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An Efficient Filter To Remove Universal Noise In High Noise Density Images

Premnath D
M.E. Communication Systems, Loyola Institute of Technology, Chennai, India
S.Uma Maheswari
Assistant Professor, ECE Department, Loyola Institute of Technology, Chennai, India

Abstract:

Digital Images are generally corrupted by Impulse noise during the image acquisition process, while Gaussian noise is encountered during transmission. These noises seriously affect the quality of images. It causes degradation of image spatial resolution, loss of image details and distortion of important image features. Therefore it is essential to correct corrupted pixels before using them in any applications. There are numerous approaches have been proposed to reduce these noises independently. Recently, a Switching Bilateral Filter algorithm is proposed which filters both noises using a single filter but with parameters different for Impulse and Gaussian noise.

Switching Bilateral Filter (SBF) performances poorly for Impulse noise densities beyond 35%. In this thesis, the above algorithm has been modified to detect impulse noise even at high noise densities. The proposed filter is found to yield better quality images in terms of subjective quality and PSNR values compared to Switching Bilateral Filter.

1.Introduction

Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. It is a type of signal dispensation in which input is an image, like video frame or photograph and output may be an image or characteristics associated with that image. Usually Image Processing system includes treating images as two dimensional signals while applying already set signal processing methods for them.

Digital image transmission has become a major part of communication in the digital age, but the image obtained after transmission is often corrupted with noise. The received image needs processing before it can be used in applications.

Digital images are prone to a variety of types of noise. Noise is the result of errors in the image acquisition process that result in pixel values that do not reflect the true intensities of the real scene. The presence of noise gives an image a mottled, grainy, textured, or snowy appearance. No imaging method is free of noise, but noise is much more prevalent in certain types of imaging procedures than in others. Noise increases with the sensitivity setting in the imaging device, length of the exposure, temperature, and even vary amongst different device models.

Image noise is random (not present in the object imaged) variation of brightness or color information in images, and is usually an aspect of electronic noise. It can be produced by the sensor and circuitry of a scanner or digital camera. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector. Image noise is an undesirable by-product of image capture that adds spurious and extraneous information.

The noise is most apparent in image regions with low brightness levels, such as shadow regions or in under-exposed images. Noise in imaging systems is usually either additive or multiplicative.

Classification of noise is based upon

- The shape of probability density function (analog case of noise)
- Histogram (discrete case of noise)

2.Denoising Techniques

A fundamental problem of image processing is to effectively remove noise from an image while keeping its features intact. A large number of different image denoising algorithms have been proposed and can be generalized into the spatial domain filtering and transform domain filtering. The transform domain filtering can generally achieve better image denoising performance but need higher computation cost. Considering the computational complexity and real-time computational requirement, the spatial domain filtering is a good choice.

Most algorithms for converting image sensor data to an image, whether in-camera or on a computer, involve some form of noise reduction. There are many procedures for this, but all attempt to determine whether the actual differences in pixel values constitute noise or real photographic detail, and average out the former while attempting to preserve the latter. However, no algorithm can make this judgment perfectly, so there is often a tradeoff made between noise removal and preservation of fine, low-contrast detail that may have characteristics similar to noise. Many cameras have settings to control the aggressiveness of the in-camera noise reduction.

3.Linear Filter

Linear filtering is filtering in which the value of an output pixel is a linear combination of the values of the pixels in the input pixel's neighborhood. Several principles define a linear system. The first two are the basic definitions of linearity. If a system is defined to have an input as $x[n] = ax[n1] + bx[n2]$, then the linear system response is $y[n] = ay[n1] + by[n2]$. This is known as the superposition property, and is fundamental to linear system design. The second property is shift invariance. If $y[n]$ is the response to a linear, shift-invariant system with input $x[n]$, then $y[n-n0]$ is the response to the system with input $x[n-n0]$.

Linear filtering possesses mathematical simplicity and offers satisfactory performance on images with additive Gaussian noise. However, linear techniques blur edges and fail for non-Gaussian and/or impulse noise.

4.Non-Linear Filter

The Nonlinear digital filters can overcome some of the limitations of linear digital filters. For nonlinear filters, the filter output or response of the filter does not obey the principles outlined earlier, particularly scaling and shift invariance. Moreover, a nonlinear filter can produce results that vary in a non-intuitive manner.

The simplest nonlinear filter to consider is the median or rank-order filter. In the median filter, filter output depends on the ordering of input values, usually ranked from smallest to largest or vice versa. A filter support range with an odd number of values is used, making it easy to select the output.

Median filters are known to remove impulse noise and preserve edges. General median filters often exhibit blurring for large window sizes, or insufficient noise suppression for small window sizes. Adaptive length median filter overcomes these limitations of general median filters.

5.Switching Scheme

The classical bilateral filtering (BF) was first introduced by Tomasi and Manduchi in 1998. The bilateral filtering takes into account both the spatial information and the intensity information between a point and its neighboring points. Moreover, the bilateral filtering is non-iterative filtering process with only a single pass which make it of low complexity. Due to its simple implementation and effectiveness, the classical bilateral filtering has been widely used in image denoising, photograph enhancement, video processing and etc,

Bilateral filter not only replaces noisy pixels but also preserves the edge, hence achieves good visual image quality. Bilateral filter cannot remove impulse noise hence switching bilateral filter (SBF) which removes both Gaussian and impulse noise is proposed. Based on the noise classification result in the noise detector, SBF switches between the Gaussian and impulse modes.

One of the most frequently used strategies for enhancing the performance of impulse noise filters is the switching scheme concept. It suggests that the noisy pixels should be detected first and filtered afterward, i.e., replaced by some estimated values, whereas the undisturbed pixels should be left unchanged. The switching scheme detects impulse noise pixels before filtering and re-places them with estimated values while leaving the remaining pixels unchanged. To achieve good visual image quality, it is important that the noise filter not only replaces noisy pixels but also preserves the edge. From the noise classification result in the noise detector, SBF switches between the Gaussian and impulse modes. SBF shows very good results in removing salt-and-pepper noise, uniform impulse noise and Gaussian noise.

The Noise removal process is carried out in two stages

- Detection
- Filtering.

For detection, Sorted Quadrant Median Vector (SQMV) is used. This vector includes edge or texture information. This information is utilized to calculate the reference median, which is in turn compared with a current pixel to classify it as impulse noise, Gaussian noise, or noise-free. For filtering, Switching Bilateral filter is used. SBF is a nonlinear filter.

In this method, the edge detector identifies the existence of an edge of the window. This edge information is used in the noise detector to decide the reference median for noise identification. The noise detector also decides whether a current pixel should be filtered by using an SBF or whether it should bypass the SBF.

Classification of noise is also performed on the noise detector. Based on this classification, appropriate filtering will be applied to the noisy pixels leaving the noise free pixel because the smaller image details may get lost in the process.

6.Sorted Quadrant Median Vector

When an image is corrupted by impulse noise, a portion of the pixel values are replaced with random values. Let $x_{i,j,}$ and $n_{i,j,}$ denote the intensity values of a noise-free image and the corrupted image at the pixel location. Then the noisy image can be described as follows:

$$U_{i,j} = \begin{cases} n_{i,j,} & \text{With propability p} \\ x_{i,j,} & \text{With probability 1-p} \end{cases}$$

The value of p indicates the probability that a noise-free image is corrupted by impulse noise, and $n_{i,j,}$ is the intensity value of the impulse noise at the location (*i*,*j*). The value of $n_{i,j}$ is in the range of maximum luminance value *Lmax* and minimum luminance value *Lmin*. When only takes values of either *Lmin* or *Lmax*, the noise model is called salt-and-pepper noise. And when $n_{i,j}$ takes random values from the interval with a uniform distribution the model is called uniform impulse noise. For the case of additive Gaussian noise, each noise value $n_{i,j}$ is produced from a zero-mean Gaussian distribution and the noisy image $n_{i,j}$ is related to the original image by

$$U_{i,j} = x_{i,j,} + n_{i,j}$$

For images with fine details, a processing window of size 3x3 may fail to distinguish between noise and detail. For a larger window size, such as 5x5, the resulting median value drifts from the median value of a small-size window because new textures are added into the larger window. Using a median value from a larger window may cause false noise detection and blur the image during filtering.

In the Sorted quadrant median vector, we start from a larger window but observe medians from sub windows in the larger one. The medians in the sub windows are sorted and the result vector is called SQMV. This vector reveals edge and texture information in the larger window. With the median values in the sub window and edge/texture information in the larger window, the median drifting problem in the larger window or lack of texture information problems can be avoided.

Consider a Window, W with size (2N+1) ×(2N+1). The procedure is to divide the window, W into four sub windows, each sub window of size (N+1) × (N+1), with the central pixel as the corner pixel in the four sub-windows (Fig. 1, *N=2*). Let $x_{i,j}$ be the center pixel located at (i,j) of the processing window. The set of points in the window is expressed as

$$W = \{ x_{i+s,j+t} : -N \le S \le N, -N \le t \le N \}$$

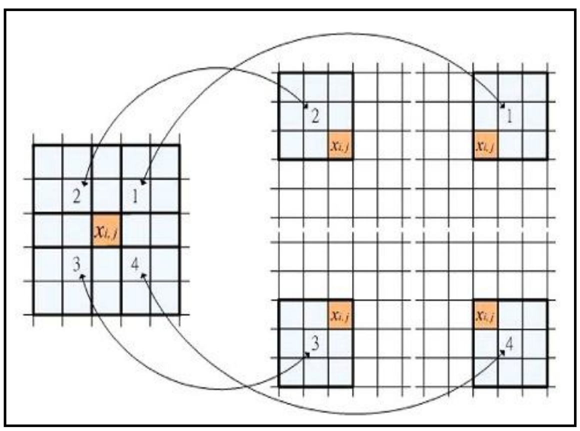

Figure 1: Four quadrant blocks in a single 5x5 window

The set of pixels in four sub windows each of size (N+1) × (N+1) are defined as

$$= \{ x_{i+s,j+t} : 0 \le S \le N, 0 \le t \le N \}$$
$$= \{ x_{i+s,j+t} : -N \le S \le 0, 0 \le t \le N \}$$
$$= \{ x_{i+s,j+t} : -N \le S \le 0, -N \le t \le 0 \}$$
$$= \{ x_{i+s,j+t} : 0 \le S \le N, -N \le t \le 0 \}.$$

Here, we use processing window of size 5x5, hence N=2 and the four quadrant blocks (Fig. 2) are of size 3x3. The median values of the quadrant blocks are expressed as

m_k = median { W_k}, k = 1 to 4

Where m_1, m_2, m_3, m_4 denote the median values of the top right, top left, bottom left, bottom right of the four quadrant blocks.

SQMV = [SQM1, SQM2, SQM3, SQM4]

Where SQM1, SQM2, SQM3, and SQM4 are the medians m1, m2, m3, and m4 sorted in an ascending order such that SQM1 ≤ SQM2 ≤ SQM3 ≤ SQM4.

7.Edge Information With Clusters Of SQMV

After sorting the four median values, some of the median values are very similar while others are different, leading to the formation of clusters. The clusters of SQMV provides edge and texture information within a window for an image.

For classifying the clusters, there are seven different patterns. Here we condense the seven patterns into three edge/texture cases based on cluster distribution. They are given as

- Without Edge
- Weak Edge
- Strong Edge or Texture

To classify the cluster, we define $SQMD_B$ and $SQMD_C$.

$SQMD_B$ is the difference between the two boundary values of the sorted quadrant median values.

$SQMD_B$ = SQM4 - SQM1

$SQMD_C$ is the difference between the two center values of the sorted quadrant median values.

$SQMD_C$ = SQM3 – SQM2

The Switching Bilateral filter proposed by Chih-Hsing Lin, Jia-Shiuan Tsai, and Ching-Te Chiu (2010) states that $SQMD_B$ and $SQMD_C$ provide a measure of the similarity between the four quadrant blocks. Based on the information of $SQMD_B$ and $SQMD_C$, three edge/texture cases without edge, weak edge, and strong edge or texture are obtained. These three cases are shown in the figure.

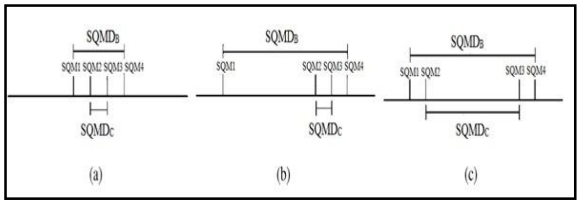

Figure 2: (a) Without edge (b) Weak edge (c) Strong edge

The 'without edge' case occurs when SQMDB is small, which means that the pixel values in the window are similar so there is no edge in it. When SQMDB is large but SQMDC is small, there is a weak edge in the window. When both SQMDB and SQMDC are large, it indicates that there is a strong edge or texture.

Edge/Texture Detector

$$= \begin{cases} \text{Without Edge, } SQMD_B \leq \varrho \\ \text{Weak Edge, } SQMD_B \geq \varrho \land SQMD_C \leq \varrho \\ \text{Strong Edge or Texture, } SQMD_c \geq \varrho \end{cases}$$

Through experimentation it is found that the best value of ϱ lies in the interval [25 - 40]. In our work, the value of ϱ is set to 40.

8.Reference Median

The comparison between the reference median and a current pixel is used for detecting whether a current pixel is noisy or noise free. Hence the next step is to calculate the reference median (SQMR) from the sorted median values.

When there is no major cluster in the SQMV, it is necessary to decide which cluster the current pixel falls into. From the order of four values, the pattern in this window can be classified into the three cases:

- Vertical edge
- Horizontal edge
- Diagonal line or texture

A direction average (dav) approach is adopted to determine which cluster is more similar to the current pixel.

When the number of medians inside the cluster is more than that inside other clusters similar to without edge or weak edge cases, the cluster with the most number of medians represents the majority feature in the window. This cluster is defined as the major cluster and the reference median is the average of SQM2 and SQM3.

For strong edge or texture, there is no major cluster in SQMV. In this case, it is necessary to decide the cluster in which current pixel is present. The pattern is classified into three classes: vertical edge, horizontal edge, diagonal edge or texture.

A directional average (dav) method is used to determine the cluster which is more similar to the current pixel. Depending on the case, the four pixels in the major pattern are averaged and is given by

$$\text{dav} = (x_1 + x_2 + x_3 + x_4)/4$$

In the case of vertical edge, if dav is close to (SQM1, SQM2), then SQM2 is chosen as the reference median. If dav is close to (SQM3, SQM4), then SQM3 is chosen as the reference median value.

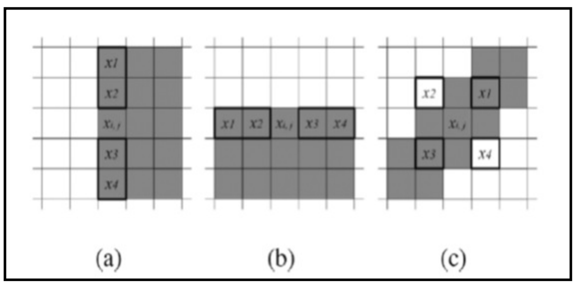

Figure 3: Direction average: (a) Vertical (b) Horizontal (c) Diagonal directions

The Reference median (SQMR) is defined as

$$\text{SQMR} = \begin{cases} \frac{\text{SQM3}+\text{SQM2}}{2}, & \text{SQMD}_C \leq \varrho \\ \text{SQM3}, & \text{SQMD}_c \geq \varrho \wedge \text{dav} \in (\text{SQM3}, \text{SQM4}) \\ \text{SQM2}, & \text{SQMD}_c \geq \varrho \wedge \text{dav} \in (\text{SQM1}, \text{SQM2}) \end{cases}$$

9.Noise Detector

The noise detector is used to determine whether the current pixel is corrupted or not. This decision is made using the reference median (SQMR). This method is more effective than using the single median value.

When the current pixel is very different from the reference median, the pixel is identified as an impulse noise. When the difference between the current pixel and the reference median is not very large, it may be a Gaussian noise or noise-free pixel. The decision making mechanism is realised by employing a reference median and the two thresholds (Tk_1 and Tk_2).

The Pseudo-code for noise detector is given below

If (| $x_{i,j}$ – SQMR | ≥ Tk_1)

$S_1 = 1, S_2 = 1$ ($x_{i,j}$ is an Impulse noise)

Else if (| $x_{i,j}$ – SQMR | ≥ Tk_2)

$S_1 = 1, S_2 = 0$ ($x_{i,j}$ is an Gaussian noise)

Else

$S_1 = 0, S_2 = 0$ ($x_{i,j}$ is an Noise-free)

End

Tk_1 and Tk_2 are the thresholds for identifying impulse noise or Gaussian noise. The threshold values [$Tk_{1,}$Tk2] = [30,15] yields satisfactory results in filtering Salt and Pepper noise, while setting [$Tk_{1,}Tk_2$] = [25,5] performs well in removing uniform impulse and Gaussian noise.

10.Switchiing Bilateral Filter (SBF)

The Switching Bilateral filter proposed by Chih-Hsing Lin, Jia-Shiuan Tsai and Ching-Te Chiu (2010) removes both Gaussian and Impulse noise without adding another weighting function. The range filter inside the bilateral filter switches between the Gaussian and the Impulse noise modes based on the noise classification result.

Each pixel is replaced by a weighted average of the intensities in the window. The weighting function gives a high weighting to those pixels that are both near the central pixel and similar to the central pixel.

The bilateral filter shows great results in removing Gaussian noise while keeping the edge, but it is difficult to remove impulse noise. Because the noisy pixel is very different from its neighbors, the surrounding weights are too small to change the noisy pixel in the range filter. In order to remove impulse noise and Gaussian noise using a bilateral filter, Chih-Hsing Lin, Jia-Shiuan Tsai, and Ching-Te Chiu (2010) proposed a switching bilateral filter.

Let $x_{i,j}$ be the current pixel, and let $x_{i+s,j+t}$ be the pixels in the (2N+1) x (2N+1) window that surrounds $x_{i,j}$. (i,j) and ($i+s, j+t$) are the location of $x_{i,j}$ and $x_{i+s,j+t}$.

The output of the bilateral filter $y_{i,j}$ is defined as follows:

$$y_{i,j} = \frac{\sum_{s=-N}^{N}\sum_{t=-N}^{N} W_G(s,t)W_R(s,t)x_{i+s,j+t}}{\sum_{s=-N}^{N}\sum_{t=-N}^{N} W_G(s,t)W_R(s,t)}$$

Where, $W_G(s,t) = \exp - \frac{(i-s)^2 + (j-t)^2}{2\sigma_S^2}$

W_G(s,t) is a Gaussian filter.

The Euclidean distance between the $x_{i,j}$ and $x_{i+S,j+t}$ is calculated in the Gaussian filter.

$$W_{SR}(s,t) = \exp - \frac{(I - x_{i+S,j+t})^2}{2\sigma_R^2}$$

$$I = \begin{cases} SQMR, S2 = 1\ for\ SBF_{im} \\ x_{i,j}, S2 = 0\ for\ SBF_{ga} \end{cases}$$

There are two parameters σ_R and σ_S that control the bilateral filter. There is no single set of σ_R and σ_S that is optimal for all images. In our experiment we take $\sigma_R = 40$ and $\sigma_S = 3$ for the impulse noise model. In case of Gaussian noise these parameters vary corresponding to the standard deviation of the Gaussian noise.

11.Proposed Method

Impulse noises in digital images are present due to bit errors in transmission or introduced during the signal acquisition stage. There are two types of impulse noise, they are salt and pepper noise and random valued noise. Salt and pepper noise can corrupt the images where the corrupted pixel takes either maximum or minimum gray level. The switching bilateral filter proposed by Chih-Hsing Lin, Jia-Shiuan Tsai, and Ching-Te Chiu, for removal of impulse noise does not effectively remove noise in images for values of noise density greater than 30%. Hence modifications are done for yielding better results.

In this proposed method, the noisy pixels are detected using the Sorted Quadrant Median Vector method. Then the detected noisy pixels are replaced by the median of the noise free pixels in the selected window, previously the noisy pixels were replaced by the median of all the pixels in the window. The window size is varied from 5 x 5, 7 x 7, 9 x 9, 11 x 11 depending on the noise density. The window size is not increased more than 11x11 as this size gives efficient results. This performs better than the switching bilateral filter for impulse noise removal, but as the noise density increases beyond 40%, some of the noise pixels are not detected by using sorted quadrant median vector (SQMV) method. Hence to detect all the noisy pixels, Sorted Quadrant Median Vector method is altered.

In this method, after sub dividing 5x5 window into four 3x3 sub windows, the noisy pixels (0 and 255) are removed from the window. Then the Sorted Quadrant Reference Median (SQMR) is calculated from the median values of the four sub windows. Finally the detected noisy pixels are replaced with the median of the selected window. The size of the window varies depending on the noise density.

12.Results And Discussion

The proposed method is implemented in MATLAB. The images filtered using both the SBF and the proposed method are compared in terms of subjective quality, impulse detection rate, classification accuracy and Peak Signal to Noise Ratio (PSNR).

Quantitative measures such as Impulse detection rate, Classification accuracy and PSNR.The Impulse detection ratio (IDR) represents the number of detected impulses divided by the total number of impulses. The classification accuracy ratio (CAR) represents the number of correctly classified pixels (correctly detected noise plus correctly detected noise-free pixel) divided by the total number of pixels.

The Peak Signal to Noise Ratio is used as a quantitative measure for comparison. It is measured in decibel (dB). The higher the PSNR in the restored image, the better is its quality. If u is an original MxN image and $\tilde{u}$ is a restored image of u, the PSNR of $\tilde{u}$ is given by,

$$\mathrm{PSNR}(\tilde{u}) = 10\log\frac{255^2}{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(\tilde{u}_{i,j} - u_{i,j}\right)^2}$$

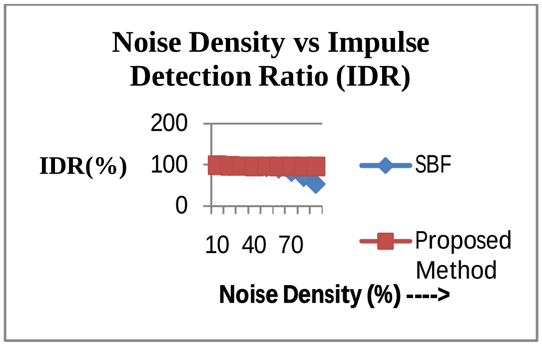

Figure 4: Graph for Impulse detection ratio and ND

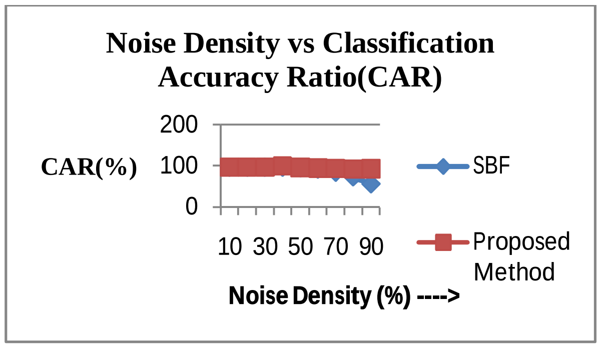

Figure 5: Classification accuracy ratio and ND

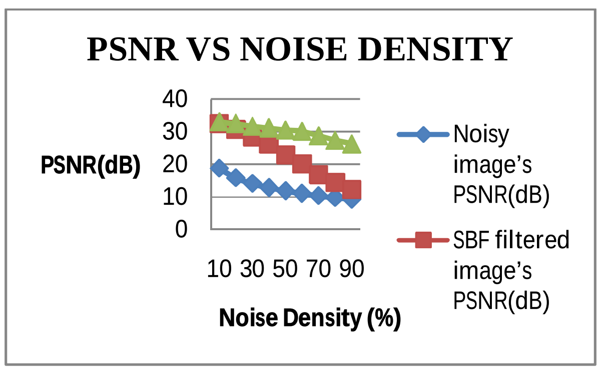

Figure 6: PSNR (dB) of Noisy, SBF & Proposed method

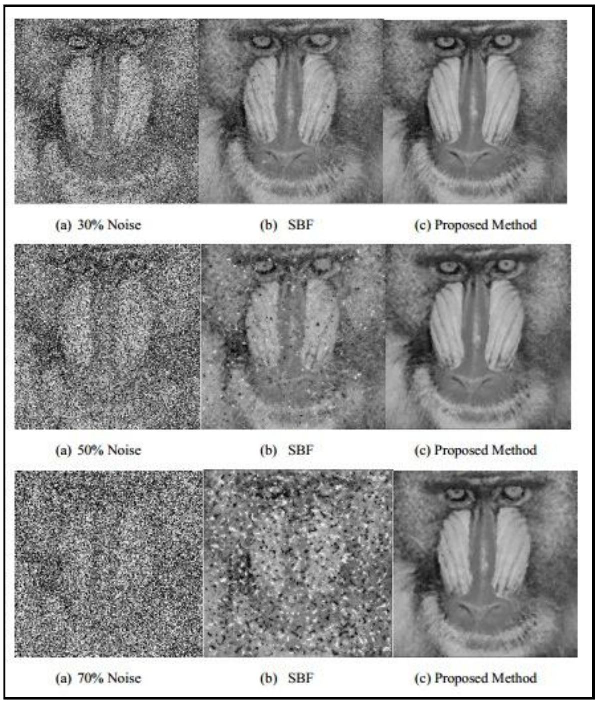

Figure 7: Comparison of SBF and proposed filter for various noise densities

It can be seen from Figure 7 & Figure 8 that the SBF performance is not satisfactory for impulse noise densities above 35%. The results obtained using the proposed method are significantly better than those obtained using SBF even for higher noise densities.

13.Conclusion

Switching Bilateral Filter (SBF) does not work efficiently for impulse noise densities beyond 35%. In this thesis, changes have been made to the detection algorithm in order to detect impulse noises efficiently at higher noise densities. Then the detected noisy pixels are filtered using a median filter. The proposed filter is found to yield better quality images in terms of subjective quality and PSNR values compared to SBF.

Hybrid algorithm has to be developed combining Switching Bilateral Filter and proposed method for removal of Gaussian and impulse noise.

14.Reference

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