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CORRELATION COEFFICIENT BASED DETECTION ALGORITHM FOR REMOVAL OF RANDOM VALUED IMPULSE NOISE IN IMAGES

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Abstract

This paper aims to present an alternative and novel method for removal of Random Valued Impulse Noise in corrupted images which is a challenging task as compared to the removal of fixed valued impulse noise. The proposed algorithm i.e. "Correlation Coefficient Based Detection Algorithm" (CCBD) is a two stage filter. The Detection stage of CCBD utilises the Correlation Coefficients of the absolute differences of the pixels in detection window with their Mean, the Central Pixel and a predefined value respectively. The Filtering stage of CCBD utilises the Fuzzy Switching Weighted Median filter (FSWM) for restoration of the corrupted image. The performance of CCBD has been compared to some of the existing methods e.g. Rank Order Absolute Difference (ROAD), Rank Order Logarithmic Difference (ROLD), Triangle Based Linear Interpolation (TBLI) and Adaptive Switching Median (ASM) algorithms. The Comparative analysis in terms of MSE, PSNR and SSIM show that the CCBD is superior to the existing methods in all parameters.

Keywords:

Random Valued Impulse Noise, Correlation Coefficient, High Density Noise, Fuzzy Switching Weighted Median Filter, Noise Removal, Correlation Coefficient based Detection Algorithm.

1. INTRODUCTION

Digital images usually get corrupted by different kinds of noise due to various reasons such as malfunctioning pixels in camera sensors, faulty memory locations and transmission in noisy channel [1]. In Random Valued Impulse Noise (RVIN), noisy pixels randomly assume a value between 0 and 255 and it is very difficult to detect them [2]. The noise removal from noisy images in such situations becomes a challenging problem. There exist several methods and algorithms which attempt to remove RVIN from corrupted images [3]-[14]. However, these algorithms have their own assumptions, advantages and limitations. Some of them alter all the pixels irrespective of the level of noise corruption whereas certain other schemes first carry out the detection of impulsive noise followed by the altering of the noisy pixels.

The existing methods which have been considered for comparison with the proposed method (CCBD) are the Rank Order Absolute Difference Algorithm (ROAD) [15], Rank Order Logarithmic Difference (ROLD) [16], Triangle Based Linear Interpolation Algorithm (TBLI) [17] and Adaptive Switching Median Algorithm (ASM) [18]. At lower Noise Densities, these algorithms perform satisfactorily. However, at higher Noise Densities, these filtering schemes produce images which have blurring effect, unpreserved edges and poor resolution due to miss detection of noisy pixels as noise free and vice versa. Therefore, a novel method of noise detection named "Correlation Coefficient based Detection" Algorithm (CCBD) has been proposed in this paper which is better than the existing algorithms as shown by its performance on various metrics.

In ROAD [15], the detection stage is based on the absolute differences between the Central Pixel (CP) and other pixels. After calculating the absolute values, it is arranged in an ascending order. Predefined threshold is utilised to ascertain whether a pixel is noisy or noise free. The ROAD algorithm works well for low noise densities.

The ROLD algorithm is similar to the ROAD. The advantage of the ROLD is that it takes the logarithmic function of the absolute differences for comparison [16]. The detection stage of ROLD gives better results as compared to the ROAD because it can easily differentiate between the noisy and noise free pixels. The main drawback of the algorithm is misdetection at higher noise densities.

TBLI method [17] utilises the Triangle-Based Linear Interpolation [19], [20] to detect noisy and noise free pixels. It is designed to suppress the RVIN while preserving image details. Differential Evolution algorithm [21] is used to optimize the tuning parameter which is used in TBLI to control the process of detection stage.

In the ASM algorithm, the noisy pixels are detected by using the absolute deviation of the Central Pixel (CP) with the mean value which is then compared with a threshold value [18], [22], [23]. If the absolute deviation is greater than the threshold value, the pixel under consideration is treated as noisy pixel otherwise it is treated as noise free. Only noisy pixels are subjected to filtering process.

The proposed algorithm CCBD is also a two stage filter. The detection stage of CCBD involves 3 conditions to be verified in order to accurately detect noisy pixels. These conditions are based on the Correlation Coefficients of the absolute differences of the pixels in detection window (except CP) with their Mean (μ), the Central Pixel (CP) and a predefined value explained later. The filtering stage of CCBD is based on the Fuzzy Switching Weighted Median filter (FSWM) to replace only the noisy pixels detected in the detection stage while leaving noise free pixels unaltered [24]-[26].

The CCBD filter yields better results than the existing methods in all the performance parameters like MSE, PSNR and SSIM. Although there is some misdetection in CCBD filter, it gives satisfying results even at very high noise densities like 95% RVIN.

2. PROPOSED DETECTION ALGORITHM

2.1 NOISE MODEL

This filter uses the random valued impulse noise model (RVIN) of unequal probability. The Probability density function, $F(Q_{i,j})$, can be expressed as,

$$F\left(Q_{i,j}\right)=\begin{cases}\dfrac{N_{D1}}{2} & 0\le Q_{i,j}<d,\\ 1-N_D & Q_{i,j}=P_{i,j},\\ \dfrac{N_{D2}}{2} & \left(255-d\right)<Q_{i,j}<255,\end{cases}\tag{1}$$

where, $Q_{i,j}$ is the $(i,j)^{th}$ pixel in the corrupted image, $P_{i,j}$ is the i,j^{th} pixel in the original image, N_D is the Noise Density and d is the noise intensity level. Here, $N_D = (N_{D1} + N_{D2})$ and N_{D1} and N_{D2} represent the pepper and salt noise densities, respectively which are different i.e. ($N_{D1} \neq N_{D2}$). The dynamic range of the image intensity values is [0, R-1], where $R = 2^z$ and z is the number of bits per pixel. Here, an 8-bit gray image is assumed and hence, $z = 8$ and $R = 256$.

2.2 CORRELATION AND DEPENDENCE

Correlation or dependence or association between two variables or datasets is a statistical relationship which may or may not be causal. Correlation generally refers to the extent to which two datasets have a linear relationship. Correlations can be applied for ascertaining the behaviour of a parameter in some instances because they indicate a predictive relationship between that parameter and another.

Though the presence of a correlation alone is not sufficient to infer the presence of a causal relationship yet it provides an indication of a possible relationship which has to be established by other conditions. The correlation can be viewed as synonymous with dependence in informal parlance but it refers to one of the several specific types of relationship between the mean values in a technical sense. Therefore, a correlation can be considered as an evidence for a possible causal relationship but it cannot indicate as to what such causal relationship might be, if any.

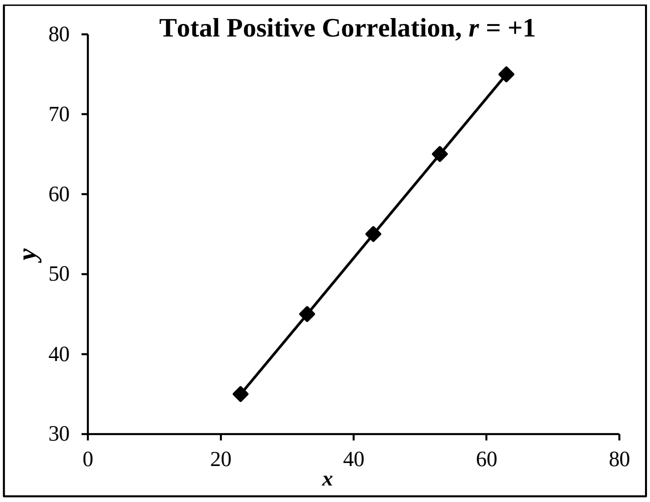
2.3 CORRELATION COEFFICIENT

The correlation coefficient (r) measures the linear dependence between the two variables or datasets. There are different types of correlation coefficients. The research uses the Pearson's correlation coefficient in the proposed algorithm. The mathematical formula for computing correlation coefficient between two datasets x and y is as follows,

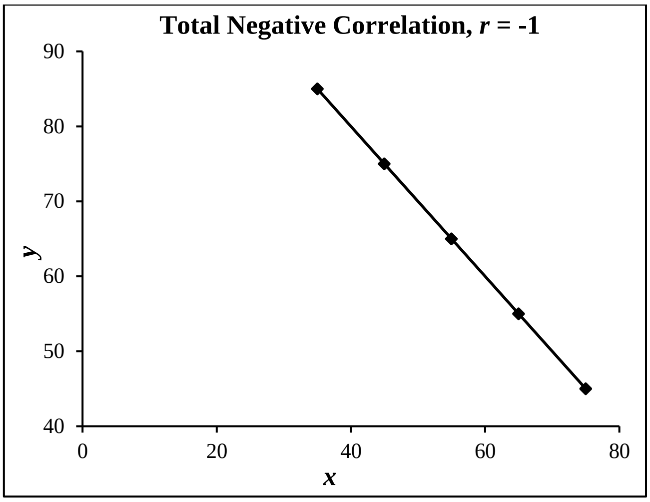
$$\gamma_{xy}=\frac{\sum_{i=1}^{n}\left(x_i-\bar{x}\right)\left(y_i-\bar{y}\right)}{\sqrt{\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^2}\sqrt{\sum_{i=1}^{n}\left(y_i-\bar{y}\right)^2}}\tag{2}$$

where, $\{x_1,x_2,\ldots,x_n\}$ and $\{y_1,y_2\ldots,y_n\}$ are two datasets containing n values and $\bar{x}$ and $\bar{y}$ are mean values of these datasets respectively.

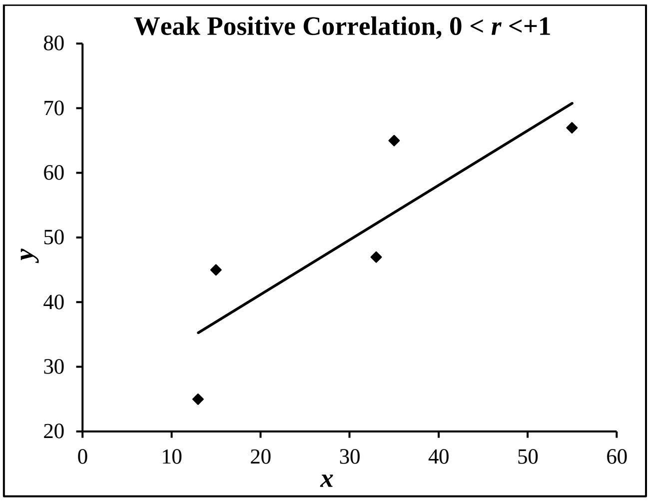
As explained earlier, the Correlation Coefficient indicates the strength and the direction of the linear relationship between two datasets. It may take any value from -1 and +1. A value of +1 shows total positive linear correlation, 0 shows no linear correlation at all and -1 shows total negative linear correlation between two datasets. A perfect Correlation of ±1 occurs only when all the points of the dataset fall on a single straight line. A value greater than 0.8 generally signifies a strong correlation between the datasets whereas a value less than 0.5 generally signifies a weak correlation. The Fig.1 below shows the different values of the Correlation Coefficient between two datasets x and y and their inter-relationship graphically.



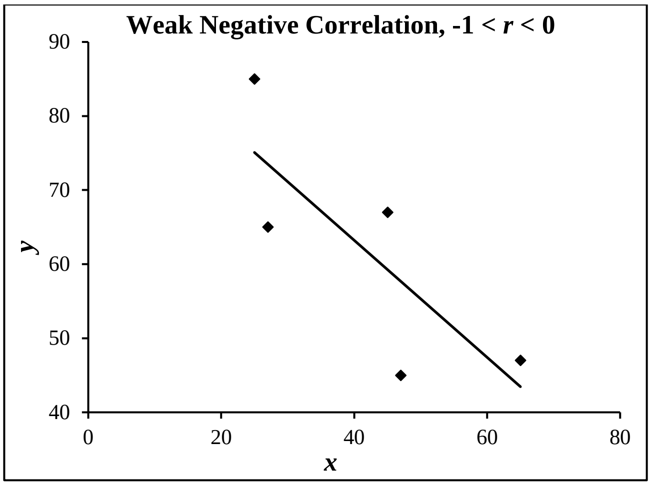
(a)



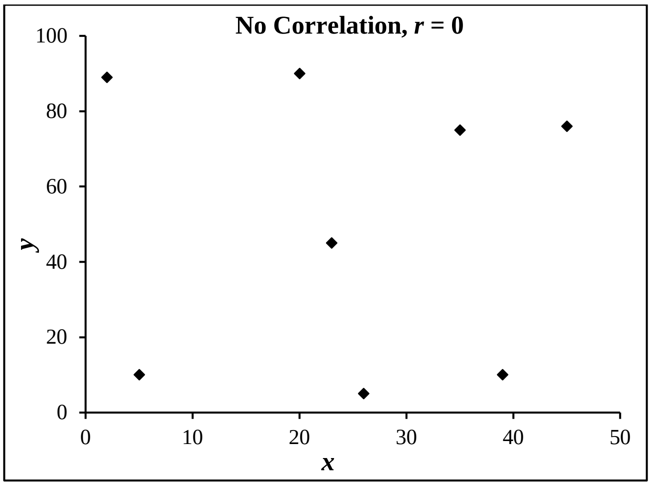
(b)



(c)



(d)



(e)

Fig.1. Graph of Correlation Coefficients for different kinds of Correlations: (a) Total Positive Correlation, (b) Total Negative Correlation, (c) Weak Positive Correlation, (d) Weak Negative Correlation, (e) No Correlation

2.4 CORRELATION COEFFICIENT BASED DETECTION ALGORITHM (CCBD)

Correlation Coefficient Based Detection (CCBD) Algorithm makes use of three Correlation Coefficients calculated mutually for three datasets obtained by taking absolute differences of pixels in the detection window (except CP) with its Mean (μ), Central Pixel (CP) and number 127.5 (which is the average luminescence value i.e. the average of 0 and 255). Then by applying three predefined conditions, we segregate noisy pixels from non-noisy pixels.

The reason for choosing the concept of correlation coefficient for detection of noisy pixels is following. If the CP is a noisy pixel, the absolute differences of all pixels in a window (except CP) with the CP will throw up an array which will not have close Correlation with an array formed of the absolute differences of those pixels with their Mean (μ) or the average luminescence value (i.e. 127.5). In contrast, if the CP is non-noisy, the arrays obtained as above will have close Correlation with each other. As seen earlier, a Correlation below 0.5 depicts a weak association between the datasets. Therefore, the conditions used in this Algorithm are based on the value 0.5 which is taken as a Threshold for correlation coefficient below which the CP will be termed as noisy. However, if the value of the correlation coefficient is higher than 0.5, further conditions need to be verified to detect the noisy pixels.

The step wise Algorithm is given as below:

Step 1: Let's take a 5×5 window as detection window. Then calculate the Mean of all pixels of this window except the CP and denote it as μ.

Step 2: Calculate A_{ij} as Absolute differences of μ with all pixels of the detection window except CP and get 24 such values.

Step 3: Calculate B_{ij} as Absolute difference of CP with all pixels of the detection window except CP and get 24 such values.

Step 4: Now, calculate C_{ij} as Absolute difference of the number 127.5 with all pixels of the detection window except CP and get 24 such values.

Step 5: Now, calculate following Correlation Coefficients by using the formula in Eq.(2),

r_{ba} = Correlation Coefficient of arrays B_{ij} and A_{ij} (3)

r_{bc} = Correlation Coefficient of arrays B_{ij} and C_{ij} (4)

r_{ac} = Correlation Coefficient of arrays A_{ij} and C_{ij} (5)

Step 6: Now, apply the first condition as follows-

If $r_{ba} < 0.5$,
CP is noisy,
Else $r_{ba} \geq 0.5$
Check the second condition
End

Step 7: Now, apply the second condition as follows-

If $0.5 \leq r_{ba} < 0.95$ and $r_{bc} < 0.5$,
CP is noisy,
Else $r_{ba} \geq 0.95$,
Check the third condition,
End

Step 8: Now, apply the third condition as follows-

If $r_{ba} \geq 0.95$ and $r_{bc} < 0.5$ and $r_{ac} < 0.5$,
CP is noisy,
Else,
CP is non-noisy,
End

By this Algorithm we detect all the noisy pixels in the corrupted image and feed them to the Filtering stage for restoration.

3. FILTERING ALGORITHM

In the filtering stage, we consider only the noisy pixels without altering the noise free pixels. The fuzzy switching weighted median filter (FSWM) is utilised in the filtering stage of CCBD [24]-[26]. The FSWM filter is an improvisation over the Median Filter and the Fuzzy Switching Median Filter which give limited restoration results [27]-[30]. The FSWM provides better replacement results because the noisy pixels after detection alone are replaced by the fuzzy switching weighted median value of the noise-free pixels in its surrounding. The restoration value in FSWMF is a linear equation of the original pixel value, Fuzzy function and the weighted median value. The steps involved are as follows:

Step 1: To extract Local Information, we first calculate the absolute luminance difference $\delta_{i,j}$ in a window $W(3,3)$ as follows

$$\delta_{i+k,j+l} = \left|W_{i+k,j+l} - W_{i,j}\right| \tag{6}$$

where, $(i+k,\ j+l) \neq (i,j)$ and $-N \leq k, l \leq N$

Step 2: The maximum absolute luminance difference in the filtering window i.e. Local Information is defined as:

$$\Delta_{i,j} = \max\left\{\delta_{i+k,j+l}\right\} \tag{7}$$

Step 3: Then the Fuzzy reasoning is applied to the Local Information $D_{i,j}$. The fuzzy membership function $FF_{i,j}$ is defined as follows

$$FF_{i,j} = \begin{cases} \dfrac{N_D}{2} & 0 \leq Q_{i,j} < d, \\ 1 - N_D & Q_{i,j} = P_{i,j} \\ \dfrac{N_D}{2} & (255-d) < Q_{i,j} < 255, \end{cases} \tag{8}$$

Step 4: The next step is the calculation of the weighted median (*MED*) by using the noise-free pixels. The weights of a pixel are decided on the basis of the gradient of the surrounding pixels as follows

$$w_{m,n} = \begin{cases} 3 & \text{if } \delta < 5 \\ 2 & \text{if } 5 < \delta < 10 \text{ and} \\ 1 & \text{if } \delta > 10 \end{cases} \tag{9}$$

$$MED = median\left\{w_{m,n} \times W_{i+m,j+n}\right\} \tag{10}$$

with $Q_{i+m,j+n}$ as noise free pixel.

The idea behind choosing only the noise-free pixels in calculation of *MED* is to avoid the vitiation of the weighted median by the noisy pixels if at all they are also taken into account.

Step 5: The restoration term is thus defined as linear combination of original pixel value and median value, i.e.

$$S_{X,Y} = (1 - FF_{X,Y}) \times Q_{X,Y} + FF_{X,Y} \times MED \tag{11}$$

In this manner, the pixels which are marked noisy alone are replaced in the filtering stage and the noise-free pixels are retained the same without any modification. This ensures an accurate restoration of corrupted image even at higher noise densities.

4. SIMULATION RESULTS AND DISCUSSIONS

To demonstrate the effectiveness of the proposed method CCBD, we have considered various standard test images like Lena, Boat, Cameraman, Barbara, Baboon, Monarch, Pepper and Rice which are extensively used in literature to measure the performance of the existing methods. Further, TID2008 database (a set of 25 images) was considered to demonstrate the effectiveness and robustness of the CCBD over a variety of images. The size of the images has been chosen as 512×512 and RVIN of unequal probability ($N_{D1} = 0.25N_D$; $N_{D2} = 0.75N_D$) with noise intensity level up to 4 (i.e. $d = 4$) has been used to corrupt these images before filtering. Simulations have been carried out in Matlab R2013a for a noise density varying from 75% to 95% RVIN and comparison of CCBD is done with different filters like ROAD [15], ROLD [16], TBLI [17] and ASM [18].

From the detected outputs of the existing methods, it can be seen that there is a large number of miss detection of noisy pixels as non-noisy and vice versa. However, in the proposed CCBD, miss detection is substantially minimized and only noisy pixels are detected as noisy. Some miss detection occurs in CCBD which will be addressed in our future works.

Mean Square Error (*MSE*) and Peak Signal-to-Noise Ratio (*PSNR*) in dB provide the quantitative measurement of restoration performance. These are defined as,

$$MSE = \left(\frac{1}{MN}\right)\left[\sum_{i=1}^{M}\sum_{j=1}^{N}\left(S(i,j) - P(i,j)\right)^2\right] \tag{12}$$

$$PSNR = 10 \times \log_{10}\left(\frac{255^2}{MSE}\right) dB \tag{13}$$

where, M and N are the total number of pixels in the horizontal and vertical dimensions of the image, and $S(i,j)$ and $P(i,j)$ are the pixel values in the $(i,j)^{th}$ locations of the restored image and the original image, respectively.

The structural similarity (SSIM) index is another parameter used for measuring the similarity between the original and restored images. It is designed to give better results than the traditional methods like MSE and PSNR which give results only in numbers and fail to capture the visual perception. For two images, u and v, the *SSIM* index is defined as,

$$SSIM(u,v) = [l(u,v)]^{\alpha} \cdot [c(u,v)]^{\beta} \cdot [s(u,v)]^{\gamma} \tag{14}$$

where, $l(u,v)$, $c(u,v)$, and $s(u,v)$ are the Luminance, Contrast and Structure components of the index respectively. Typical values of the constants are taken as $\alpha = \beta = \gamma = 1$. Matlab specific functions are used to calculate the MSE, PSNR and SSIM.

The Fig.2, Fig.3 and Fig.4 depicts the restoration results of different filters i.e. ROAD [15], ROLD [16], TBLI [17], ASM [18] and CCBD for Lena, boat and cameraman images corrupted by 95% of RVIN respectively. As already mentioned, the CCBD method uses a level by level verification to avoid miss detection of noise free pixels as noisy pixels.

From Fig.2, Fig.3 and Fig.4 we can see that the existing methods fail to restore the images at higher noise densities whereas the proposed method CCBD restores the corrupted images efficiently. Not only the restoration of images is satisfactory but the edge preservation and contrast are also better.

(a) (b) (c)

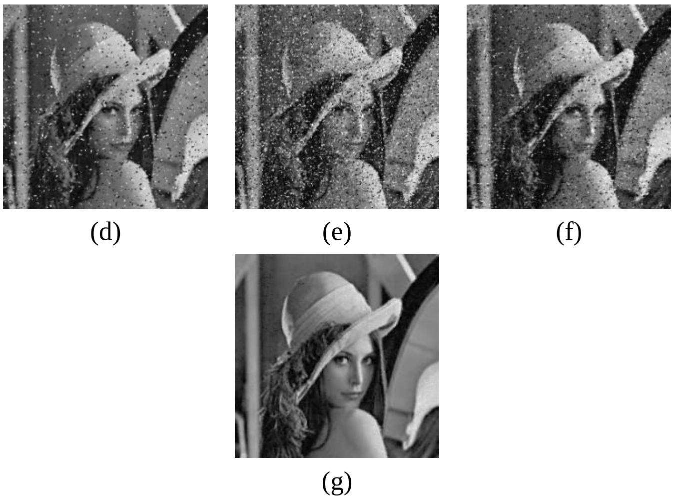


Fig.2. Comparison of Restoration of Lena image corrupted by 95% RVIN: (a) Original Image, (b) Noisy Image, (c) ROAD [15], (d) ROLD [16], (e) TBLI [17], (f) ASM [18], (g) CCBD

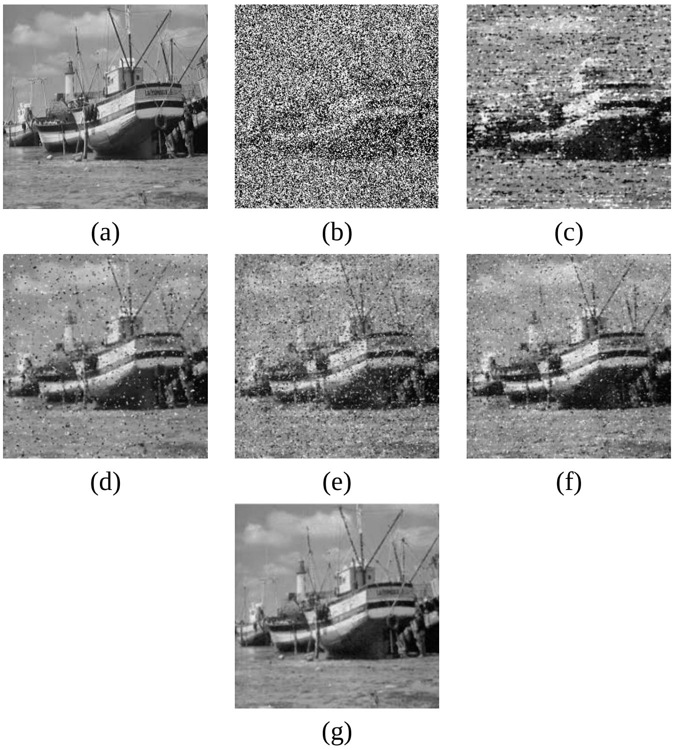
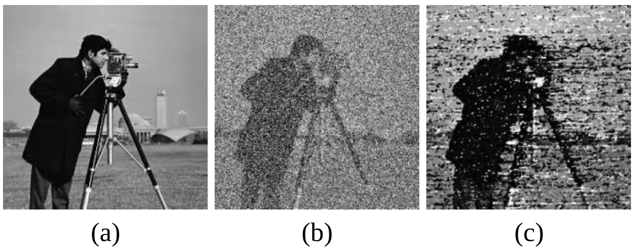


Fig.3. Comparison of Restoration of Boat image corrupted by 95% RVIN: (a) Original Image, (b) Noisy Image, (c) ROAD [15], (d) ROLD [16], (e) TBLI [17], (f) ASM [18], (g) CCBD



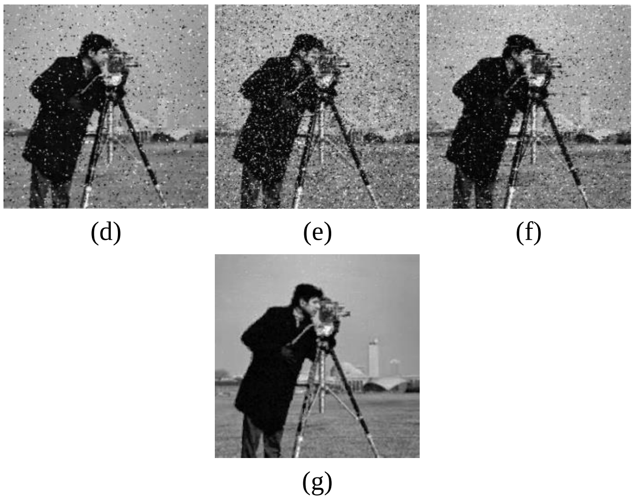


Fig.4. Comparison of Restoration of Cameraman image corrupted by 95% RVIN: (a) Original Image, (b) Noisy Image, (c) ROAD [15], (d) ROLD [16], (e) TBLI [17], (f) ASM [18], (g) CCBD

From simulations we have seen that ROAD [15] algorithm provides good results only up to 50% noise density beyond which miss detection is very high. Although the ROLD [16] provides better results than the ROAD [15], it also is not satisfactory after 60% noise density. TBLI [17] detection algorithm is also good only up to 75% noise density beyond which miss detection increases and picture quality worsens. ASM [18] though provides better value of MSE, it does not give good quality picture restoration because of miss detection at higher noise densities.

In contrast, the CCBD method provides very good results because it is based on adaptive conditions and its algorithm is robust. Due to less miss detection, the restoration of corrupt images by CCBD is of very high quality. The FSWM filtering used in CCBD also contributes towards the accurate restoration. It is seen that the performance of the CCBD filter is far better than the other filters even when the noise density is 95%.

The Table.1, Table.2 and Table.3 below respectively show the comparison of MSE, PSNR and SSIM of CCBD with existing methods for “Lena”, “Boat” and “Cameraman” images corrupted with noise densities from 75% to 95%. The Fig.5(a) and Fig.5(b) below show the graph of PSNR vs. Noise Density and SSIM vs. Noise Density for different methods for Lena and Boat respectively.

Table.1. Comparison of MSE of CCBD with existing methods for ‘Lena’, ‘Boat’ and ‘Cameraman’ images corrupted with RVIN of different Noise Densities

Noise Density	Image	ROAD [15]	ROLD [16]	TBLI [17]	ASM [18]	CCBD
75%	Lena	26.4	18.8	17.8	14.2	**9.4**
	Boat	32.4	21.8	21.2	22.1	**11.6**
	Cameraman	25.8	16.6	15.1	14.5	**12.9**
80%	Lena	31.8	21.5	19.7	15.5	**9.7**
	Boat	41.1	24.0	24.0	25.6	**12.3**
	Cameraman	27.9	18.4	18.3	16.7	**13.1**
85%	Lena	33.8	23.4	23.2	17.0	**10.0**

	Boat	44.1	26.6	27.3	27.9	**12.8**
	Cameraman	33.3	20.7	20.2	18.3	**13.4**
90%	Lena	38.8	27.4	25.5	18.7	**10.7**
	Boat	51.0	29.5	29.7	31.3	**13.5**
	Cameraman	38.8	23.5	23.1	21.4	**13.7**
95%	Lena	43.7	29.5	28.9	20.9	**11.2**
	Boat	57.9	33.1	33.4	34.9	**13.8**
	Cameraman	43.8	26.3	25.8	23.9	**13.9**

Table.2. Comparison of PSNR of CCBD with existing methods for 'Lena', 'Boat' and 'Cameraman' images corrupted with RVIN of different Noise Densities

Noise Density	Image	ROAD [15]	ROLD [16]	TBLI [17]	ASM [18]	CCBD
75%	Lena	33.9	35.3	35.6	36.5	**38.3**
	Boat	32.8	34.7	34.8	34.6	**37.4**
	Cameraman	34.0	35.9	36.3	31.5	**36.9**
80%	Lena	33.0	34.7	35.1	36.2	**38.2**
	Boat	32.3	34.3	34.3	34.0	**37.2**
	Cameraman	33.6	35.4	35.4	35.8	**36.9**
85%	Lena	32.8	34.4	34.4	35.8	**38.1**
	Boat	31.9	33.8	33.7	33.6	**37.0**
	Cameraman	32.9	34.9	35.0	35.4	**36.8**
90%	Lena	32.2	33.7	34.0	35.3	**37.8**
	Boat	31.2	33.4	33.4	33.1	**36.8**
	Cameraman	32.2	34.4	34.4	34.8	**36.7**
95%	Lena	31.7	33.4	33.5	34.9	**37.6**
	Boat	30.8	32.9	32.8	32.7	**36.7**
	Cameraman	31.7	33.9	34.0	34.3	**36.6**

Table.3. Comparison of SSIM of CCBD with existing methods for 'Lena', 'Boat' and 'Cameraman' images corrupted with RVIN of different Noise Densities

Noise Density	Image	ROAD [15]	ROLD [16]	TBLI [17]	ASM [18]	CCBD
75%	Lena	0.168	0.318	0.301	0.385	**0.772**
	Boat	0.206	0.336	0.329	0.454	**0.845**
	Cameraman	0.186	0.313	0.296	0.442	**0.779**
80%	Lena	0.131	0.262	0.254	0.344	**0.783**
	Boat	0.166	0.295	0.285	0.402	**0.854**
	Cameraman	0.151	0.267	0.252	0.395	**0.797**
85%	Lena	0.102	0.224	0.214	0.301	**0.797**
	Boat	0.125	0.248	0.241	0.355	**0.858**
	Cameraman	0.118	0.227	0.217	0.350	**0.809**
90%	Lena	0.083	0.187	0.187	0.266	**0.807**
	Boat	0.100	0.212	0.202	0.315	**0.863**
	Cameraman	0.092	0.194	0.179	0.308	**0.818**
95%	Lena	0.066	0.162	0.153	0.230	**0.818**
	Boat	0.073	0.183	0.173	0.276	**0.864**
	Cameraman	0.072	0.168	0.157	0.265	**0.823**

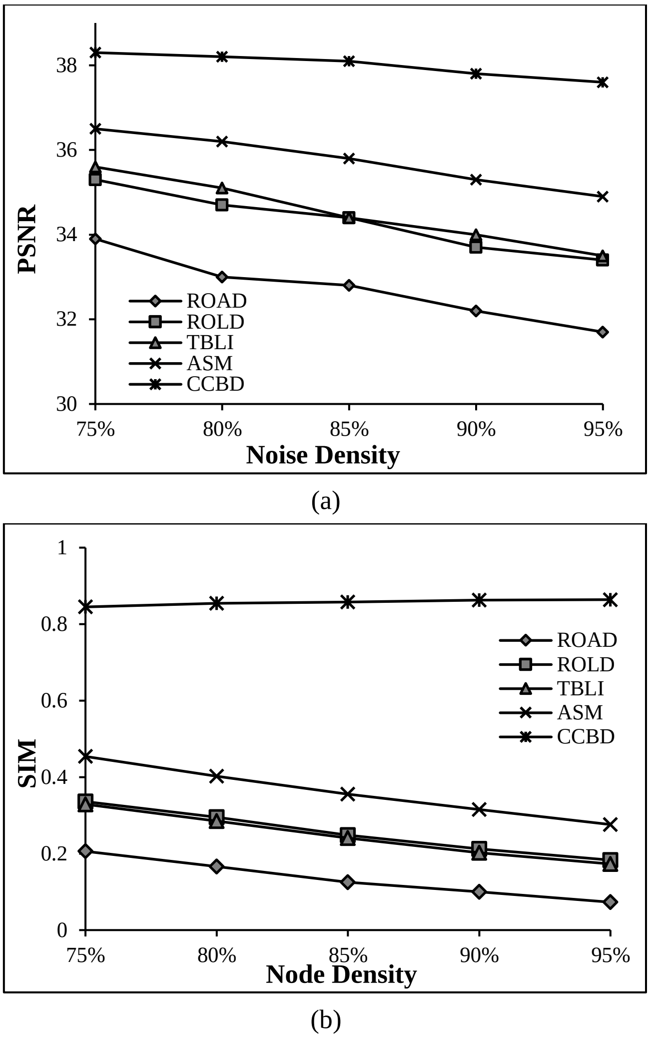


Fig.5. Graphical Comparison of Performance Parameters of CCBD with existing methods: (a) PSNR vs Noise Density for Lena, (b) SSIM vs. Noise Density for Boat

From the Table.1, it can be seen that the CCBD achieves a significantly low MSE value even at 95% noise density. This is primarily because of the relatively better noise detection and efficient fuzzy switching weighted median filtering compared to the median filtering used in other methods. It is again evident from the Table.2 and Fig.5(a) that the CCBD consistently returns the higher values of PSNR as compared to the other methods.

From the Table.3 and Fig.5(b), it's clear that the CCBD filter provides best results in SSIM even at very high noise densities. The higher values of SSIM yielded by CCBD are also supported by the visual comparison of the original and corrupted images, whereby it's evident that the CCBD filter is able to preserve the thin lines when compared with the other filters. In fact, the uniqueness of the CCBD is that the SSIM of the results increases with increase in the noise density. This phenomenon has been discussed later in this paper.

In addition to the three standard images (i.e. Lena, Boat and Cameraman), simulations have also been carried out on the TID2008 database. Average values of MSE, PSNR and SSIM have been calculated for the existing methods and compared with the CCBD for the TID2008 database in the Table.4, Table.5 and Table.6.

Table.4. Restoration Results in average MSE for TID2008 database corrupted by RVIN

Noise Density	ROAD [15]	ROLD [16]	TBLI [17]	ASM [18]	CCBD
75%	27.64	10.29	10.34	17.65	**11.23**
80%	32.77	16.79	17.42	19.29	**11.84**
85%	38.67	23.62	24.86	21.28	**12.43**
90%	43.27	28.03	26.89	23.89	**12.76**
95%	48.56	30.31	28.54	26.35	**13.01**

Table.5. Restoration Results in average PSNR for TID2008 database corrupted by RVIN

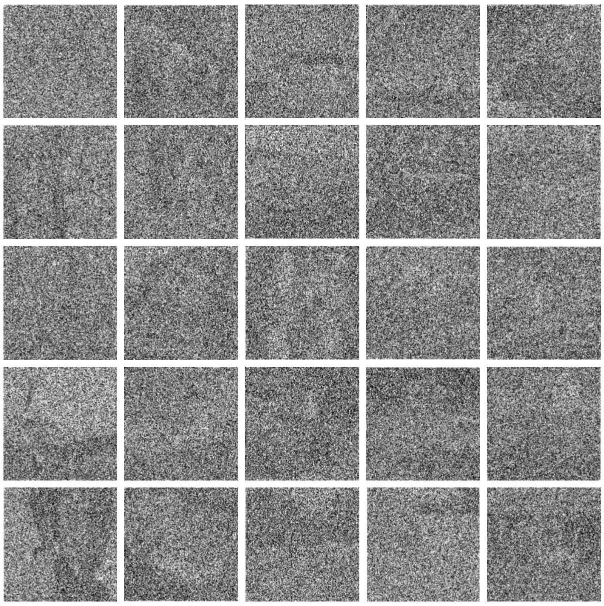
Noise Density	ROAD [15]	ROLD [16]	TBLI [17]	ASM [18]	CCBD
75%	33.27	34.82	35.45	33.37	**37.48**
80%	32.77	34.56	35.04	33.73	**37.27**
85%	31.92	34.12	34.65	34.28	**37.12**
90%	31.47	33.87	34.09	33.69	**37.01**
95%	30.95	33.27	33.52	33.27	**36.89**

Table.6. Restoration Results in average SSIM for TID2008 database corrupted by RVIN

Noise Density	ROAD [15]	ROLD [16]	TBLI [17]	ASM [18]	CCBD
75%	0.193	0.325	0.315	0.413	**0.789**
80%	0.158	0.295	0.287	0.396	**0.802**
85%	0.115	0.234	0.231	0.321	**0.819**
90%	0.098	0.204	0.198	0.293	**0.831**
95%	0.071	0.171	0.169	0.258	**0.848**

These simulations demonstrate that the proposed algorithm provides superior results than the existing methods at higher noise densities for a wide range of images. Since the restored picture quality is also comparably good in CCBD, its SSIM values at higher noise densities are better than that of ROAD, ROLD, TBLI and ASM. The restoration results of CCBD on TID2008 image database for 95% noise density are shown in the Fig.6.

(a)



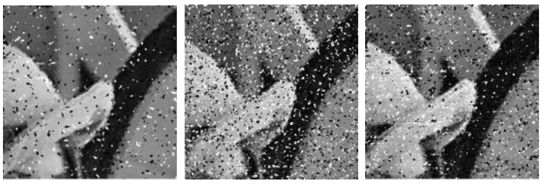
(b)

(c)

Fig.6. Restoration of CCBD algorithm on TID2008 database corrupted with 95% RVIN (a) Original Images (b) Noisy Images (c) Restored Images by CCBD

Therefore, for high noise densities i.e. after 75%, the proposed method CCBD consistently yields better values of the performance parameters as compared to the ROAD [15], ROLD [16], TBLI [17] and ASM [18] algorithms. Further, the picture quality returned by the CCBD is superior to other methods up to very high noise densities. With the increase in the noise density, CCBD's performance remains more or less steady up to 90 to 95% Noise Density whereas the performance of other methods deteriorate very sharply. This is possible because the CCBD method satisfactorily attempts to address miss detection up to 95% whereas other methods fail to do so. The Fig.7 below shows the restoration of cropped Lena image by existing methods and CCBD.

(a) (b) (c)



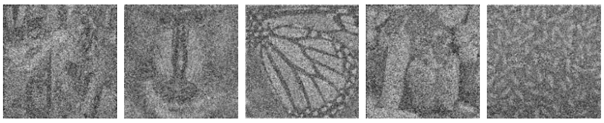
(d) (e) (f)

(g)

Fig.7. Comparison of Restoration of cropped 'Lena' image corrupted by 95% RVIN (Special emphasis on Hat, Mirror and Eyebrow in the image): (a) Original Image, (b) Noisy Image, (c) ROAD [15], (d) ROLD [16], (e) TBLI [17], (f) ASM [18], (g) CCBD

Here, we can see that neither of the existing methods is able to restore the Hat and Mirror portion of the cropped Lena image properly. Since their detection is satisfactory only up to 50 to 75% noise density, miss detection beyond that results in blurring and haziness. In contrast, the detection in CCBD is satisfactory up to 95% with minute miss detection. This results in better restoration of image and better contrast as compared to the existing methods. In restoration of cropped Lena image, though there are rare spots of miss detection, the fine double borders of the Hat and Mirror have been properly restored. Similarly, the other minute details such as the Eyebrow have been restored properly.

(a)



(b)

(c)

Fig.8. Restoration performance of CCBD on different images corrupted by 95% RVIN (a) Original Images (From left to right: 'Barbara', 'Baboon', 'Monarch', 'Pepper' and 'Rice') (b) Corrupted Images with 95% RVIN and (c) Restored Images by CCBD Algorithm

The Fig.8 shows the restoration of 'Barbara', 'Baboon', 'Monarch', 'Pepper' and 'Rice' images corrupted by RVIN of 95% noise density by the CCBD.

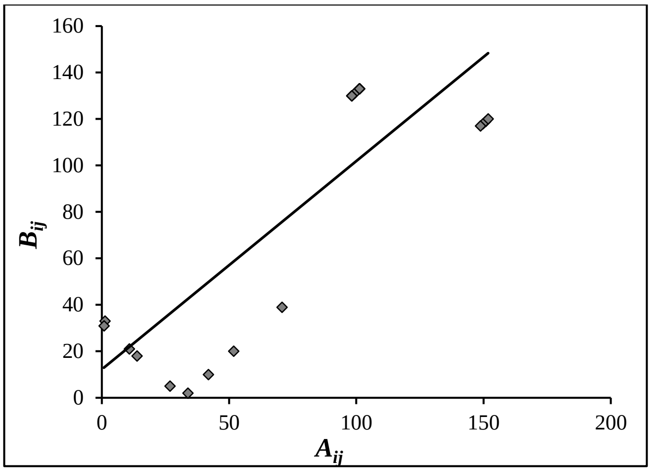
From the above results we can conclude that the proposed method provides satisfactory results even up to very high noise densities e.g. 95% for the above images. Since the quality of the restored picture is comparably very good in CCBD, its SSIM values at higher noise densities are also very high. Further, to avoid miss detection, the CCBD uses three conditions involving various calculations thereby taking slightly higher calculation time as compared to above methods. Our future work will be to attempt to reduce the calculation time as well as reduction of the minute miss detection present now.

5. ROBUSTNESS OF CCBD ALGORITHM

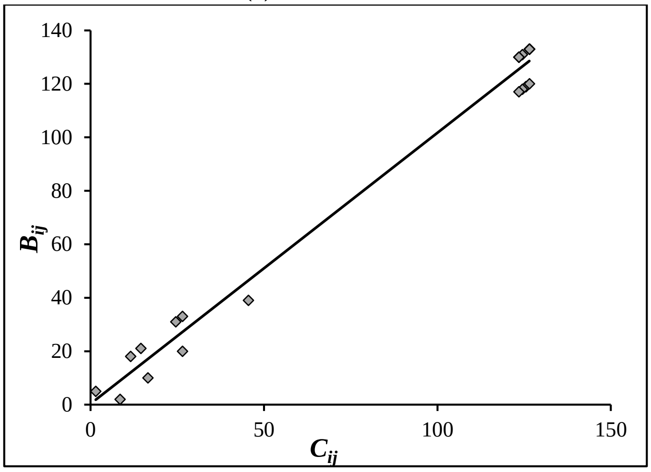
The CCBD algorithm is a robust algorithm which has been especially designed for very high noise densities. Since the algorithm uses a 5×5 window, we get enough number of pixels to create sufficiently long arrays of absolute differences which returns useful values of Correlation Coefficients. The three conditions used in detection algorithm have been arrived at after carrying out numerous simulations on Matlab. Though the algorithm is not completely miss detection proof, yet the detection of noisy pixels by this algorithm is far superior to that of the existing methods as already discussed. We will now discuss three cases of Central Pixels (CP) including one noise free pixel and two noisy pixels.

101	103	116	253	251
113	1	4	252	1
129	136	134	4	1
1	1	1	144	4
253	173	3	254	154

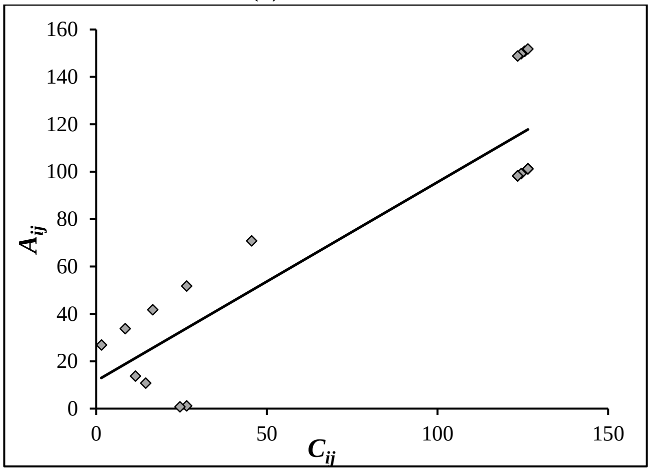
Adjoining is a real 5×5 detection window taken from the CCBD's Matlab simulation where the CP is noise free with a value of 134. Values of various Correlation Coefficients used in CCBD i.e. r_{ba}, r_{bc} and r_{ac} are calculated and shown in the Fig.9. As we can see from the graphs below, the value of r_{ba}, r_{bc} and r_{ac} are all greater than 0.5 and hence none of the three conditions of the CCBD algorithm gets satisfied resulting in the detection of the CP as noise free which is true as can be seen from the detection window.



(a) r_{ba} = 0.8305



(b) r_{bc} = 0.993



(c) r_{ac} = 0.8836

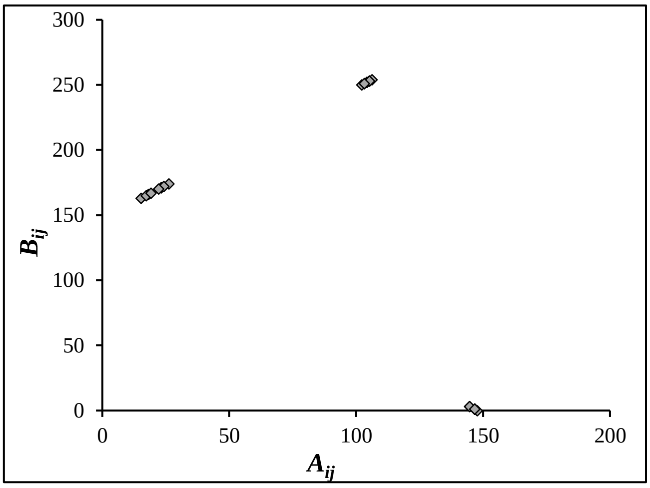
Fig.9. Graphs of Correlation Coefficients for a non-noisy pixel (value of CP = 134): (a) Correlation Coefficient r_{ba}, (b) Correlation Coefficient r_{bc}, (c) Correlation Coefficient r_{ac}

2	252	4	2	4
2	164	166	168	171
253	167	1	253	2
254	251	172	172	254
1	175	255	173	252

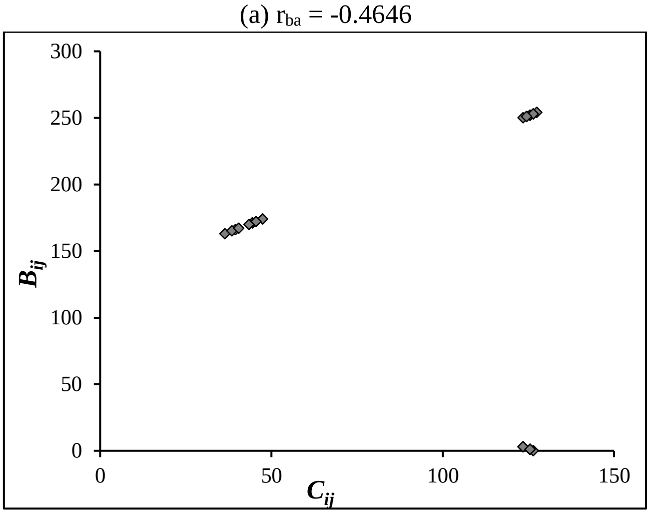
Now we take another real 5×5 detection window where the CP is noisy with a value of 1. Values of various Correlation Coefficients used in CCBD are calculated and shown in the Fig.10. From the graphs in Fig.10 below, we see that the values of r_{ba} and r_{bc} are less than 0.5 and value of r_{ac} is more than 0.5 i.e. the first condition itself is satisfied and there is no need to verify the other two. Hence, the CP is detected as noisy pixel which is true as can be seen from the detection window.

253	3	254	4	4
119	114	3	252	3
252	115	251	254	252
252	116	255	1	130
110	255	126	3	1

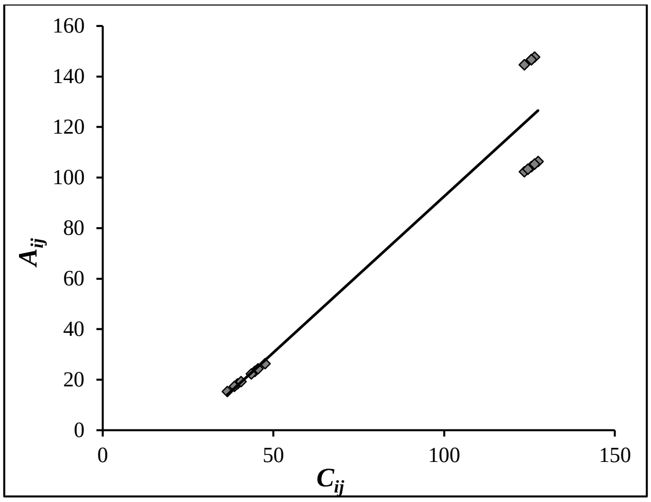
Now we take another real 5×5 detection window where the CP is noisy with a value of 251. Values of various Correlation Coefficients used in CCBD are calculated and shown in the Fig.11. From the graphs in Fig.11 below, we again see that the values of r_{ba} and r_{bc} are less than 0.5 and value of r_{ac} is more than 0.5 i.e. the first condition itself is satisfied and there is no need to verify the other two. Hence, the CP is again detected as noisy pixel which is true as can be seen from the detection window.



(a) r_{ba} = -0.4646

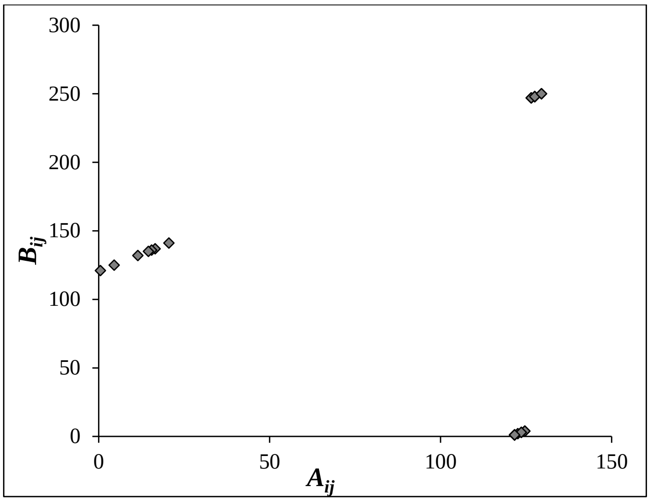


(b) r_{bc} = -0.1147

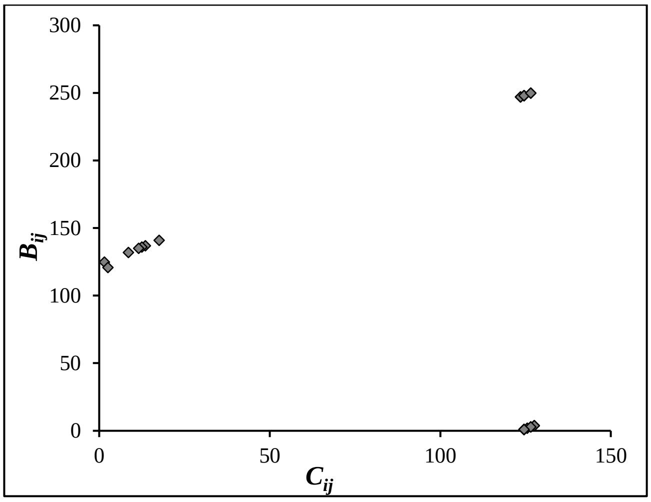


(c) r_{ac} = 0.9488

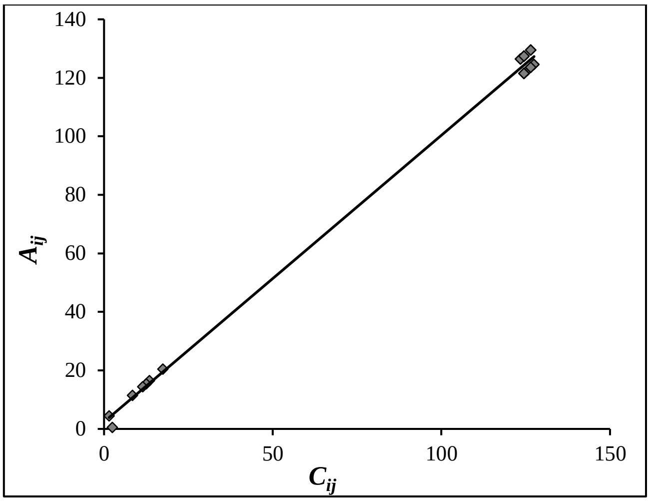
Fig.10. Graphs of Correlation Coefficients for a noisy pixel (value of CP = 1): (a) Correlation Coefficient r_{ba}, (b) Correlation Coefficient r_{bc}, (c) Correlation Coefficient r_{ac}



(a) r_{ba} = -0.0204



(b) r_{bc} = -0.0378



(c) r_{ac} = 0.999

Fig.11. Graphs of Correlation Coefficients for a noisy pixel (value of CP = 251): (a) Correlation Coefficient r_{ba}, (b) Correlation Coefficient r_{bc}, (c) Correlation Coefficient r_{ac}

Further, as mentioned earlier, the proposed method i.e. CCBD is very unique in performance. As shown in the Table.7 and Fig.12, the value of SSIM of CCBD increases with increase in the Noise Density. This phenomenon is neither seen in the existing methods which have been taken for comparison in this paper nor in other algorithms mentioned in the references. This behaviour of CCBD makes it more suitable for higher Noise Densities. Though the slope of curve representing the SSIM vs. Noise Density varies for different images yet the slope is positive in all cases which mean that the CCBD invariably yields higher values of SSIM for higher Noise Densities.

Table.7. Increasing Trend of SSIM calculated by CCBD method for 'Lena', 'Boat', 'Cameraman' and TID2008 database images corrupted with RVIN of different noise densities

Noise Density	Lena	Boat	Cameraman	TID2008
75%	0.772	0.845	0.779	0.789
80%	0.783	0.854	0.797	0.802
85%	0.797	0.858	0.809	0.819
90%	0.807	0.863	0.818	0.831
95%	0.818	0.864	0.823	0.848

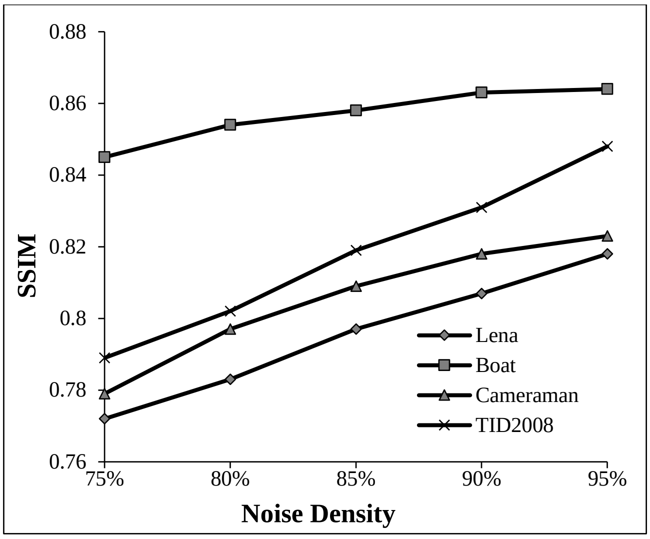


Fig.12. Graph of SSIM for different images calculated by CCBD

6. CONCLUSION

In this paper, a novel method is presented for effective removal of RVIN in images which is based on Correlation Coefficient. Numerous Simulation results have demonstrated the efficacy of this method in removing high density RVIN while preserving image details. The proposed method is found to suppress up to 95% of noise satisfactorily due to the effective use of Correlation Coefficient concept. Further, the results establish that the proposed method CCBD performs far better than the existing state-of-the-art filtering approaches as discussed in this paper.

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