

Efficient Techniques for Denoising of Highly Corrupted Impulse Noise Images

Suresh Velaga, Sridhar Kovvada

Abstract— In this paper, different types of impulse noise removal techniques are presented. Because of adaptive nature of mask size depending on the noise quantity in the image, adaptive median filter works better in removing the salt and pepper noise. To show the performance of Adaptive Median filter, median filter, Lee filter, Frost and Kuan filters and DWT and Duqal tree Complex Wavelet Transform are considered. Adaptive median filter is compared with other filters and also the transformations. The superiority of Adaptive Median filter in removing the Highly Corrupted with impulse noise in images are presented. Graphs are drawn between the input PSNR and output PSNR for impulse noise removal techniques.

Keywords— Dual-Tree CWT, Adaptive median Filter, DWT

I. INTRODUCTION

At the time of image acquiring or transmitting, digital images are often contaminated by different types of noise primarily impulse noise. Due to a number of non-idealities in the imaging process the noise usually corrupts images by replacing some of the pixels of the original image with new pixels having luminance values near or equal to the minimum or maximum of the allowable dynamic luminance range. This is called impulse noise. This occurs mostly when there are quick transients and faulty switching[1]. So these noisy images are most often occurring at transmission. In most applications, it is very important to remove these noises from image data, since the performances of subsequent image processing tasks are strictly dependent on the success of image noise removal operation. However, this is a difficult problem in any image processing system because the restoration filter must not distort the useful information in the image and preserve image details and texture while removing the noise. A large number of methods have been proposed to remove impulse noise from digital images. Section two gives the brief of Median filter. Section three gives about Frost filter. Section four tells about Kuan filter. Section five tells about Lee filter. Section six gives the brief of Discrete Wavelet Transform. Section seven gives the explanation of Dual Tree Complex Wavelet Transform. Section eight gives the detail description of Adaptive Median Filter and section nine gives the results and discussions.

II. MEDIAN FILTER

The implementation of median filter consists of computing the median of the grey-level values within the square or rectangular filter window surrounding each pixel. For example, let the mask is a 3X3 and the pixel values in the nine positions are given by the following table. This filter arranges all the grey level values in the ascending order and selects the middle value and replaces the middle pixel of that set of pixel

values. 09, 34, 43, 67, 134, 178, 209, 210 and 234. The middle pixel value 43 is replaced with 134.

178	234	67
209	43	134
34	210	09

III. FROST FILTER

The implementation of this filter consists of defining a circularly symmetric filter with a set of weighting values M for each pixel

$$M = e^{-A*T}$$

Where $A = damp*(V/I^2)$, T is the absolute value of the pixel distance from the centre pixel to its neighbors in the filter window. $damp$ is the exponential damping factor, V is the variance of the grey level in the filter window, I^2 is the square of the mean grey level in the filter window the resulting grey-level value R for the smoothed pixel is [1]

$$R = (P_1 * M_1 + P_2 * M_2 + \dots + P_n * M_n) / (M_1 + M_2 + \dots + M_n)$$

Where $P_1 \dots P_n$ are grey levels of each pixel in filter window and $M_1 \dots M_n$ are weights for each pixel.

IV. KUAN FILTER

Kuan performs spatial filtering on each individual pixel in an image using the grey level values in a square window surrounding each pixel. The dimensions of the filter must be odd, and can be from 3x3 to 11x11 pixels. All pixels are filtered. In order to filter pixels located near edges of the image, edge-pixels are replicated to give sufficient data. The resulting grey-level value R for the smoothed pixel is: [2]

$$R = C_p * W + I * (1 - W)$$

Where, $C_u = 1/N_{look}$, $C_i = Var/I$,

$$W = (1 - C_u / C_i) / (1 + C_u)$$

I = Mean grey level in the filter window, C_p = central pixel in filter window, Var = Variance in filter window, N_{look} = Number of Looks.

V. LEE FILTER

Speckle noise in SAR images is generally assumed a multiplicative error model. In the Lee filter, the multiplicative model is first approximated by a linear model. Then the minimum mean square error criterion is applied to the linear model. The resulting grey level value R for the smoothed pixel is [3]

$$R = I_c * W + I_m * (1 - W)$$

Where $W = 1 - \frac{C_u^2}{C_i^2}$,

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Suresh Velaga, Department of ECE, Chaitanya Engineering College, Visakhapatnam, A.P., India

Sridhar Kovvada, Assistant Professor, Department of ECE, Chaitanya Engineering College, Visakhapatnam, A.P., India.

$C_u = \text{Sqrt}(1/N_{look})$, $C_i = S/I_m$, I_c is the centre pixel of filter window. I_m = mean value of intensity within window, S = standard deviation of intensity within window, the C_u above is the estimated noise variation coefficient. C_i is the image variation coefficient. W is a weighting function.

VI. DISCRETE WAVELET TRANSFORM

When radar reflectivity undergoes significant variations due to the presence of strong scatterers or structural features (edges or contours) in processing window, such speckle filtering is less effective.

As a typical transform tool, wavelets have properties of multiscale, good time-frequency localization. Then, wavelets-based filter techniques are widely used in SAR image speckle reduction [4]. However, efficiency of standard two-dimension (2-D) wavelets is limited by spatial isotropy and lacking of shift-invariance of their basis functions, which leads to artifacts (Gibbs-like phenomena) along line singularities with high anisotropy.

VII. DUAL TREE COMPLEX WAVELET TRANSFORM

It is well known that the ordinary discrete wavelet transform is not shift invariant [5] because of the decimation operation during the transform. A small shift in the input signal can cause very different output wavelet coefficients. This is the main limitation of wavelet in pattern recognition. One way of overcoming this is to do the wavelet transform without decimation. The drawback of this approach is that it is computationally inefficient, especially in multiple dimensions. Kingsbury introduced a new kind of wavelet transform called the dual-tree complex wavelet transform, that exhibits approximate shift invariant property and improved angular resolution. The success of the transform is because of the use of filters in two trees, a and b. He proposed a simple delay of one sample between the level 1 filters in each tree, and then the use of alternate odd-length and even-length linear-phase filters. As he pointed out that there are some difficulties in the odd/even filter approach. Therefore, he proposed a new Q-shift dual-tree where all the filters beyond level 1 are even length.

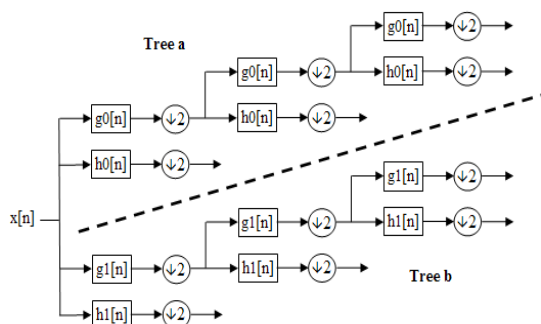


Fig: 1 Dual Tree Complex Wavelet Transform

The filters in the two trees are just the time-reverse of each other, as are the analysis and reconstruction filters. The new filters are shorter than before, and the new transform still satisfies the shift invariant property and good directional selectivity in multiple dimensions. As will be shown later, this dual-tree complex wavelet can be successfully used in invariant feature extraction for pattern recognition shown later, this dual-tree complex wavelet can be successfully used in invariant feature extraction for pattern recognition.

Dual Tree Complex Wavelet Transforms is a revolution based on wavelet transform and multiscale analysis, which has the advantages of both wavelet multiscale analysis and the geometric regularity of image intrinsic structures. DTCWT has characteristics of anisotropy and multi-directionality to represent high-dimensional signals more effectively.

VIII. ADAPTIVE MEDIAN FILTER

The adaptive media filter is a processing of removing the salt and pepper noise efficiently. It has two steps. The first step is identifying the noise pixel and the second step is cancelling the noise.

A. Noise Identification:

There are two main purposes of this stage. The first one is to identify the “noise pixel”, and the second one is to roughly approximate the noise level of the image. We assume that the two intensities that present the impulse noise are the maximum and the minimum values of the image’s dynamic range (i.e. 0 and $L-1$). Thus, in this stage, at each pixel location (x, y) , we mark the mask α by using the following equation:

$$\alpha(x, y) = \begin{cases} 1: f(x, y) = L-1 \\ 1: f(x, y) = 0 \\ 0: otherwise \end{cases} \quad (1)$$

Where the value 1 presents the “noise pixel” [6]and the value 0 presents the “noise-free pixel”. Next, after we classify the pixels using (1), we calculate the total number of the “noise pixel”, K . This is given by (2).

$$K = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \alpha(x, y) \quad (2)$$

Using the value of K , we can roughly estimate the impulse noise level η that corrupts the image. The value of η [7] is the ratio of the “noise pixels” to the total number of pixels contained in the image, as defined in the following equation:

$$\eta = K/(MN) \quad (3)$$

The value of η is in between 0 and 1 (i.e. $0 \leq \eta \leq 1$). This value and the noise mask α will be used in the following stage, which is for the noise removal.

B. Noise Cancellation

In this stage, we filter the input image f , and produce the filtered image g . Similar to many switching median filter methods, the output is defined as:

$$g(x, y) = [1 - \alpha(x, y)]f(x, y) + \alpha(x, y)m(x, y) \quad (4)$$

Where α is the noise mask, defined by (1) in Stage 1, where m is the median value obtained from our adaptive method [8] – [12]. The determination of m will be explained later. As $\alpha(x, y)$ only can take value of either 0 or 1, as defined by (1) the output value $g(x, y)$ is either equal to $f(x, y)$ or $m(x, y)$. Thus, the calculation of $m(x, y)$ is only done when $f(x, y)$ is a “noise pixel” (i.e. $\alpha(x, y) = 1$). For the “noise-free pixel” (i.e. $\alpha(x, y) = 0$), the value of $f(x, y)$ is copied directly as the value of $g(x, y)$.

This significantly speeds up the process, because not all pixels need to be filtered. Thus, alternatively, $g(x, y)$ can be re-written as:

$$g(x, y) = \begin{cases} f(x, y) : \alpha(x, y) = 0 \\ m(x, y) : otherwise \end{cases} \quad (5)$$

The window size is adaptive. If initially takes the window size as 3X3. If the number of impulse noise pixels are greater than or equal to 8, then it increases the size to 5X5. The mask size we have selected is always odd since to take the median we have to have odd number of values. This happens only when the mask size is odd. This methodology is fast [13] – [14] because it does the median filtering operation only on the impulse noise corrupted pixels.

The processing in removing the impulse noise in this method is given in the following steps.

1. Initially take the mask size as 3X3 and apply on the current pixel.
2. Calculate the total number of noise free pixels contained in the mask.
3. Calculate the total number of noisy pixels in the mask. If it is greater than 8 then increase the mask size of dimension 2.
4. Compute the value of $m(x, y)$ based on the noise free pixels contained in the mask.
5. Update the value of $g(x, y)$ using the equation (4).
6. Repeat the process for every noisy pixel in the image.

IX. RESULTS AND DISCUSSIONS

To show the performance of filters and transformations in removing the speckle noise in the images four filters and two transformations are considered. The filters are Median, Frost, Kuan and Lee filters and the transformations are Discrete Wavelet Transform and Dual Tree Complex wavelet Transform. Adaptive median filter has some effect on the noisy image only when there are some impulse noises (either '0' or '255' values). Since the speckle noisy image filtered by the median filter cannot have any value, so adaptive median filter is not considered as one of the speckle noise removal technique. All these 20 sets of speckle noisy images are passed through these filters and applied DWT and CT-DWT. The PSNR of these denoised images has been calculated. The graph has been drawn between the input PSNR and the output PSNR in dB. The results show that dual tree complex wavelet transform has superior performance over Discrete Wavelet Transform and all other traditional filters in removing the speckle noise.

In removing the impulse noise all the five filters and the two transformations are considered. Median filter is performing well among all the filtering techniques and also performing well in comparison with transformations. Though the Wavelet Transform techniques both DWT and CT-DWT are best for speckle noise, nonetheless they are performing poorly for salt and pepper noisy images. The reason is because the wavelet transform cannot discriminate the pixel value of '255' or '0' values which is noise with noise free pixel while applying the transformation. In contrast the median filter discriminates and also sends all the noisy pixels to both the extremes and takes only the middle value which is purely noise free pixel. The size of the mask is adapted according to the amount of noise present in the mask. If the amount of noise present in the mask is more, the mask size also increases as 3X3, 5X5, 7X7 etc... The results show that

the adaptive median filter is performing better for impulse noisy images.

$$PSNR = 20 \log_{10} \left[\frac{\max i / P_i}{RMSE} \right]$$

Where Root Mean Squared Error, $RMSE = \sqrt{MSE}$, and the Mean Squared Error

$$MSE = \frac{1}{k} \sum_{i=1}^k (P_i - Q_i)^2$$

To demonstrate the importance of speckle filters namely Kuan, Lee, Frost filters, DWT and CT-DWT the below graph has been shown. In the graph shown in Fig. 3 the Adaptive median filter is not considered because it is exclusively for removing the highly corrupted impulse noise.

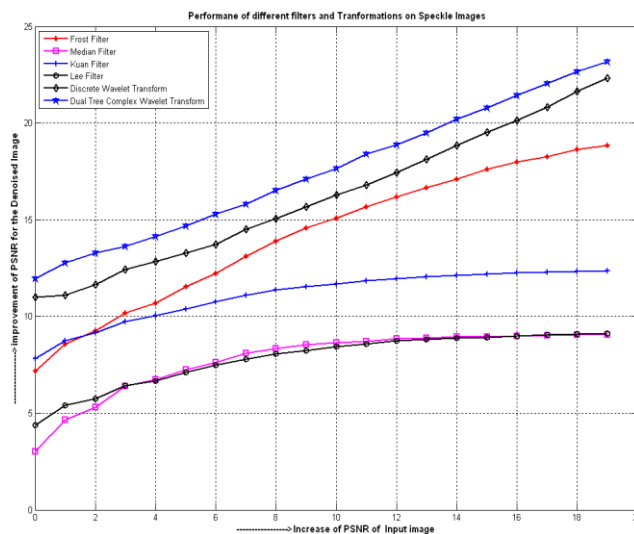


Fig. 3 Performance of different filters and transformations on speckle noisy images

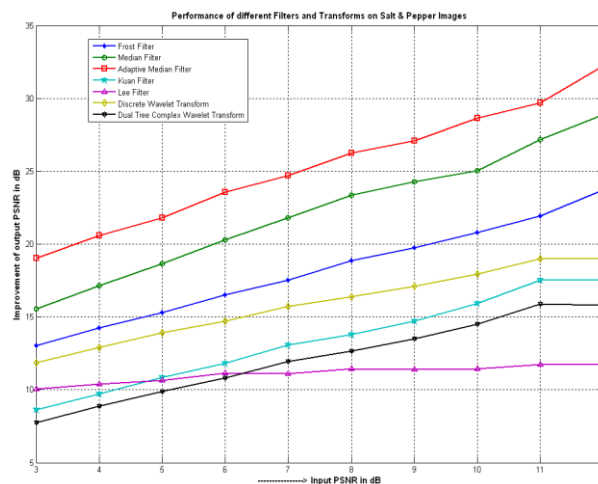


Fig. 3 Performance of different filters and transformations on salt & pepper noisy images

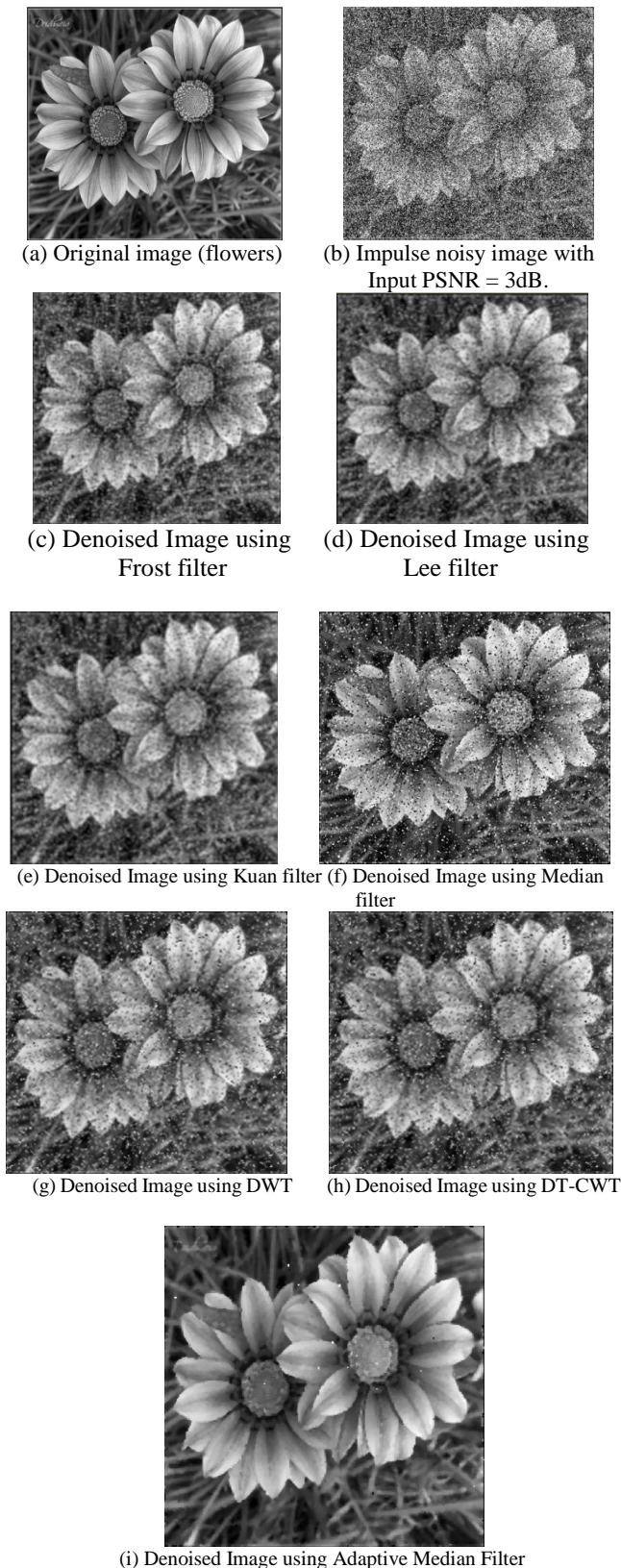


Fig: 4 (a) Original Flower Image, (b) Impulse noisy image with input PSNR 0dB (c) Frost filtered Image with o/p PSNR 7.3dB (d) Lee filtered image with o/p PSNR 4.5dB (e) Kuan filtered image with o/p PSNR 7.6dB (f) Median filtered image with o/p PSNR 3.6dB (g) DWT image with o/p PSNR 11.1dB and (h) DT- CWT image with o/p PSNR 12.0dB (i) Adaptive Median Filter Image with o/p PSNR 15.9dB.

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AUTHORS PROFILE



Mr. Suresh Velaga, obtained his B. Tech. degrees from JNT University, Hyderabad in the year 2009. He is presently pursuing M. Tech. from Chaitanya Engineering College, Visakhapatnam, AP. His areas of interests are Image Processing, Speech processing.



Mr. Sridhar Kovvada, obtained his B. Tech. and M. Tech degrees from JNT University; Hyderabad He is presently working as Assistant Professor in Chaitanya Engineering College, Visakhapatnam, AP. His areas of interests are Image Processing, Speech processing.