International Journal of Application or Innovation in Engineering & Management (IJAIEM)
Web Site: www.ijaiem.org Email: editor@ijaiem.org
Volume 6, Issue 7, July 2017 **ISSN 2319 - 4847**

CURVELET TRANSFORM BASED IMAGE DE-FOCUS USING FEED FORWARD NEURAL NETWORK

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ABSTRACT

It is seen that pictures get degraded because of presence of noise in processes like image acquisition, storage, retrieval or transmission. With completely different sorts of noise and its extent, de-noising becomes difficult. Historically, a bunch of techniques have thought of spacial, applied mathematics and multiple domain approaches for de-noising. Yet, the scope forever exists for exploring and innovation which suggests of performing arts de-noising for enhancing image quality Within the planned work, we tend to gift ANN (Artificial Neural Network) approach to de-noise pictures by combining the options of structure separate Curvelet rework and Feed Forward Artificial Neural Network (FF-ANN). In this paper we use two techniques i.e., DWT (Discrete Wavelet Transform) and FDCT (Fast Discrete Curvelet Transform) to denoise an image. We have a tendency to apply our rule to de-noise the photographs corrupted by a form of increasing noise referred to as speckle noise. The results show that the planned methodology proves effective for a variety of variations and is appropriate for essential applications.

Keywords: Image acquisition, de-noising, Discrete Wavelet Transform, Feed Forward Artificial Neural Network, speckle noise.

1. INTRODUCTION

Image denoising could be a difficult task within the digital image process paradigm. The noise is incorporated within the image acquisition stage, thus it is needed to boost the standard of an image. There are several approaches to get rid of noise from the image [1]. In this case, separation of the blurred and sharp regions of an image may be necessary so that post-processing or restoration algorithms can be applied without affecting the sharp regions, or so that image features are only extracted from in-focus regions [2]. A picture may be denoised by using DWT and FDCT techniques [3].

Using DWT, the image is divided into sub bands and then with the help of neural network the original image is reconstructed to get the defocus blur image.

In FDCT the image can be divided into any number of sub bands and in any shape [4]. The noise is suppressed from every element, and so the parts are reworked into the abstraction domain to get the denoised image. Curvelet rework represents the image employing a fastened curvelet basis wherever the natural pictures have an upscale quantity of various native structural patterns [5]. The problem of CT is also resolved by many ways in which a spatially adaptational Principle Element Analysis (PEA) based mostly on denoising theme has been planned that computes the regionally fitted basis to rework the image. Another PEA primary approach is to make an attempt on the native component grouping. If the image is gently diagrammatical then by employing a shape adaptive distinct circular function rework to the neighbourhood, it may be denoised effectively [6] - [7]. An image is often denoised by averaging the similar pixels in keeping with their intensity distance [8].The bilateral filter ways try on the similar plan that average image pixels in keeping with each spacial and intensity similarities [9] - [10]. A cooperative image denoising approach has been planned that uses transformation techniques and FFNN to represent a picture.

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2. IMPLEMENTATION

2.1 Existing system analysis

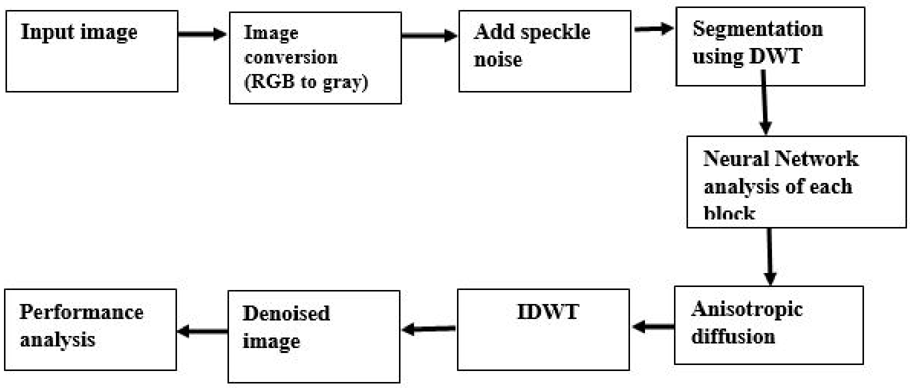


Figure1 Existing system by using DWT

In the existing system we use Discrete Wavelet Transform (DWT) to denoise an image.

In the first step the given input image is converted from RGB to gray as any method of pre-processing can't be applied to a coloured image. Then some amount of speckle noise i.e., 0.02 is added to the input image to create a noisy image. The segmentation of noisy image is done using DWT [11]. At the outset, the wavelet is split into two parts i.e., DWT1 and DWT2 using multilevel wavelet transform. Then each wavelet is decomposed into 4 sub bands (LL, LH, HL, HH) using haar process [12].

The first wavelet consists of sub bands – LL1, LH1, HL1, and HH1.
The second wavelet consists of sub bands – LL2, LH2, HL2, and HH2.

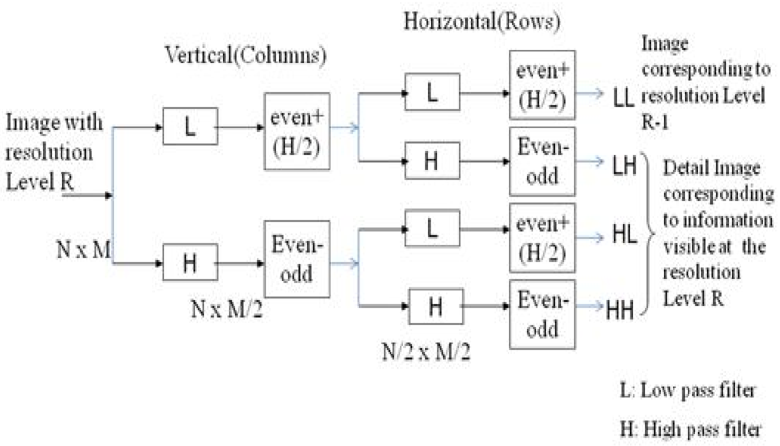


Figure2 Wavelet Decomposition Process

An image that undergoes Haar transform is divided into four bands at each transformation level [13].
The first band represents the filtered input image and is compressed to 0.5. The other three bands represent details where the high pass filter is applied. These bands contain directional characteristics; the size of each of the bands is compressed to 0.5. Specifically, the second band contains vertical characteristics, the third band shows characteristics among the horizontal direction and additionally the last band represents diagonal characteristics of the input image. Conceptually, Haar transform is extraordinarily simple and easy to perform. Moreover, the Haar computation is fast since it only contains two coefficients and it doesn't look like multi-level transformation. Thus, each pixel during an image that will endure the transform computation is used only on one occasion and no pixel overlapping takes place throughout the computation [14].
.Next, ANN is used as a classifier to classify the image whether it is normal or abnormal, noisy or noiseless. ANNs conserve their role as non-parametric classifiers, non-linear regression operators, or (UN) supervised feature extractors [15]-[16]. So neural network is applied on each sub band separately. For example,
ll1= NN (LL1).

Then anisotropic diffusion, a technique aiming at reducing image noise without removing significant parts of the image content, typically edges, lines or other details that are important for the interpretation of the image, is applied for all sub bands.

IDWT (Inverse Discrete Wavelet Transform) is applied to each wavelet separately to get the output image (denoised image) in the following manner.
Out = idwt1 (ll1, lh1, hl1, hh1,'haar');
Out= idwt2 (out, lh2, hl2, hh2,'haar');

To the output of the IDWT, a median filter is used to still denoise the image.

out1= medfilt2 (out1)

The resultant (denoised) image is validated to calculate parameters like mean square error and peak signal to noise ratio.

2.1.1 Mean Square Error

It is the cumulative squared error between the compressed and the original image.

$$MSE = sum(sum((Input\ image - Reconstructed\ image)^{\wedge}2))/(M * N) \quad (1)$$

2.1.2Peak Signal to Noise Ratio

It is the quantitative relation of the utmost signal to noise within the Watermarked Image.

$$PSNR = 20log10\{(255 * 255)/(MSE)\} \quad (2)$$

2.1.3 Disadvantages

- In DWT the image can be segmented only into 4 sub bands.
- Mean Square Error is high.
- PSNR is also high.

2.2Proposed system analysis

The proposed system is completely by using Fast Discrete Curvelet Transform (DCT) and Feed Forward Artificial Neural Network (FF-NN) for analysis of good results.

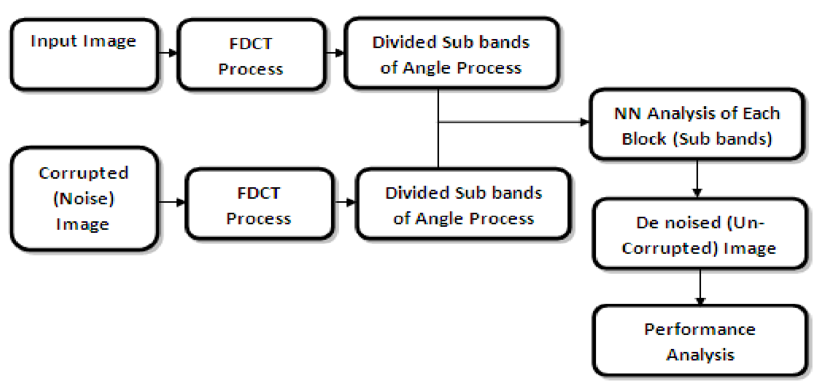


Figure 3 Proposed System by using the FDCT

In the first step the given input image is converted from RGB to gray as any method of pre-processing can't be applied to a coloured image. Then some amount of speckle noise i.e., 0.02 is added to the input image to create a noisy image. The segmentation of noisy image is done using FDCT. Unlike DWT by which an image can be segmented into only 4 sub bands, in FDCT the image can be segmented into 8 or 12 sub bands and the segmentation can be done in any shape i.e., triangle, circle or rectangle. ANN is used as a classifier to classify the image whether it is normal or abnormal, noisy or noiseless. ANNs conserve their role as non-parametric classifiers, non-linear regression operators, or (UN) supervised feature extractors. So neural network is applied on each sub band separately. For example, consider a sub band D1,
D1= nn(D1)
Then anisotropic diffusion is applied for all sub bands.
IFDCT (Inverse Fast Discrete Curvelet Transform) is applied to reconstruct the original image.
out1 = ifdct_wrapping (xx, is real, m, n);

To the output of the IFDCT, a median filter is used to denoise the original image effectively.
out1= medfilt2 (out1)

The resultant (denoised) image is validated to calculate parameters like mean square error and peak signal to noise ratio.

2.2.1 Denoised image generation

The four neighbours of an element (noisy image) constitute to make a denoised pixel. Figure shows that the worth of a pixel is taken into account at (i,j) is pi,j. A pixel (i,j) has four neighbours as (i-1,j), (i,j-1), (i+1,j) and (i,j+1). A pattern is felt the trained neural network. The output of the neural network is taken into account because the denoised pixel is settled at (i, j). During this case, ifi-1/j-1 is a smaller amount than one, it's thought of as one. If i+1/j+1 is larger than N/M, i+1/j+1 is taken into account as N/M.

	$p_{i-1,j}$	
$p_{i,j-1}$	$p_{i,j}$	$p_{i,j+1}$
	$p_{i+1,j}$	

Figure 4 The values of a pixel (i, j) and its four neighbours

The process is continual for all the pixels of the segmented image. Finally, a denoised image is generated that has the dimension of the segmented image.

2.2.2 Advantages:

- In FDCT the image can be segmented into any number of sub bands and the sub bands can be of any shape.
- Mean Square Error is reduced.
- PSNR is also reduced

3. PROJECT REQUIREMENTS

3.1 Hardware requirements

- Single PC20 GB Hard disc space
- 1GB RAM

3.2 Software requirements

- Windows XP/7.
- MATLAB 2013.

4. RESULT AND DISCUSSION

FF-NN is applied on the segmented pictures. The segmented images are generated from the first benchmark pictures by adding Gaussian racket of various customary deviations (σ). The constituent values of segmented images are normalized by dividing each value with 255. The denoised image is generated by applying the constituent values of the segmented image to the NN as mentioned within the section. The outputs of the NN are increased by 255 to create the denoised image.

The outputs of DWT and FDCT are as follows

4.1 Existing Output:

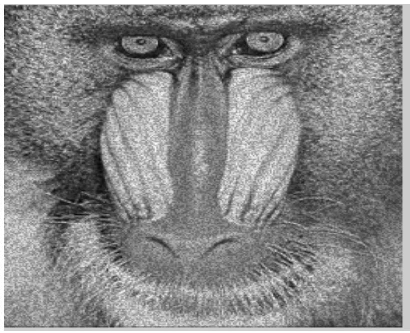


Figure5 Input image

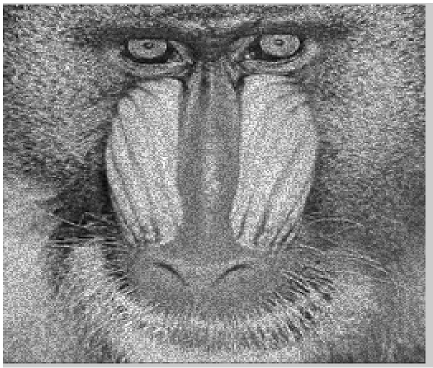
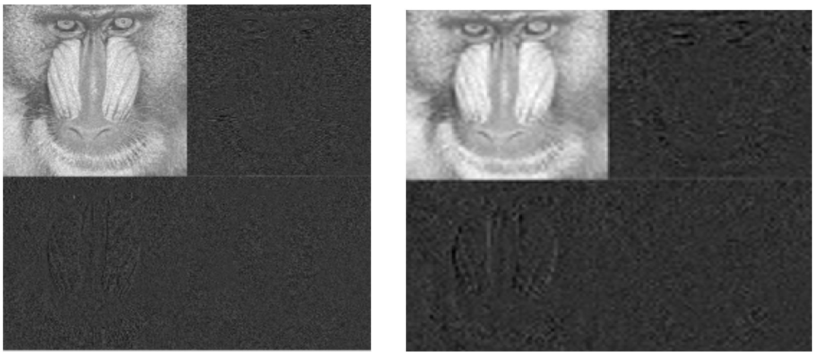


Figure6 Noisy image



(a) **(b)**

Figure7 Sub bands of DWT method

Figure8 Denoised image

4.2 Proposed Output:

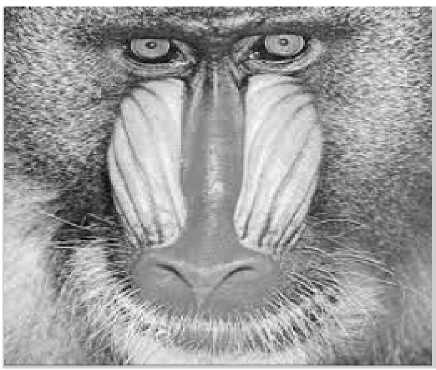


Figure9 Input image

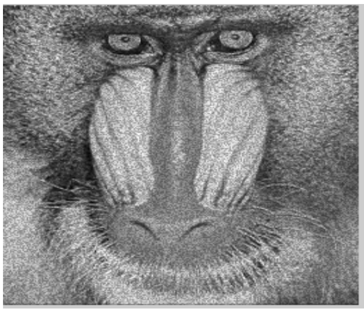


Figure10 Noisy image

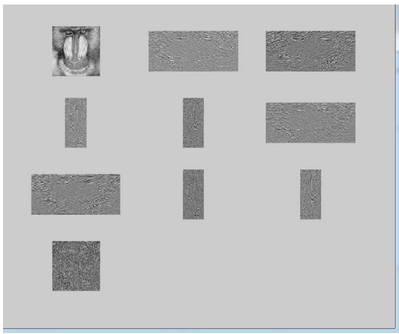


Figure11 Sub bands of FDCT method

Figure12 Denoised image

4.3 Comparison of outputs between DWT and FDCT

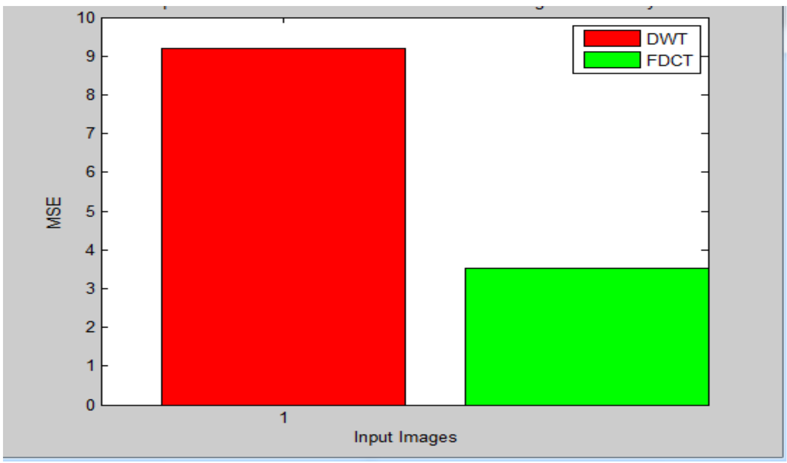


Figure 13 Comparison of MSE between DWT NN and FDCT NN using Fusion Analysis

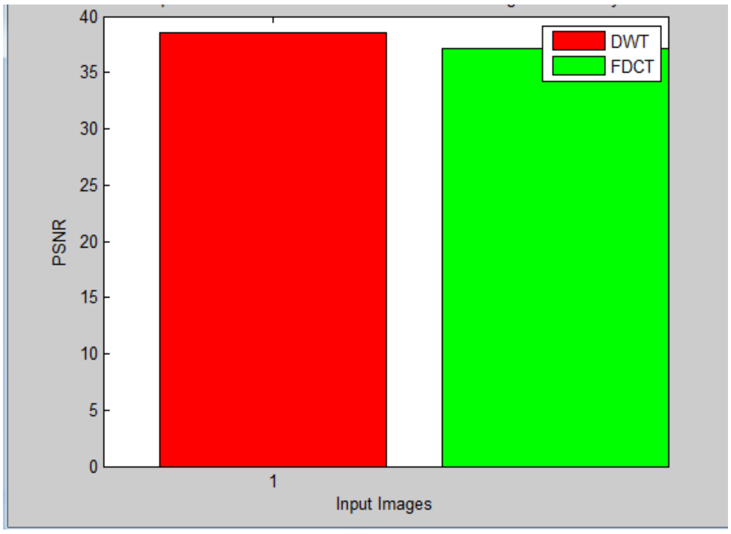


Figure 14 Comparison of PSNR between DWT NN and FDCT NN using Fusion Analysis

From these two figures it can be concluded that PSNR and MSE is very much high in DWT method than FDCT.

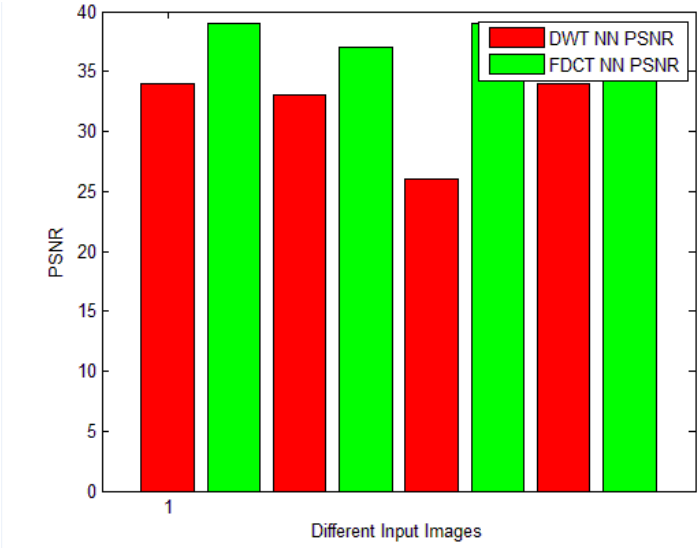


Figure 15 Comparison of different input images for PSNR with DWT and FDCT Methods

5.CONCLUSION

Improving the image quality is a vital step within the digital image process, since noise is doubtless introduced within the image acquisition method. During this paper we have a tendency to review the image segmentation technique supported by curvelet rework and neural network application. In this study we have found that curvelet rework is vital for neural network input process. Neural network additionally plays a necessary role in image segmenting. For the thresholding of curvelet the process of neural network is a nice combination of image segmenting. We have proposed a very simple and easy method for defocus blur segmentation.

In future we have a tendency to use cascaded model of neural network for image segmenting and to observe that FF-NN is capable to enhance the standard of an image in terms of PSNR and MSE. The visual review suggests that the denoised image is considerably sensible than the clamant image.

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