does not involve the distance calculation and following ordering of the vectors of a window. But for the other deviations of the VMF, the distance calculation and assembling of the vector pixels is achieved for all of the image vectors. This is happened by the capacity of the detection component of the vector median filter to identify the degraded pixels. The advantages are low noise percentages per Channel, less duration for treating a noise corrupted image, stable performance and the computational complexity is low [6].

Jafar, I.F., et al., [2011] proposed a Boundary discriminative noise detection (BDND) filter strictly enforces a situation on the size of the filtering window and not about the noise density. This produces higher quality images. But, expanding the window may not solve the problem and uncorrupted pixels increases nonlinearly with high noise densities [7].

Esakkirajan et al., [2011] proposed an improved decision-based unsymmetrical trimmed median filter for the enhancement of gray scale and color images which might be quite corrupted through impulse noise. This procedure switches the corrupted pixel with the trimmed median value for different pixel values, 0's and 255's are existing in the selected kernel, and when all the pixel values are 0's and 255's, then the corrupted pixel is replaced by using mean value of all of the elements existing within the particular kernel. This filtering scheme is best suitable for low, medium and high intensity levels of noise on both gray scale and color images. The limitations of this algorithm are it is fruitful if the total pixels inside the window are noisy. And for a multichannel image, the algorithm wants to be operated one by one on every color channel [8].

Bhadouria, et al., [2013] proposed an adapted decision-based coupled window median filter algorithm which is used for the vastly degraded with impulse noise on gray scale and color images. This procedure uses sliding window of expanding dimension, centered at any pixel and replaced the noisy pixels successively by the median value of the window. This approach provides improved PSNR, IEF, SSIM and IQI values than the existing system. The procedure is powerful for impulse noise elimination in pictures at higher noise densities [9].

Roy, A., and Laskar, R.H., [2015] proposed a new impulse noise removal technique based on Support Vector Machine (SVM).With the Support vector machines, the feature selection is the important part and the features are mean, minimum and maximum pixel, and error of the central pixel. With the feature data set, in training phase optimal hyperplane is formed and in testing phase, the feature set is to be processed pixel by pixel. This method provides better performance for high density impulse noise. But the limitation is high algorithmic complexity and it makes time consuming process [10].

III. PROBLEM IDENTIFICATION

It is very essential to reduce noise from images before using them for other image processing methods like edge detection, segmentation, feature extraction, registration. Mainly impulse noise is a short-duration noise of high energy with either relatively high density or low density. Many filters are introduced to reduce the impulse noise but the entire existing filters applied images are not visually enhanced. Visual quality in an image is very poor so that this system proposes the combined use of adaptive vector median filter and weighted mean filter for the reduction of impulse noise with high density from colour images.

IV. PROPOSED MODELING

The corrupted and good pixels are categorized based on the non-causal linear prediction error (NCLPE). It is used to identify whether the pixel under operation is corrupted or not around a (5×5) kernel. Each pixel is represented by R, G, and B color values. Find the error coefficients separately to find the linear prediction error. A correlation exists amongst the pixels over the neighborhood when an image is corrupted by impulse noise; there is a chance of losing homogeneity amongst the pixel.

Let the window of the image is considered as $W_{(5x5)}$ and the pixel under the image is given by $I_{x,y}$. This pixel is under the operation of window $W_{(5x5)}$ is given by,

$$W_{(5x5)} = [I_{(u,v)}], \quad x-2 \leq u \leq x+2, \quad y-2 \leq v \leq y+2 \qquad (1)$$

Where, $I_{(u,v)}$ denotes processing window pixels and $I_{(u,v)}$ represented by

$$I_{(u,v)} = [I_{(u,v)R}, I_{(u,v)G}, I_{(u,v)B}] \qquad (2)$$

Hence each pixel in a color image consists of Red (R), Green (G), and Blue (B) channels. The flow diagram of in this phase is given below,

In image processing, the image between the pixels have strong correlation over the two dimensional neighborhood. In this proposed work, the current pixel value is calculated with the neighborhood pixel based on weighted linear combination. Therefore the corrupted pixel is easily identified from the image because it losses the homogeneity amongst the pixels.

The R, G and B of each channel are calculated using a non-causal linear prediction error. The entire pixel under the window is processed through the detection criterion.

The predicted pixel value of the pixel under operation for R channel, G channel and B channel is given by:

$$P_{(x,y)R} = \sum_{u=x-2}^{x+2} \sum_{v=y-2}^{y+2} a_{(u,v)R} I_{(u,v)R} \qquad (3)$$

$$P_{(x,y)G} = \sum_{u=x-2}^{x+2} \sum_{v=y-2}^{y+2} a_{(u,v)G} I_{(u,v)G} \qquad (4)$$

$$P_{(x,y)B} = \sum_{u=x-2}^{x+2} \sum_{v=y-2}^{y+2} a_{(u,v)B} I_{(u,v)B} \qquad (5)$$

Where, $a_{(u,v)R}$ is the linear prediction coefficient for R channel for the position *(u,v).* Same way all the pixel in the G channel and B channel are represented by $a_{(u,v)G}, a_{(u,v)B}$. The predicted pixel is depends on the linear prediction coefficient.

The error is represented by $e_{(x,y)R}$, the error is a difference between the central pixel $I_{(u,v)R}$ and the predicted pixel $P_{(x,y)R}$ for R channel is given by:

$$e_{(x,y)R} = |I_{(u,v)R} - P_{(x,y)R}| \qquad (6)$$

The same way the error for the G channel and B channel is given by

$$e_{(x,y)G} = |I_{(u,v)G} - P_{(x,y)G}| \qquad (7)$$

$$e_{(x,y)B} = |I_{(u,v)B} - P_{(x,y)B}| \qquad (8)$$

The error of the pixel under operation $e_{(x,y)}$ is given by

$$e_{(x,y)} = MAX\,(e_{(x,y)R}, e_{(x,y)G}, e_{(x,y)B}) \qquad (9)$$

Threshold Process

The threshold value is based on the experiments already taken for each image. The error value (threshold) considered as 10, it gives better system performance. The error value $e_{(x,y)}$is greater than or equal to the error threshold value, the pixel under the operation is considered as 'detected noisy pixel'. This noisy pixel is processed through adaptive vector median filter. The error value $e_{(x,y)}$is smaller than the error threshold value, the pixel under the operation is considered as 'detected non-noisy pixel'. This non-noisy pixel is processed through weighted mean filter.

4.1 PROPOSED ARCHITECTURE MODELING

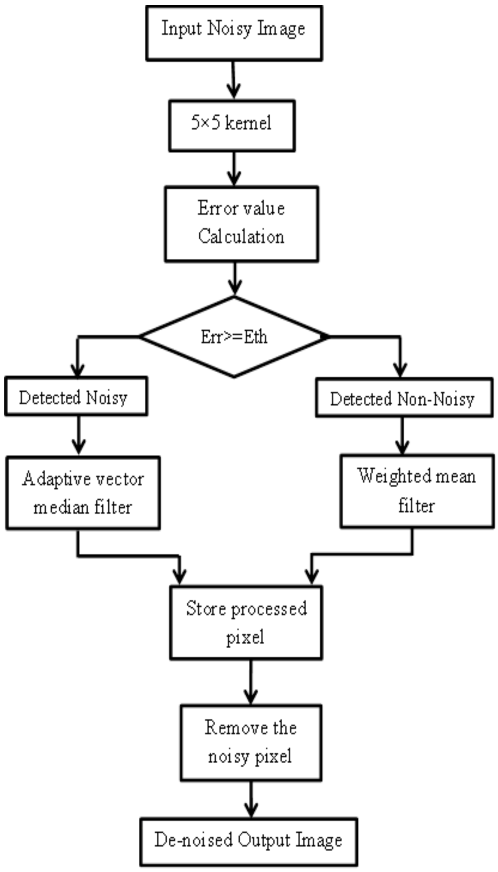


Fig 4.1 Architecture Diagram

Adaptive Vector Median Filter

The median filter is a digital filtering technique. It is used to remove the noise from the color images. This filter helps to improve the results of image processing. Two types of median filters are scalar median filter (SMF) and vector median filter (VMF). Scalar median filter is used to decrease noise in scalar geographical data. It applied each component of a vector field and it consumes more time complexity. In this paper, an extension of the SMF to vector median filter is processed under the pixel. The flow diagram of adaptive vector median is as following,

The detected noisy pixel is applied to the Vector Median Filter (VMF). The considered window size s = 5, and for each local window, the median filter can be expressed using a 5 × 5 convolution kernel matrix. The kernel matrix is the pixel value of the image with the related center co-ordinates. Median filtering is a nonlinear process useful in reducing the impulsive noise.

In Vector median filter the number of good pixels in ε denoted as η, it take the minimum value 0 and the maximum value 25 in the kernel size. The range of η is divided into five levels. The adaptive vector median filtering is shown in the below equation. The set η represents the availability of good pixels. The variable window size is processed in the adaptive vector median filter. The size of the window is increased with the decreased number of good pixels.

First level is mapped to (11 x 11) window for [0 - 5], second level is mapped to (9 x 9) window for [6 -10], third level is mapped to (7 x 7) window for [10 - 15], fourth level is mapped to (5 x 5) window for [16 - 20], and the final level is mapped to (3 x 3) window for [21 - 25]. The variation of the window size W_s is given by

$$W_s = \begin{cases} (11\ x\ 11)\ if\ 0 \le \eta \le 5 \\ (9\ x\ 9)\ \ if\ 6 \le \eta \le 10 \\ (7\ x\ 7) if\ 11 \le \eta \le 15 \\ (5\ x\ 5) if\ 16 \le \eta \le 20 \\ (3\ x\ 3) if\ 21 \le \eta \le 25 \end{cases}$$

The adaptive filter under the operation of pixel is substituted by vector median value that is represented by

$$I_{(x,y)}^{new} = VMF\left\{W_{(MxM)}\right\}$$

The minimum number of good pixels denotes a probability of having more noise within the kernel. Hence the size of the window is increased with the fewer amounts of good pixels. Therefore, the adaptive filter window size is $W_{(M\ x\ M)}\ and$ the adaptive filter is (M x M).

If the number of good pixels in the kernel is 0 or 1, then the image $I_{x,y}$ pixel under the operation is applied to the weighted mean filter. The good pixels are processed through the weighted mean filtering for each channel (R, G, and B) separately.

Total weighted mean is given by

$$I_{(x,y)}^{new} = \frac{1}{\sum_{p=1}^{\eta} \partial_p} \sum_{p=1}^{\eta} \partial_p \cdot \varsigma_p$$

Let, ξ_p is a set of good pixels (1<= η<= p) within the processing kernel in a channel. The average value of good pixel is denoted by ξ_{avg}. The deviation of good pixels for the average pixel is represented by D_p $(1 <= \eta <= p)$. The distance is inverse of the each deviation distance is calculated and it represented by ∂_p .

The pixel under operation $I_{(x,y)}^{new}$ is modified accordingly. The entire pixel under the filter operation is stored based on the pixel value. This process continues up to all the pixel proceeds to the calculation of error. All the pixel filtered each window is moved to next kernel within the whole image.

Weighted Mean Filter

Every pixel in the image is assigned with binary weight 0 and 1. This binary weight is depends on intensity value of the pixel. The intensity value of the central pixel in the filtering window is replaced by a weighted mean. The mean filter is also used to reduce the noise from the image.

The detected Non-noisy pixel is applied to the Weighted Mean Filter (WMF). The Non-noisy pixel is called as good pixels and these pixels within processing window are calculated. Replace the picture element under process by weighted mean value. Weighted mean filter is used to smoothing the image.

The deviation between the R and G channels, G and B channels and B and R channels are given by $\Delta_i^{rg}, \Delta_i^{gb}$ *and* Δ_i^{br}. Where i represents the value from 1 to 25 with the processing window $W_{(5x5)}$. The number arranged from left to right and from top to bottom. The average value of each deviation is given by $\Delta_{avg}^{rg}, \Delta_{avg}^{gb}$ *and* Δ_{avg}^{br}.

The total average value can be represented as follows:

$$\Delta_{avg}^{j}=\mathrm{E}[\Delta_i^j] \quad (10)$$

where E is the expectation operator. The absolute deviation (ad) of each channel difference is given by:

$$ad_i^j = |\Delta_i^j - \Delta_{avg}^j| \quad (11)$$

Where, j represents the channel differences i.e, j= rg, gb and br and i represents the pixel within processing window. The average value of the absolute deviation of each channel difference is given by ad_{avg}^{rg}, ad_{avg}^{gb}, and ad_{avg}^{br} respectively.

Now, the position of each pixel is difference between the average absolute deviation and absolute deviation of each channel. It's given by,

$$d_i^j = |ad_i^j - ad_{avg}^j| \quad (12)$$

The difference value of each channel is less than the average value of the absolute deviation of each channel difference and then the pixel under operation is considered as a good pixel. This condition is checked for all the pixels within the kernel (5x5) window i.e) 1 to 25 value.

$$\varepsilon = d_i^{rg} < ad_{avg}^{rg} \quad (13)$$

Where ε contains the good pixels in the processing window. The above equation only for R and G channels. Accordingly the G and B, B and R channels are represented by,

$$\varepsilon = d_i^{gb} < ad_{avg}^{gb} \quad (14)$$

$$\varepsilon = d_i^{br} < ad_{avg}^{br} \quad (15)$$

Table 4.1 Comparison of PSNR (dB) values of image denoising using the combination of AVMF-WMF with the existing methods

Test Images	ND %	Noisy	PSNR in dB for Existing Methods						PSNR for Proposed Method
			ACWVM	MDBUTMF	DBCWMF	HFC	MHFC	MSVMAF	CAVMFWMF
Lena	10	18.566	34.32	37.51	37.91	38.66	51.52	52.72	25.689
	50	11.450	20.69	28.18	32.49	25.81	30.63	30.69	23.389
	60	10.615	18.77	26.43	31.22	21.17	24.82	25.52	22.532
	70	9.9505	15.09	24.30	29.72	17.22	19.62	22.59	20.691
	80	9.343	12.55	21.70	26.41	13.63	15.25	20.02	16.732
Peppers	10	18.281	32.27	36.84	40.42	48.71	49.62	41.98	25.846

	50	11.177	19.22	27.69	32.05	23.03	28.08	28.14	23.358
	60	10.352	17.36	23.79	30.70	20.18	23.87	24.22	22.2608
	70	9.6604	14.09	23.48	28.55	16.25	20.64	21.67	20.3801
	80	9.0338	11.11	20.88	25.37	12.34	15.12	19.11	16.3006
Mandrill	10	18.869	32.13	36.63	39.91	48.08	49.13	41.65	20.037
	50	11.720	18.89	27.25	31.22	22.73	27.67	27.88	19.227
	60	10.914	17.14	25.56	29.88	20.05	23.41	24.02	18.802
	70	10.194	13.77	23.37	27.76	16.07	20.55	20.84	17.817
	80	9.571	11.04	20.48	24.87	12.12	14.89	19.17	15.426
Gold Hill	10	18.656	32.59	37.23	40.89	49.33	50.05	42.56	21.146
	50	11.281	20.04	27.91	32.39	23.81	29.35	29.37	20.344
	60	10.374	17.68	26.15	31.11	20.53	24.17	24.78	19.835
	70	9.639	14.84	24.13	29.07	16.17	21.17	22.12	18.858
	80	8.985	11.73	21.27	25.86	12.27	15.32	20.27	15.816

V. RESULT AND DISCUSSION

To verify the image denoising capability of the proposed image noise reduction scheme, experiments are conducted on standard bench mark 512×512 [28], colour test images such as Lena, Peppers, Mandrill and Gold Hill. Figure shows the test images used.

5.1 PERFORMANCE ANALYSIS

From Table, it is obvious that the AVMF-WMF combination overtakes the existing methods for all the cases in terms of PSNR and visual quality. Fig. 4.2 shows the denoising results of the image Lena corrupted with the impulse noise. The denoising results for the Lena corrupted with the impulse noise and the noise reduction image is presented in Fig. (b) and (e). Figure shows the denoising outcomes of the Peppers image corrupted with the impulse noise. The denoising results for the Peppers image corrupted with the impulse noise and the noise reduction image is shown in Fig. (b) and (c). In the denoising experiments, noise is generated in a random manner. Thus the PSNR values are different for each run. Therefore, the results tabulated for all the experiments are shown in table. From the results it can be determined that the proposed new image denoising scheme is best suited for the reduction of impulse noise irrespective of its types.

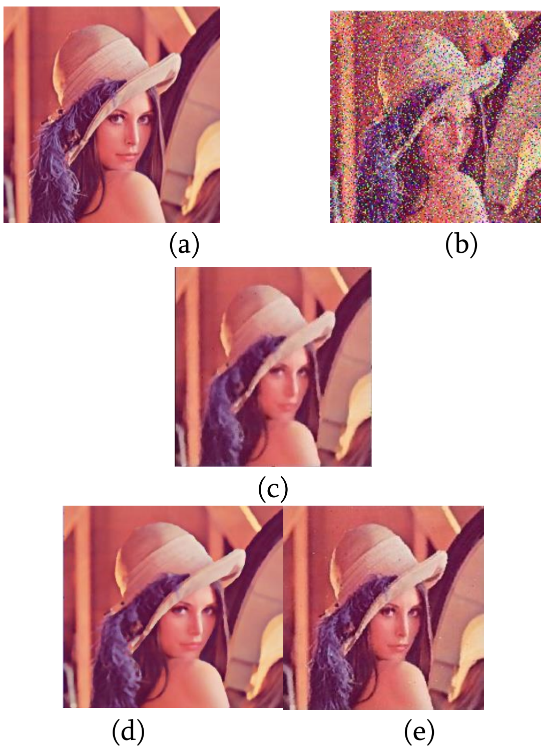


Fig. Image Denoising Results

a) Original Lena Image b) Image with Impulse Noise c) MHFC d) MSVMAF e) CAVMFWMF

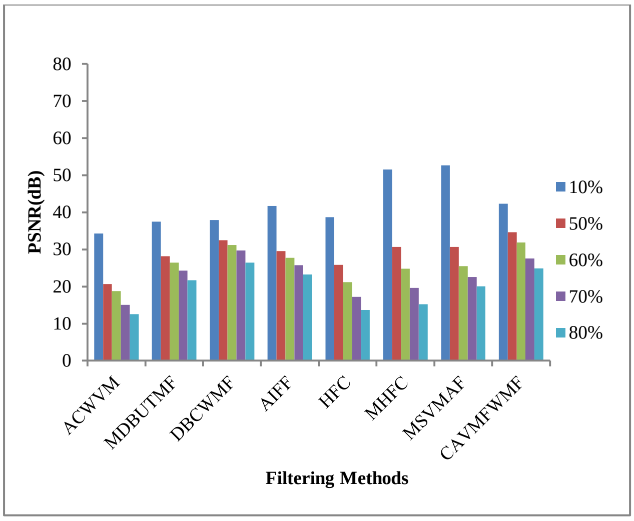
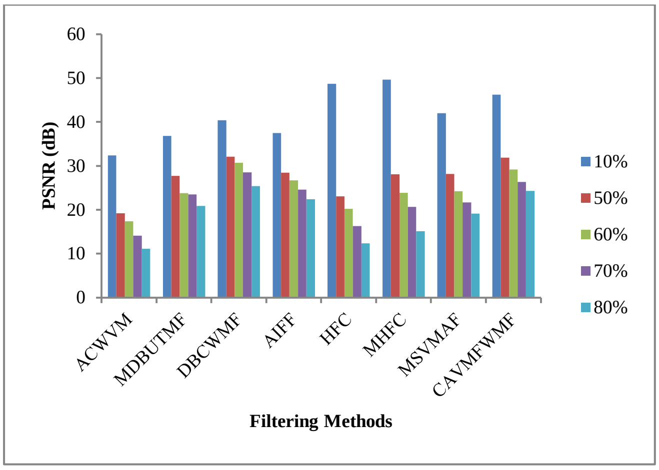


Fig. 5.1 Comparison of image denoised results using the combination of AVMF-WMF with the existing methods for the test image Lena with impulse noise



[Fig. 5.2 Comparison of image denoised results using the combination of AVMF-WMF with the existing methods for the test image Peppers with impulse noise

Structural Similarity Index Measure (SSIM)

Performance of the suggested filter is measured in terms of Structural Similarity Index Measure (SSIM) when the images are corrupted with impulse noise at different noise densities of impulse noise. SSIM defines the structural similarity between original and reconstructed image. On the other hand, SSIM of the suggested filter is increased using CAVMFWMF than that of other two filters. AVMF and WMF combination is compared with MDBUTMF, DBCWMF and MHFC. SSIM of the images are calculated and is tabulated as follows:

Table 4.2 Comparison of SSIM values of image denoising using the combination of AVMF-WMF with the existing methods for Lena and Mandrill Images

Test Images	ND %	Noisy	SSIM			SSIM
			Existing Methods			Proposed Method
			MDBUTMF	DBCWMF	MHFC	CAVMFWMF
Lena	10	18.566	0.99	0.99	0.992	0.384
	50	11.450	0.93	0.93	0.900	0.107
	80	9.943	-	-	0.233	0.0424
Mandrill	10	18.869	-	-	0.981	0.5837
	50	11.720	-	-	0.892	0.1789
	80	9.571	-	-	0.211	0.0612

The main role of the above-said image denoising scheme is the design of the filter by combining AVMF and WMF for the reduction of impulse noise. Extensive simulations revealed that this approach can be utilized for the efficient reduction of impulse noise.

VI. CONCLUSION

This system introduces an innovative impulse noise reduction procedure in colour images. Non-causal linear prediction error together with distance centered measure is modified for finding the corrupted and non-noisy pixels. For that reason, CAVMFWMF is functioned over the corrupted and good picture elements through the noise reducing process. For uniform impulse noise, image enhancement is besides detected at various density levels of impulse noise. Hence, CAVMFWMF method offers best performance at low density of impulse noise as well as offers at adequate performance at high density. Similar perfection is observed for uniform / random valued noise too. This particular study also proposes that CAVMFWMF implements improved at diverse compactness of impulse noise. Therefore, it can be determined that the recommended procedure offers better performance not only for salt and pepper noise but also for uniform impulse noise regardless of various density levels of noise. This upgraded piece of work is succeeded on the basis enlarged computational complexity.

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