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# REMOVAL OF DIFFERENT TYPES OF ARTIFACTS AND IMPULSE NOISE IN GRAY SCALE IMAGES

# <sup>1</sup> S.SURESH KUMAR, <sup>2</sup> DR. H. MANGALAM

<sup>1</sup>Assistant Professor, Department of ECE, Coimbatore Institute of Engineering and Technology, Tamilnadu, India <sup>2</sup> Professor and Head, Sri Krishna College of Engineering & Technology, Tamilnadu, India E-mail: <u><sup>1</sup>sureshkumar.sundaram@yahoo.com</u>, <sup>2</sup>hmangalam2@gmail.com

#### ABSTRACT

An adaptive based artifacts removal algorithm is proposed for removal of blocking artifacts, strip lines, drop lines, blotches and impulses in images. The algorithm detects noise variance level and then proper method is selected depending upon the variance. The algorithm changes the maximum size of window during the filtering operation depending on noise level. The output of the filter is a particular value which replaces the current pixel value at that point on which the value is centered at that time. Thus window size is automatically modified based on the density of noise in the image. It replaces a number of independent algorithms required for removal of blocking and other different artifacts and gives better result. The performance of the algorithm is evaluated in terms of Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Correlation, Feature Similarity (FSIM), Mean Structural Similarity (MSSIM) and Visual signal-to-noise ratio (VSNR). The computation time is compared with other algorithms that already exist.

# **Keywords:** Strip Lines, Blotches, Blocking Artifacts, Noise Variance, Adaptive Based Artifact Removal Algorithm, Feature Similarity.

#### 1. INTRODUCTION

It is proven that linear filters are not quite effective in the presence of non Gaussian noise. At present, some of the limitations of linear filters are overcome by non-linear filters [1].Simple median filters (SMF) are a class of non linear filters and had produced excellent results when linear filters had generally failed [2].The main advantage of median filters is removal of impulse noise with no information loss of edge information. In remote sensing, white and black strip lines, blotches and drop lines and impulse noise occur along with the results of an aggressive data compression scheme applied to an image that discards some data that is determined by an algorithm to be of lesser importance to the overall content but which is perceptible and objectionable to the client. Compression artifacts occur in many common file formats such as Joint Pictures Experts Group (JPEG) and Moving Pictures Experts Group (MPEG). Standard median

filters are not useful to remove these artifacts. This paper describes the adaptive based artifacts removal (ABAR) algorithm to remove all blocking and various artifacts. This paper is organized as follows. Section 2 discusses the previous work. Section 3 discusses the proposed method to remove impulse noise, blocking and various artifacts. Section 4 compares the results of the proposed work with other techniques and Section 5 gives the conclusion.

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#### 2. RESEARCH BACKGROUND

Blotches are impulsive type degradations that are randomly distributed over the image with irregular shapes at same intensities. Strip lines are caused by unequal responses of elements of a detector array to the same amount of incoming electromagnetic energy and causes heterogeneity in brightness of adjacent lines. Shahrokhy [3] dealt drop lines that occur for a short period when a detector

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does not work properly. Due to disturbing microwave energies in the sensors, impulse noises appear and make the system to degrade continuously. To overcome these artifacts, generally different methods are employed. According to Corte-Real et al [4], a positive type film is suffered from bright scratches and a negative type film is suffered from dark scratches. It gives a solution to remove the blotches and line scratches in images but considered only vertical narrow lines and with constant intensity irregular shape blotches. By using temporal filtering, Kokaram [5] has given a remedy for removal of scratches and restoration of missing data in the image sequences. In spatial filtering, the gradient energy is used to classify the image into homogeneous and highly textured regions. Homogeneous regions are heavily smoothed to reduce staircase blocking artifacts [6]. Decision based algorithm (DBA) is one of the fastest and efficient algorithm to remove impulse noise. The corrupted pixels are replaced by median or the immediate neighborhood pixel [7][8].Improved adaptive statistic estimation filter to remove salt and pepper noise with a value estimated by using Lorentzian estimator as an influence function is used to remove salt and pepper noise but the computation time is more [8].

Due to the huge data requirements for multimedia, the attention is focused towards getting more compression and less visual defects. To remove the blocking effects, several deblocking techniques have been proposed in the literature as post process mechanisms after JPEG compression, depending on the perspective from which the deblocking problem is dealt with. Reeves and Lim [10] have suggested that the easiest way of looking at this problem is to low-pass the blocky JPEG image. Crouse and Kannan [11] have dealt with the approach which will reduce the effect of high frequency tendency but the image will be blurry and some details will be wiped out. Going further step in complexity and applying a simple nonlinear smoothing to the pixels will add another obstacle to the solution. Zhigang and Fu [12] have dealt with more sophisticated approach which involves segmentation and smoothing that will reduce the ringing artifacts due to sharp variations. Yung-Kai et al [13] have dealt with the classification of small local boundary regions according to their intensity

distribution and to employ this information in designing proper predictors. Images with sharp variations cannot be easily configured with low order predictive filters. To improve the accuracy of the classified patterns, an iterative method for block removal using block classification and space frequency filtering is proposed.

The features of the wavelet theory add another tool of exploration to the blocking problem; several ideas based on soft threshold approach in the wavelet domain are successfully implemented for deblocking JPEG coded images Gopinath et al [14]. The principle of these techniques is to make use of Donho's algorithm for denoising Gaussian noise and modifying the denoised wavelet coefficients to remove the effect of other types of noise. Direct application of Donoh's algorithm for removing blocking effect can be found [15]. The further step has been adopted by presenting a simple and efficient denoising algorithm that exploits correlations among cross-scale wavelet coefficients to extract edge information and protect these edges during threshold operation [16]. Several algorithms are available for removal of impulse noises, blocking and different artifacts in images as mentioned above. However none of the algorithms addressed these problems of artifacts in images. The objective of the proposed adaptive based artifacts removal algorithm is to remove all the artifacts simultaneously with preserving edge. The advantage of the proposed algorithm is that a single algorithm is capable of replacing several independent algorithms required for removal of different artifacts with less computation time.

#### 3. PROPOSED ALGORITHM

Median filter is a nonlinear filter, which preserves edges while effectively removing impulse noise. General median filters often exhibit blurring for large window sizes, or insufficient noise suppression for small window sizes. Adaptive based artifacts removal algorithm overcomes these limitations of general median filters. Line scratches are narrow vertical, bright/dark lines that affect a column or a set of columns of the image. Blotches are originated by dust, warping of the substrate or emulsion, dirt or other unknown causes. Blotches in image can be either bright or dark spots. They

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are impulse type artifacts. It is not possible to propose a common mathematical model for the effect of the abrasion of the image causing the scratches due to the high number of variables that are involved in the process [9]. Line scratches can be categorized based on i) a considerable higher or lower luminance than their neighborhoods ii) their tendency to extend over most of the vertical length of the image and are not curved and iii) quiet narrower with widths of 10 pixels for an image. These make to create a degraded model as

$$f(x,y) = g(x,y)-g(x,y).d(x,y) + d(x,y).c(x,y)$$
(1)

where g(x,y) is the pixel intensity of the uncorrupted signal, d(x,y) is a variable which is set to one whenever pixels are corrupted and zero otherwise, c(x,y) is the observed intensity in the corrupted region. This model is applied in this paper to images degraded by blocking artifacts, strip lines, drop lines and blotches

if d(x,y) = 1

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then f(x,y)=c(x,y)

Observed pixel value in the corrupted region else

f(x,y) = g(x,y)

Observed pixel value in the uncorrupted region end.

An image containing impulsive noise can be modeled as follows

$$c(x, y) = \begin{cases} n(x, y) & \text{with probability p} \\ y(x, y) & \text{with probability } 1 - p \end{cases}$$
(2)

where n(x, y) is the impulse corrupted pixel that takes the minimum or maximum pixel value with probability p and 1-p. However, the existing impulse filtering methods do not remove blotches and scratches effectively. In section 3.1, an adaptive based artifacts removal filter algorithm is developed that removes different artifacts along with impulse noise.

# 3.1 Noise variance calculation and appropriate filter selection

Let consider an image corrupted with impulse and different artifacts.

for x = 1 to row

for y=1 to column

Set the window size is 3. Processing pixels are stored in  $c_{x,y.}$  h=hist ( $c_{x,y}$ ) // finding the histogram value of the current window.

Find the maximum value in h.

Determine the estimated value by using the value of h & size of the h.

 $\chi =$  estimated value\*0.2661-0.787

If  $\chi > T$ 

Process of adaptive based artifacts removal algorithm

else

Process of edge preserving adaptive based algorithm

end

end

end

A threshold value is chosen which is normally varies for different images. If the calculated noise variance is greater than this threshold a dynamic artifacts removal algorithm is used. Otherwise edge preserving adaptive algorithm is used. Threshold value of 33 is found after doing many simulations on variety of images. The block diagram of proposed algorithm is shown in Fig.1.

#### 3.2 Proposed algorithm

Step 1: Initialize W,  $S_{max}$  maximum allowed size, find the  $P_{min}$ ,  $P_{med}$ ,  $P_{max}$  value from  $S_{x,y}$ .

Step 2: Determine the value of  $P_{med}\text{-}P_{min\ \&}\ P_{med}\text{-}P_{max.}$ 

Step 3: If the value  $P_{min} < P_{med} < P_{max}$ .  $P_{med}$  is not a noise pixel then go to step 5.

Step 4:  $P_{med}$  is a noise pixel then increases W size. if w<=  $S_{max}$ 

then go to step 2

else replace with  $P_{x,y}$  value.

Step 5: Determine the value of  $P_{x,y}$ -  $P_{min}$ &  $P_{x,y}$ -  $P_{max}$ .

 $\begin{array}{l} \mbox{Step 6: If the value $P_{min}$<$P_{x,y}$<$P_{max}$,$P_{x,y}$ is not an impulse then replace with $P_{x,y}$.} \end{array}$ 

else replace with P<sub>med</sub> value.

Step 7: Repeat step 2 through 6 for all the pixels in the image.

Step 8: Find the edge information for the denoised image from Step 1-7 and then do one to one correspondence between them.

Maximum window size used for different noise densities is 19x19. Depending on the value of $\chi$ , the appropriate filter is selected. If the noise

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variance is less than threshold value, then edge preserving adaptive algorithm is processed as follows. First edge detection is applied for the image. It refers to the process of identifying and locating sharp discontinuities in an image. The discontinuities are abrupt changes in pixel intensity which characterize boundaries of objects in a scene. A popular gradient magnitude computation is the Sobel operator. Based on this onedimensional analysis, the theory can be carried over to two-dimensions as long as there is an accurate approximation to calculate the derivative of a two-dimensional image. The Sobel operator performs a 2-D spatial gradient measurement on an image. Typically, it is used to find the approximate absolute gradient magnitude at each point in an input grayscale image. The kernels can be applied separately to the input image to produce separate measurements of the gradient component in each orientation [18]. These can then be combined together to find the absolute magnitude of the gradient at each point and the orientation of that gradient. The gradient magnitude is given by:

$$|G| = \sqrt{Gx^2 + Gy^2} \tag{3}$$



Fig.1.Block Diagram Of The Proposed Method

Typically, an approximate magnitude is computed using:

$$|G| = |Gx| + |Gy|$$
(4)

This is much faster to compute. The angle of orientation of the edge (relative to the pixel grid) giving rise to the spatial gradient is given by

$$\theta = \tan^{-1}(Gy|Gx)$$

(5)

#### 3.3 Steps in edge detection

(1) Smooth the input image ( $\hat{f}(x, y) = f(x, y) * G(x, y)$ ) (2) f x = f(x, y) \* Gx(x, y)(3) f y = f(x, y) \* Gy(x, y)(4) magn(x, y) = |f x| + |f y|(5) dir(x, y) = tan-1(f y/f x)

(6) If magn(x, y) > T, then possible edge point.

Second, low pass filtering is a filter that attenuates high frequency components and retains low frequency components unchanged. This results a in smoothing filter in the spatial domain since high frequency components are blocked. Gaussian filters are important in many signal processing, image processing and communication applications [18]. These filters are characterized by narrow bandwidths, sharp cutoffs, and low overshoots. A key feature of

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Gaussian filters is that the Fourier transform of a Gaussian is also a Gaussian, so the filter has the same response shape in both the spatial and frequency domains. The form of a Gaussian low pass filter in two-dimensions is given by

 $H(u,v) = e^{(-D(x,y)^2/2\sigma^2")}$ (6)

Where D(x,y) is the distance from the origin in the frequency plane. The parameter  $\sigma$  measures the spread or dispersion of the Gaussian curve. Larger the value of  $\sigma$ , larger the cutoff frequency and milder the filtering is. The important point to keep in mind is that the filtering process is based on modifying the transform of an image (frequency) in some way via a filter function, and then taking the inverse of the result to obtain the filtered image

Filtered Image =  $\Im$  <sup>-1</sup>[G (u, v)] (7)

Third, ABAR filter is applied for the same image then finally reconstruction is done by combining the above three steps such as edge detection, low pass filtering and ABAR filtering. Finally, the output image is retrieved in a better manner.

#### 4. EXPERIMENTAL RESULTS AND ANALYSIS

The algorithm is tested with different types of artifacts, namely, blocking artifacts, strip lines, drop lines, blotches and impulse noise. The results are compared with those of standard median filter (SMF), adaptive median filter (AMF), Decision based algorithm (DBA), trimmed median filter (TMF), non linear decision based filter (NDBF).In this section, results are presented to illustrate the performance of the proposed algorithm. Two images are selected. They are lena and baboon. The result of the removal of impulse noise with 30% and 70% densities along with degradations are shown in Fig.2 and Fig.3.



Fig.2.Results of different filters Lena image corrupted by 30% impulse noise along with different artifacts.

In Fig.2 and Fig.3, the simple median filter [1] causes blur in the images and do not remove the blotches (Fig.2(c) and Fig.3(c)). Adaptive median filter [6] removes strip and drop lines but the edges are not preserved properly (Fig.2(c) and Fig.3 (c)). The output of Progressive Switching Median Filter (PSMF) [19] has improved performance but its noise removing capacity is very poor at higher noise densities. Trimmed Median Filter (TMF) [20] has improved performance than AMF but is not removing blotches and the edges are not preserved (Fig.3 and Fig.3). Decision based algorithm (DBA) [8] has very good noise removing capability and excellent edge preservation but at higher noise densities it produces streaking is shown in Fig.3 (h) and Fig.3 (h). Non linear Decision Based Filter (NDBF)[21] has shown that removes noises but causes blur in Fig.2 (g) and Fig.3(g). Fig.4- Fig.7 shows the quantitative performance of the different algorithms for lena image. It can be observed that the proposed algorithm removes noise with degradation effectively at higher noise densities and preserves the edges while maintain lower computational complexity when compared to non linear decision based and adaptive median filters. Tables 1-7 display the quantitative

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(d) AMF

(g) NDBF



(f) TMF

(i)

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measures. It is observed that proposed algorithm gives better results than other conventional algorithms that already available.Fig.7 represents the computation time required for different algorithms with various noise densities for lena image and the results are also tabulated in Table 8.





(a)Original image





(c) SMI

(VSNR), computational time of the algorithms. The results showed improved performance in terms of these measures.

(e) PSMF

(h) DBA

70% impulse noise along with different artifacts.

Fig.3. Results of different filters Lena image corrupted by

A quantitative comparison is done between several filters and the proposed algorithm in terms of Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Correlation, and Feature

SIMilarity (FSIM), Mean Structural SIMilarity

(MSSIM) and Visual signal-to-noise ratio

Tabla	1.	Noise	Donsity	110	MSE	
rabie	1.	Noise	Density	VS	MSE	

Noise +	MSE							
Different artifacts	SMF	AMF	PSMF	TMF	DBA	NDBF	PA	
20	17.33	6.07	4.74	10.47	2.60	3.58	3.22	
30	19.89	8.48	7.01	11.75	3.60	5.10	3.97	
40	21.19	11.11	10.70	14.13	4.86	7.12	5.20	
50	21.31	13.94	15.98	18.58	7.27	10.41	7.20	
60	21.05	17.38	39.02	24.61	8.99	13.34	8.63	
70	23.72	23.45	58.40	37.54	12.29	18.72	10.97	
80	28.77	30.41	80.58	59.54	17.97	29.59	15.83	

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Table 2: Noise Density vs PSNR									
Noise +		PSNR							
Different artifacts	SMF	AMF	PSMF	TMF	DBA	NDBF	PA		
20	35.82	40.30	41.37	38.14	44.29	42.90	43.42		
30	35.11	38.85	39.67	37.49	42.70	41.22	42.10		
40	35.01	37.67	37.84	36.62	41.14	39.66	40.95		
50	34.96	36.69	36.09	35.59	39.88	38.33	39.87		
60	34.81	35.73	32.22	34.20	38.35	36.65	38.67		
70	34.32	34.43	30.47	32.14	37.09	35.06	37.51		
80	33.25	33.30	29.07	30.40	35.73	33.58	36.19		
	Tab	le 3: Noise L	ensity vs MSS	IM					

Noise +	MSSIM							
Different artifacts	SMF	AMF	PSMF	TMF	DBA	NDBF	PA	
20	0.734	0.852	0.816	0.885	0.505	0.917	0.892	
30	0.698	0.816	0.741	0.843	0.439	0.888	0.870	
40	0.625	0.771	0.614	0.798	0.424	0.841	0.829	
50	0.537	0.719	0.471	0.698	0.423	0.777	0.784	
60	0.375	0.673	0.175	0.608	0.420	0.716	0.721	
70	0.201	0.559	0.104	0.445	0.359	0.626	0.639	
80	0.095	0.386	0.052	0.279	0.312	0.481	0.543	
Table 4: Noise Density vs ESIM								

Noise + Different artifacts	FSIM				-		
	SMF	AMF	PSMF	TMF	DBA	NDBF	РА
20	0.858	0.903	0.921	0.936	0.959	0.805	0.948
30	0.841	0.876	0.899	0.918	0.947	0.739	0.937
40	0.828	0.841	0.865	0.893	0.928	0.689	0.922
50	0.803	0.835	0.816	0.863	0.911	0.685	0.911
60	0.747	0.800	0.764	0.828	0.875	0.696	0.879
70	0.685	0.774	0.546	0.786	0.836	0.708	0.857
80	0.578	0.729	0.459	0.701	0.792	0.697	0.830

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	1	able 5: Nois	e Densily vs I.	LF					
Noise +		IEF							
Different artifacts	SMF	AMF	PSMF	TMF	DBA	NDBF	PA		
20	9.42	11.82	12.99	17.19	4.43	50.44	38.73		
30	10.17	8.67	11.70	15.37	5.01	46.34	40.10		
40	9.43	6.77	9.23	15.16	6.47	38.59	35.02		
50	7.70	6.47	6.51	12.46	8.52	30.10	32.31		
60	5.30	6.52	2.18	11.52	10.76	25.93	28.87		
70	2.94	6.08	1.81	7.39	11.46	17.13	20.15		
80	1.95	4.45	1.36	5.02	9.33	12.12	16.33		

(

The metric for comparison are defined as follows:

$$PSNR = 10 log 10 \left(\frac{255^2}{MSE}\right)$$
(8)

$$MSE = \frac{1}{MN} \sum_{i=0}^{M} \sum_{j=1}^{N} (o_{ij} - r_{ij})^{2}$$
(9)

Correlation =

$$\frac{\sum_{M}\sum_{N}(o_{MN}-\overline{o}).(r_{MN}-\overline{r})}{\left(\sqrt{\left[\sum_{M}\sum_{N}(o_{MN}-\overline{o})^{2}\right]}\sqrt{\left[\sum_{M}\sum_{N}(r_{MN}-\overline{r})^{2}\right]}\right)}$$
10)

$$SSIM(o,r) = \frac{(\bar{o}\bar{r}+T_1)(2\sigma_{or}+T_2)}{(\bar{o}_0^2 + \bar{r}_r^2 + T_1)(\sigma_0^2 + \sigma_r^2 + T_2)}$$
(11)

$$MSSIM = \frac{1}{G} \sum_{q=1}^{G} SSIM (o_q, r_q)$$
(12)

Where  $o_{ij}$  is the original image,  $r_{ij}$  is the reconstructed image and  $\bar{o}$  is the mean of  $o_{ij,}$   $\bar{r}$  is the mean of  $r_{ij}$ ,  $\sigma_o$  and  $\sigma_r$  are standard deviations of original and restored images,  $o_{ij}$  and  $r_{ij}$  are the image contents of  $q^{th}$  local window and G is the number of local windows in the image.  $T_1$  and  $T_2$  are positive constant and both values are fixed for all the images. The Structure SIMilarity (SSIM) index between the original image and reconstructed image is discussed in SSIM [22].

The computation of Feature SIMilarity (FSIM) index Consists of Two stages. In the first Stage, the local Similarity map is computed, and then in the second Stage, then group the map values into a single Similarity Score [23].

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Fig. 4. Comparison Graphs Of MSE And PSNR At Different Noise Densities



Fig.5 Comparison Graphs Of FSIM And MSSIM At Different Noise Densities

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Fig.6 Comparison Graphs Of IEF And Correlation At Different Noise Densities



Fig.7. Comparison Graphs Of VSNR And Computation Time At Different Noise Densities

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Noise + VSNR **Different artifacts** SMF AMF PSMF TMF DBA NDBF PA 20 13.58 13.63 9.23 25.57 24.24 15.68 16.11 30 13.09 11.60 13.06 14.32 7.50 22.79 21.98 10.08 40 11.62 11.02 13.02 7.49 19.12 19.88 8.60 9.25 6.49 11.75 7.40 18.07 50 17.52 60 5.25 8.21 1.50 8.47 8.08 13.39 15.48 70 1.67 6.36 -0.69 5.81 7.88 10.42 12.53 80 -0.79 5.28 -1.66 2.86 6.03 7.46 10.57

#### Table 7: Noise Density vs VSNR

Table 8: Noise Density vs Computation Time

Noise +	COMPUTATION TIME						
Different artifacts	SMF	AMF	PSMF	TMF	DBA	NDBF	PA
20	0.0886	0.3420	0.1816	0.2109	0.6202	4.9422	0.3040
30	0.0894	0.3612	0.1972	0.2089	0.6635	6.6055	0.3025
40	0.0892	0.4012	0.2306	0.2091	0.6086	5.3661	0.3034
50	0.0889	0.4679	0.1953	0.2175	0.5983	6.0670	0.3112
60	0.0894	0.6330	0.1408	0.2251	0.6100	6.0891	0.3377
70	0.0977	0.9938	0.1532	0.2260	0.6137	7.0378	0.3539
80	0.1105	1.7512	0.1361	0.2190	0.6604	7.1847	0.3757

The Feature Similarity separates the measurement between  $o_{ij}$  and  $r_{ij}$  into Two Components, each for Phase congruency (PC) or Gradient magnitude (GM). The FSIM index between  $o_{ij}$  and  $r_{ij}$  is defined as

$$FSIM = \frac{\sum_{x \in \Omega} S_L(x).PC_m(x)}{\sum_{x \in \Omega} PC_m(x)}$$

(13)

Where,  $S_L(x) = S_{PC}(x) \cdot S_G(x)$ .

 $S_{PC}(x) = \frac{(2PC_1(x).PC_2(x)+T_{10})}{(PC_1^2(x)+PC_2^2(x)+T_1)}$ 

$$S_{G}(x) = \frac{(G_{1}(x).G_{2}(x)+T_{2})}{(G_{1}^{2}(x)+G_{2}^{2}(x)+T_{2})}$$

(15)

(14)

Visual signal-to-noise ratio (VSNR) has two stages. Contrast thresholds for detection of distortions in the presence of natural images are computed via wavelet-based models in order to determine whether the distortions in the distorted



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image are visible. If the distortions are below the threshold of detection, the distorted image is considered to be of perfect visual fidelity. If the distortions are above threshold, then it operates based on the low-level visual property of perceived contrast, and the mid-level visual property of global precedence [24].VSNR is computed based on a simple linear sum of these distances.

#### 4. CONCLUSION

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An adaptive based artifacts removal algorithm for removal of strip lines, drop lines, blotches and impulse noise is developed. The proposed algorithm detects noise variance level and then proper method is selected depending upon the variance. The output of the filter is a particular value which replaces the current pixel value at that point on which the value is centered at that time. The performance of this algorithm is evaluated in terms of MSE, PSNR, MSSIM, FSIM, IEF and VSNR. The results show that the algorithm is more efficient to remove strip lines, drop lines, blotches along with impulse noise varying up to 80%. The improvement in this algorithm is that it replaces the several independent algorithms required to remove different artifacts. The proposed algorithm gives better result for low to high noise densities and preserves edges satisfactorily. It can be further improved for the application in video.

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