Use of Discrete Sine Transform for A Novel Image Denoising Technique

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Abstract

In this paper, we propose a new multiresolution image denoising technique using Discrete Sine Transform. Wavelet techniques have been in use for multiresolution image processing. Discrete Cosine Transform is also extensively used for image compression. Similar to the Discrete Wavelet and Discrete Cosine Transform it is now found that Discrete Sine Transform also possess some good qualities for image processing; specifically for image denoising. Algorithm for image denoising using Discrete Sine Transform is proposed with simulation works for experimental verification. The method is computationally efficient and simple in theory and application.

Keywords: Denoising, Multiresolution, Image Transform, Discrete Sine Transform, Sub Bands.

1. INTRODUCTION

Different types of noise corrupt images during its capture, storage, transmission, etc. When noise creeps in image, its visual quality is reduced. Moreover, depending on the amount of noise, important features of the image become disguised and are not readily available for identification and use[1]. The only way to solve these problems is to denoise (remove noise) the image.

Several denoising techniques have been proposed during the last two/three decades. However, so called perfect denoising algorithm is yet to be developed; especially in the case of color images. Removal of noise is not yet complete in all respects [2].

One of the comparatively recent successful denoising techniques makes use of multiresolution capability of image transforms. It was originally proposed by Stephen Mallat (1988/89) with the use of Wavelet Transform (WT) for image processing [3]. However, WT is not the only transform which exhibit multiresolution capability [4, 5]. Discrete Sine Transform (DST) is now seen to possess multiresolution property. In this paper, Multiresolution DST is proposed for denoising of images. Rest of the paper is organized as Noise in Images in section 2, Some Denoising Techniques in Images in section 3, Multiresolution Techniques in Image Processing in section 4, DST and Multiresolution Analysis in section 5, Implementation of the DST Algorithm in section 6, Experimental results in section 7, and Conclusions in section 8.

2. NOISE IN IMAGES

Generally noise is generated along with the signal in most of the image production mechanisms. Photographic image is obtained using digital camera. Almost all cameras now available use Charge Coupled Devises (CCD) or Charge Injection Devices (CID) or Complementary Metal Oxide Semiconductor (CMOS) in its construction, making use of integrated circuit (IC) technology. Due to the imperfections in its fabrication, dark currents, unequal currents, clock noise, etc. produce noise (Gaussian, Impulse, etc.) in the images photographed by these cameras [6, 7]. In addition, varying levels of illumination on the objects and back ground light also introduce noise in images. Further, signal conditioning (amplification, quantization, etc.) applied to the image signal add electronic device noise due to imperfect operation of active and passive devices. Medical images are another category of images which are widely used by clinicians for diagnostic purposes. Techniques such as Ultrasound (US), Magnetic Resonance(MR), Computed Tomography(CT), X-rays, Positron Emission Tomography(PET), etc. are used in the generation of medical images[8, 9]. All of these images contain different types of noise (speckle, Poisson, etc.) due to the imperfect operation of respective instruments. Satellite images are remote sensed images obtained by high resolution/ low resolution cameras and provide amazing information about earth's surface, roads, rivers, buildings, etc. These images are basically noisy. Variations in natural environments, limitations of cameras, etc are some of the reasons for noise in such images [10].

3. SOME DENOISING TECHNIQUES IN MAGES

Image denoising techniques can be broadly classified as i) Spatial Domain and ii) Frequency Domain. In spatial domain, pixel by pixel processing is done for removing noise [11]. Some kind of moving masks are used to locate each pixel in the image and neighborhood operation is done to filter the noise. Using suitable weights [12] in elements of mask, convolution or correlation is done with the neighborhood of pixel and elements of mask to get new pixel values for replacing the noisy pixel. This operation is known as filtering. The method works well in some environments. But it processes all pixels whether noisy or not and hence introduces some distortions. Noise detection before denoising improved the situation to some extent.[13, 14].

In the frequency domain method, the image is transformed in to its frequency domain, using suitable image transform and then processing is done. One of the early and widely used transform is 2dimensional Discrete Fourier Transform (2DDFT) implemented [1] using fft2 in MATLAB. Using this transform, the image pixel coefficients are represented by equivalent sine and cosine coefficients having different frequencies and amplitudes. This transform gives complex coefficients. Also DFT does not give information about the time at which a particular frequency component has occurred. Using short windows of time for groups of pixels in the image, and computing DFT (named as STFT), some amount of non- stationary analysis could be carried out. STFT has the limitation of constant resolution. A better method is to get variable resolution (multiresolution) for non-stationary images. Wavelet transform is the appropriate solution in this respect.[15] It has multiresolution analysis capability. Wavelet transform in its various forms (decimated, undecimated, orthogonal, biorthogonal, etc) and new generations (curvelet, contourlet, etc) have been in use in multiresolution approach for several image processing, including image denoising[16, 17] .

4. MULTIRESOLUTION TECHNIQUES IN IMAGE PROCESSING

Multiresolution refers to characteristics of the image analysis such that a feature in an image can appear at different resolutions and scales.[1, 3]. In multiresolution analysis, some features that go undetected at one resolution may be easy to spot at another resolution. Wavelet transform is a pioneer in this category of transforms. In its discrete implementation, known widely as Discrete Wavelet Transform (DWT), digital FIR filters are used to separate (decompose) the images in to its frequency bands.

In one level of decomposition, using filters and down sampling by two, four subimages are obtained. They are called as LL1, LH1, HL1 and HH1 bands. The band LL1 contains low frequency information and is called approximation sub band. The other three sub bands (LH1, HL1 and HH1) contain higher frequency information of the image and are called as detailed sub bands. Denoising of image relies on the strategy that noise is of higher frequency as well as noise is of smaller amplitudes compared to signal amplitudes. Hence the approximation coefficients (in LL1 band) more or less represent signal and some parts (low amplitude coefficients) of detailed sub bands represent the unwanted noise. To remove noise from image, we threshold[18] the detailed sub bands, keeping higher amplitudes (signals)in these bands and removing the low amplitude (noise). Wavelet synthesis of LL1 band with thresholded detailed sub bands gives the denoised image. Results can be improved by decomposing LL1 band to the second level of wavelet decomposition giving rise to more detailed sub bands and processing these bands further on the same lines as first level decomposition.

5. DST and MULTIRESOLUTION ANALYSIS

The Discrete Sine Transform (DST) is related to DFT (and FFT). DST is used to represent signal in terms of a sum of sinusoids with its different frequencies and amplitudes [19]. However DST is not the imaginary part of FFT. To obtain DST of a digital signal, elements of the signal are reconfigured as an odd (anti-symmetric) extension of the input and then applying FFT. Total numbers of input as well as total number of DST coefficients are the same. All the DST coefficients are real, which is an advantage of DST processing over FFT (FFT gives complex coefficients). A companion transform of DST is Discrete Cosine Transform (DCT). DCT is widely used for image compression (JPEG).

The one dimensional DST of a vector of N elements can be obtained by reconfiguring the input and including the odd symmetric extension of its elements resulting in 2N elements. Depending on the symmetry used for extension of elements, there are 8 versions of DST (DST-1 to DST-8) equations. Each of them has somewhat different properties (in addition to some common properties)

The N point DST-1 is defined as in [19]

$$X(k)=\sum_{n=0}^{N-1} x(n)\sin[\frac{\pi}{N+1}(n+1)(k+1)] \qquad 0\le k\le N-1 \qquad (1)$$

where x(n) is the input signal.

The corresponding Inverse Discrete Sine Transform (IDST) is given by

$$x(n)=\sum_{k=0}^{N-1} X(k)\sin[\frac{\pi}{N+1}(n+1)(k+1)] \qquad 0\le n\le N-1 \qquad (2)$$

However, the DST is defined in MATLAB as

$$Y(k)=\sum_{n=1}^{N} x(n)\sin[\pi kn/(N+1)] \qquad 1\le k\le N \qquad (3)$$

and the corresponding IDST is

$$x(n)=\frac{2}{(N+1)}\sum_{k=1}^{N} Y(k)\sin[\pi kn/(N+1)] \qquad 1\le n\le N \qquad (4)$$

The 2D DST is an extension of 1D DST for two dimensional signals.

The 1D DST can be evaluated using fast algorithm of FFT. The DST available in MATLAB (dst) is 1D DST.

The DST has some more desirable properties as a transform for image processing. It has high energy compaction (most of the energy is confined to small number of coefficients) and sparse representation (large numbers of its coefficients are zeros.). Further, DST coefficients are real, symmetric and orthogonal. Symmetric and orthogonal property indicates that for forward and reverse transformation, computation is same except for normalization. As DST is a separable transform, the 2D DST can be implemented using twice the 1D DST. The 1D DST is first applied column wise and its result is used as the input for a second 1D DST now row wise. It is a fast transform and hence computation time is less.

Multiresolution technique can be implemented using DST to separate the frequency components of an image in to one low frequency band and three high frequency bands (as in the case of wavelet transform) in its first level decomposition. Whereas filters are used in DWT multiresolution analysis, DST and IDST operations are done selectively so as to separate low frequency part of image and high frequency parts at each level. BY repeating the operation on the low frequency part of first level, further separation of the image into coarse and fine frequency can be done.

6. IMPLEMENTATION OF THE DST ALGORITHM

Image analysis is done as shown in Figure 1. It is based on the method proposed in [20] for DCT multiresolution application in image fusion. The 1D DST available in MATLAB is made use of. Frequency domain information of noisy image is obtained by applying DST column wise on the noisy image. For an MxN image, the image is divided into N columns of Mx1 image. DST operation is done column by column and the result is stored as two (M/2)xN matrices. The first half consists of frequency components from 0 to $\pi/2$ and the second half represents frequency components from $\pi/2$ to π. IDST is now applied column wise to the first half to get L1 band which represents the low frequency components of the image. Again IDST is applied column wise to the second half to get H1 band which represents the high frequency components of the image. Now DST is applied row wise to the L1 band. To the first half of this result, IDST is applied row wise to get the LL1 band. Application of IDST row wise to the second half gives LH1 band. Similar row wise IDST operations on the first half and second half after DST operation of H1 band gives HL1 and HH1 bands. This is the first level of decomposition. The process can be repeated by taking the LL1 band as the input to give four sub bands namely LL2, LH2, HL2 and HH2. The LL1 band consists of frequency components of 0 to $\pi/2$ row wise and 0 to $\pi/2$ column wise. The LH1 band consists of 0 to $\pi/2$ row wise and $\pi/2$ to π column wise. The HL1 band consists of $\pi/2$ to π row wise and 0 to $\pi/2$ column wise. The HH1 band consists of $\pi/2$ to π row wise and $\pi/2$ to π column wise.

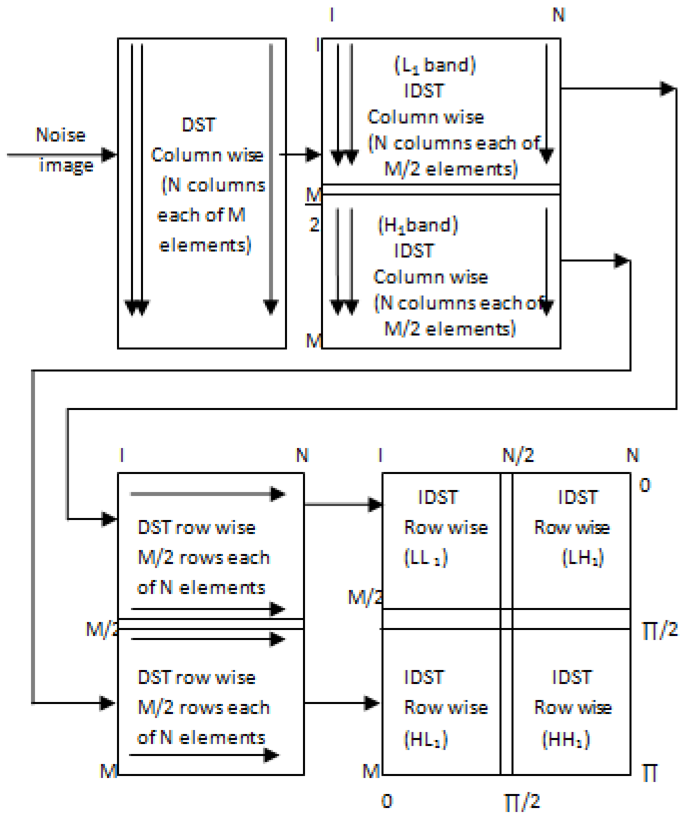

FIGURE 1: 1D DST Multiresolution Analysis.

If 2D DST is readily available, implementation of the algorithm can be modified as illustrated in Figure 2. The 2D DST is applied to the MxN size image. Four partitions are now made on the result. The first partition consists of 1 to M/2 rows and 1 to N/2 columns. IDST is applied to this partition giving rise to LL1 band. The second partition consists of 1 to M/2 rows and (N/2) +1 to N columns. IDST applied to this partition gives the LH1 band. The third partition consists of (M/2) +1 to M rows and 1 to N/2 columns. IDST applied to this partition gives HL1 band. The fourth partition is of (M/2) +1 to M rows and (N/2)+1 to N columns. IDST applied to this partition gives HH1 band. A second level of decomposition can now be obtained by repeating the steps with LL1 band as the input, giving rise to LL2, LH2, HL2and HH2 bands.

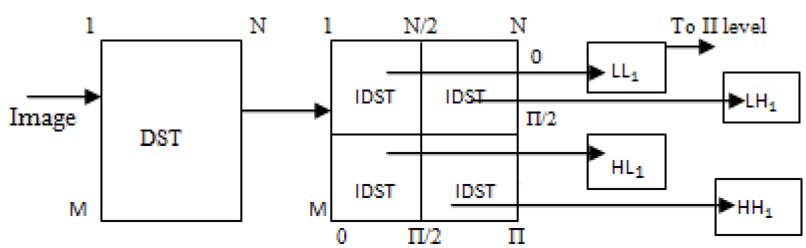

FIGURE 2: 2D DST Multiresolution Analysis.

The coarsest sub band is LL1. It consists of low frequency DST coefficients of the image and is the approximation band. All very important features of the image are represented by this band. Magnitudes of the coefficients in this band are larger than that in any other bands. Noise in this band can be assumed to be very small as the noise is generally of high frequency .The other three sub bands (LH1, HL1 and HH1) consist of DST coefficients representing high frequency information such as edges, curves, etc. Noise is also present in these bands. However coefficients representing noise are of smaller magnitudes compared to that of signal in these bands. The denoising strategy is that the low amplitude noisy coefficients are removed from these bands by suitable thresholding [1]. According to the requirements, hard thresholding or soft thresholding can be employed. Adaptive thresholding [18] is employed in this paper. The thresholded detailed sub bands and the approximation sub band are synthesized to get the denoised image. As the approximation sub band has most of the features of the original image, except for some high frequency details, resizing of approximation band to size of original image is to some extent the denoised image.

DST is as old as DCT. However whereas DCT has been extensively used for image processing(eg. image compression; JPEG) DST is not seen used, at least as much as DCT, for signal processing, although both have many similar properties [19]. In this paper, utility of DST is brought to the lime-light in the form of a multiresolution signal processing tool; specifically for image denoising. Implementation of the algorithm is much simpler than many of the recently proposed algorithms. In spite of this, attractive feature is that the performance, especially in visual quality, is as good as many of the existing methods. Computational complexity is less and hence, time taken for implementation is comparatively low.

7. EXPERIMENTAL RESULTS

Multi resolution DST is applied to the “cameraman” image and the first level of decomposition is done. Resulting LL1 band is again decomposed to get the second level of analysis. Results of the two levels of decomposition along with the original image are shown in Figure 3. Gaussian noise is added to the “Barbara” image with zero mean and 10 % standard deviation. The noisy image is decomposed to get the LL1, LH1, HL1 and HH1 bands. Denoising is done as explained in section 7. Results are shown in Figure 4. A 10 % impulse noise is added to “circles” image and denoising is done. Results are shown in Figure 5. Again impulse noise is added to “rice” image and denoising is done. Results are shown in Figure 6.

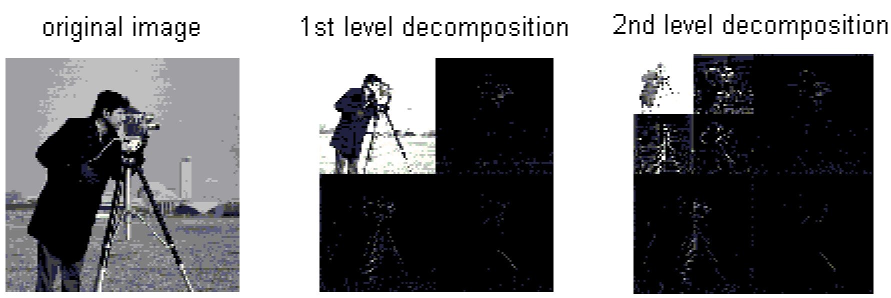

FIGURE 3: Two Level DST Decomposition.

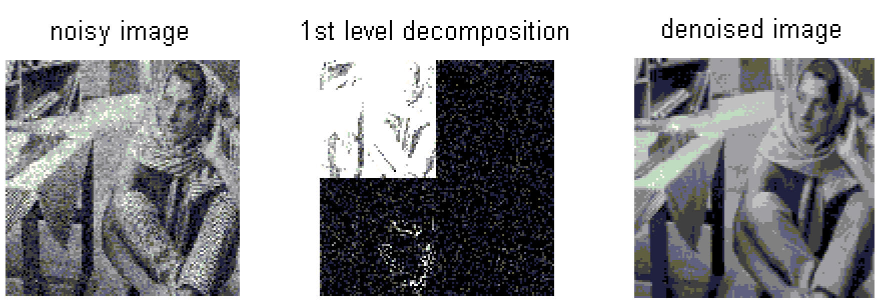

FIGURE 4: Denoising of Gaussian Noise.

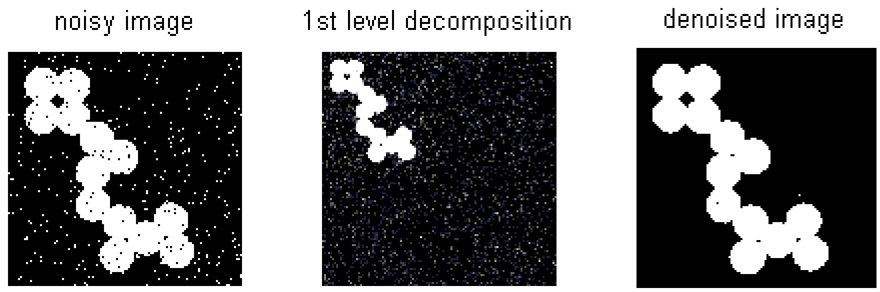

FIGURE 5: Denoising of Impulse Noise.

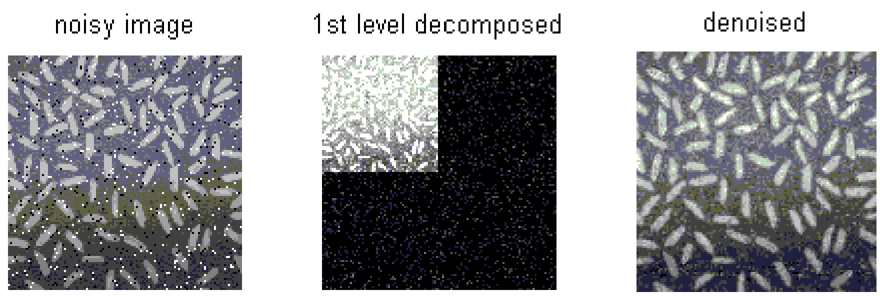

FIGURE 6: Denoising of Impulse Noise.

For color image (RGB model) denoising, as there is correlation between color components, color model has to be changed (to Ycbcr, HSV, etc.) and then processing has to be done. A color image (“autumn’) is used for demonstration of denoising. Speckle noise is added in this image. The resulting RGB image is converted to Ycbcr image. After denoising process on Y components, with the multiresolution DST, Ycbcr image is converted back to RGB image. Experimental results of denoising are shown in Figure 7. Results show that noise is removed, but there is small amount of color artifacts. Further work is to be done to rectify this defect.

FIGURE 7: Denoising of Speckle Noise from Color Image.

Performance comparison of the proposed denoising method with that of a few of the existing methods are done (1) by observing the visual quality and (2) by measuring the Peak Signal to Noise Ratio (PSNR) of denoised image. The metric PSNR is defined as

$$PSNR = 10 \log_{10} [\, 255 * 255 / MSE] \quad dB \tag{5}$$

where MSE (Mean Square Error) $= \text{sum}\,(\text{sum}\,(\,[\, Y(i, j) - Y_1(i, j)\,]^2\,))\,/\,(M*N*D)$ (6)

Y(i , j) is the original (non-noisy) image , Y_1 (i , j) is the denoised image and M, N,D are the size of the image. For Gaussian denoising, noise density is varied from 10 to 40 in steps of 10 and for each value, PSNR of Gaussian denoised image is measured. The respective PSNR for three existing methods wavelet thresholding [18], Multiresolution Bilateral Filter [21] and LPG-PCA are also obtained. Table 1 shows these PSNR values. It can be seen that the proposed method has PSNR values better than or very close to the other existing methods referred. However the second and third methods are computationally more involved (compared to the proposed method) and take much more execution time.

Methods	**PSNR**			
	σ = 10	**σ = 20**	**σ = 30**	**σ = 40**
Wavelet Threshold	30.8	27.8	25.4	23.8
Multi resolution Bilateral filter	34.1	31.5	28.8	27.2
LPG-PCA	33.2	30.5	27.2	25.3
Proposed Method	33.4	30.4	27.2	25.4

TABLE 1: PSNR of Gaussian noise removal (Barbara Image).

For Impulse denoising experiment, impulse noise is added to "circles" image with a noise level from 10% to 40 % in steps of 10 in the proposed method and PSNR are measured in each case. The procedure is repeated for "rice" image also. The respective PSNR using three existing methods, Median filter, Adaptive median filter and Modified Decision Based [14] method are also obtained. Table 2 shows all the PSNR values. It can again be seen that the performance of the proposed method is better than the first two existing methods and very close to that of the third method. However the third method is computationally much involved and requires more computer time.

Image	**"Circles"**				**"Rice"**			
Methods	**PSNR for noise levels**				**PSNR for noise levels**			
	10%	20%	30%	40%	10%	20%	30%	40%
Median Filter	26.2	25.1	24.0	22.1	27.8	26.3	25.1	24.0
Adaptive Median Filter	30.1	29.6	27.4	26.1	32.3	31.1	29.6	28.2
Modified Decision Based	32.5	31.8	30.4	28.7	33.2	32.4	30.1	29.8
Proposed Method	31.2	29.4	28,5	27.4	32.6	31.4	29.7	28.6

TABLE 2: PSNR of Impulse noise removal (Circles and Rice images) .

In terms of visual quality, the proposed method has superior visual quality compared to the existing methods referred.

8. CONCLUSIONS

Multiresolution image denoising using DST is proposed in this paper as a new method of image denoising. It has close similarity with DWT denoising. Algorithm for generating sub bands of low frequency and high frequencies using DST and IDST is given. As MATLAB does not provide function for 2D DST, implementation of algorithm using 1D DST is explained. Also if 2D DST is readily available, algorithm of implementation of denoising using 2D DST and 2D IDST is also given. Strategy of denoising is also discussed. It has close similarity with that using DWT. Approximation sub band which is substantially the original signal and thresholded detailed sub bands are synthesized to get denoised image. If some reduction in the high frequency component of the image can be tolerated, the approximation band can represent the denoised image. Experimental results using MATLAB simulation are given. It is seen that the method can remove different types of noises such as Gaussian, Impulse, Poisson, Speckle, etc. The visual qualities of the denoised images are good while its computational complexity is low. Future work has to be for getting good quality denoised color images.

This work might be extended to add sophistications to further reduce noise when the noise level is very high. Also a universal denoising algorithm can be pursued to denoise images when they are corrupted simultaneously by different types of noises. Further, improvement in the qualities of color images by modifying the proposed work could be a worth future work.

9. REFERENCES

[1] R.C.Gonzalez, R.E.Woods, "*Digital Image Processing"* Pearson, 3rd Edition, India, 2009.

[2] P.Chatterjee and P.Milanfar, "Is Denoising Dead", IEEE Transactions on Image Processing, vol.19, No.4, pp. 895-910, Apr. 2010.

[3] S.Mallat, "A theory of multi resolution signal decomposition, the wavelet representation", IEEE Transactions Pattern Anal Machine intelligence, Vol.PAM1-11, pp. 674-693., Jul 1989.

[4] Rajeesh, R.S.Moni, S.Palanikumar and T.Gopalakrishnan "Noise reduction in Magnetic Resonance Images using Wave atom shrinkage" International Journal of Image Processing (IJIP) Vol.4, Issue 2, pp 131-141, Jun 2010.

[5] M.Do, M.Vitterli "The Contourlet transform: an efficient directional multiresolution image representation" IEEE Transactions on Image Processing, Vol. 14. Issue 12, pp2091-2106, 2005.

[6] T.R.Vijayakumar, P.T.Vanathi, P.K.Kanagasabhapathy "Fast and efficient algorithm for removal of Gaussian noise in digital images" IAENG International Journal of computer Science, 37:1, Feb.2010.

[7] A.Buades, B.Coll and J.Morel "A review of image denoising algorithm with a new one" Multiscale modeling simulation ,Vol. 4, Issue. 2, pp490-530, 2005.

[8] A.Pizuria, W.Philips, I.Lemahieu and Acheroy "A versatile wavelet domain noise filtering technique for medical imaging" IEEE Transactions on medical imaging, Vol.22, Issue 3, pp 323-331, 2003.

[9] Z.Yang and M.D.Fox, "Speckle reduction and structure enhancement by multichannel median boosted anisotropic diffusion", EURASIP J. Appl. Signal processing, Vol.2004, issue. 1, pp2492-2502, Jan.2004.

[10] Lizy Abraham, M.Sasikumar "Unsupervised building extraction from high resolution satellite images irrespective of roof top structures" International Journal of Image Processing (IJIP), vol.6, Issue.4, pp 219-232, Aug. 2012.

[11] T.S.Huang and G.Y.Tang "A fast two-dimensional Median Filtering algorithm" IEEE Transactions on Acoustics, speech and signal processing, ASSP-27, pp13-18, 1979.

[12] Sung-Jea and Y. H. Lee "Center weighted median filters and their applications to image enhancement" IEEE Transactions on circuits and systems , Vol.38, No.9, pp984-993, Sep.1991.

[13] S. Zhang and M.A. Karim "A new impulse detector for switching median filters",IEEE Signal Processing Letters, Vol.9, No.11, pp 360-363, Nov.2002.

[14] S.Esakirajan, T.Veerakumar,A.N.Subramanyan and C.H.PremChand "Removal of high density salt and pepper noise through modified decision based unsymmetric trimmed median filter", IEEE Signal Processing Letters , Vol. 18, No.5, 11287-290, May 2011.

[15] Denver, I.K.Fodor, and C.Kamath "Denoising through wavelet shrinkage, an empirical study", Electronic Imaging, Vol.12, pp151-160, 2003.

[16] A.L..Pogam, H.Hanzouli, M.Halt, C.C.L.Rost and D.Visvikis "Denoising of PET images by combining wavelets and curvelets for improved preservation of resolution and quantization" Medical Imaging Analysis, Vol.17, Issue 3, pp877-891, Dec.2013.

[17] J.Starck, E.J.Cande and D.L.Donho "The curvelet transform for image denoising", IEEE Transactions on Image Processing, Vol.11, Issue 6, pp 670-684, June 2002.

[18] S.G.Chang, B.Yu, V.M.Vitterli, "Adaptive wavelet thresholding for image denoising and compression", IEEE Trans. Image Processing, Vol.9, No.9, pp. 1532-1546., Sep.2000.

[19] A.K.Jain, Fundamentals of Digital Image Processing ,PHI, India, 1995.

[20] V.P.S.Naidu, "Discrete cosine Transform based Image Fusion", Defence Science Journal, Vol.60, No.1, pp.48-54., Jan.2010.

[21] M. Zhang and B.K.Gunturk "Multiresolution Bilateral filter for image denoising", IEEE Transactions on Image Processing, Vol.17, No.12,pp 2324-2333, Dec.2008.

[22] L.Dhang, W. Dong D.Zhang and G.Shi "Two stage image denoising by principal component analysis with local pixel grouping" *Pattern Recognition,* Vol.43, pp1531-1549, 2010.