Journal of Computer and Mathematical Sciences, *Vol.8(5), 202-210 May 2017*
(An International Research Journal), *www.compmath-journal.org*
ISSN 0976-5727 (Print)
ISSN 2319-8133 (Online)

Image Reconstruction Based on the Fusion of Contourlet and Non Sub Sampled Contourlet Transform

Brijbhushan Mishra[1] and Anshuj Jain[2]

[1]PG Scholar,
Scope College of Engineering, Bhopal, INDIA.
[2]Assistant Professor,
ECE Department, Scope College of Engineering, Bhopal, INDIA.
email:bhushanmishra010@gmail.com, anshuj2008gmail.com

(Received on: May 25, Accepted: May 27, 2017)

ABSTRACT

The suppression of noise content is an important concern in the image processing. Noise in images can cause the suppression of some relevant image. The multi-dimensional and multi-scale, and shift-invariant image decomposition technique has been an effective method to reconstruct the true image from noisy image. This work is focused to calculate the relevant edges flexible using the image fusion techniques that utilizes the redundancy of the images which are given by Contourlet and NSCT transform. The principle component analysis has been used to calculate the effective weight which has been provided to the pixels Experimental analysis shows that the proposed method efficiently reduces the noise and enhances the edges in an image.

Keywords: Contourlet transform, non sub sampled Contourlet transform, principle component analysis, multi-scale pyramid, and directional bank filter.

I. INTRODUCTION

Image processing has great leap and is found to be a fundamental task for the rapid development in computer and network technology. During the acquisition, processing and transmission, the images have found to be inevitably polluted by noise. Image denoised is broadly classified in to spatial domain and transform domain. Spatial domain filter is a traditional way of filter method that is applied in either linear or non-linear way to the noisy images and reconstructs the true image utilizing some statistical parameters. The transform method decomposes the images into some other variable and utilizing some significant variables, the true image is synthesized. Moreover, the transform domain techniques are the sparse way to represent an image and are proved to be effective under the illumination and shift variance.

Wavelet is the well known multi-scale, multi-resolution analysis techniques of an image which consists of good time-frequency localization properties. The multi-resolution and multi-scale techniques have been widely used in noise suppression.

Multidimensional filter uses multi-scale, multi-direction, and shift-invariant image decomposition techniques that is very successful for integrating the relevant feature in an estimated image[8]. Most of the algorithm is designed to construct a filter bank which should have the better frequency selectivity. The work is also focused to design the filter that should have shift invariance property. Since at the point of singularities, lack of shift invariance causes the Gibbs phenomenon that leads to ringing effect.

In order to capture the more feature of an image such as edges, and contour, the redundant representation is required. The redundant information can be restored using the multidirectional filter bank with the shift invariance characteristic[9]. Contourlet transform combines the Laplacian pyramid with directional filter bank and have been proven the effective way to construct the true image. It is effective tool to get the finer details of image[10,11,12].

Further, the expansion of Contourlet transform is done by introducing the non subsample Contourlet transform. The non-sub sampled Contourlet (NSCT) uses the shift invariant property by introducing the multi-scale pyramid with multidirectional filter. This combination can be used to capture the more redundant information.

In this paper, the image fusion technique is proposed to estimate the two images by exploiting the property of Contourlet and NSCT transform. The principle component analysis method estimates the value of pixel in denoised image by providing the weight at certain location. The paper is structured as follows. In Section II, some of the previous work regarding the multi-scale analysis is explored. In Section III, the image fusion using PCA (principle component analysis is proposed to construct the true image[15]. The experimental results are compared in section IV. Concluding remarks are drawn in Section V.

II. RELATED WORK

In[1], authors proposed the multi-scale decomposition to de-noise the image using the wavelet transform. The wavelet has the limitation that it uses only vertical, horizontal and diagonal coefficient to achieve the high frequency band. The direction is limited in wavelet filter bank. The Contourlet transform proposed in[2] is a multidirectional and multiscale transform. It combines the Laplacian pyramid[2] with the directional filter bank (DFB)[18]. The Contourlet transform constructs the estimated image with very little redundancy[13,14].

In[3], nonsubsampled Contourlet transform (NSCT), provides variable multiscale, multidirectional sparse image decomposition, with shift invariance property. It also uses the non local mean to acquire the more redundant information.

In[4], authors combine the nonsubsampled Contourlet transform and the memetic algorithm. That attempted to discover the best possible image which achieved the more redundancy in the detail analysis.

In[5], the authors proposed de-noising algorithm using adaptive Bayes threshold that help to regain the weak edges in the image.

In[6], author proposed the non linear thresholding technique that utilizes the Multiwavelet transform domain. It also uses the multivariate technique to reject the false feature from an image.

In[7], different Contourlet coefficients are threshold by the statistics of such recalculated Contourlet thresholds. The method is effective but has a great computational complexity.

The main motive of this work is to calculate the relevant edges flexible using the image fusion techniques that uses the redundancy of the resultant images which is given by Contourlet and NSCT transform.

III. PROPOSED METHOD

In order to improve the visual quality of corrupted image, the image enhancement techniques should be efficient to recover the image with minimal image distortion. The proper representation of image is often hindered by the high anisotropic elements. The wavelet transform is not well suited to detect the alignments in images. Therefore, to alleviate this problem, the Contourlet transform provides the better representation of salient features such as edges, lines, curves and contours in images. It is a directional multi resolution and multi-scale edge based image enhancement techniques that outperform the traditional wavelet transform technique.

Contourlet transform links the point of discontinuity into a linear structure using the sub band decomposition and directional transform.

Sometime, it is necessary to represent the image with spatial and angular resolution. These types of representation provide the better visual quality of an image for its further processing. Laplacian pyramid decomposes the image into various levels that produces the coarse and sparse components. It generates the two types of components after applying the Laplacian mask on the image at each level. First component is a down sampled low pass version of the original image. The second component is the image intensity that comes after subtracting the original image from the predicted image. At each level, down sampled low pass version or the coarse detail of image is decomposed into further two components. Laplacian is computed by subtracting the original image from the low pass filter image at each succeeding level. At each decomposition level, a band pass filter image is generated, when stacked over another produces a tapering pyramid like structure.

The directional bank filter is applied after the Laplacian stage to single out the directional components available in the image in the form of edges and contour. The number of direction can be varied as the number of two. Using the directional filter bank, the spatial as well as the angular resolution get doubles. Laplacian pyramid reduces the scale by four at each level while the directional filter produces double direction to capture the more fine detail in an image[2,14].

The Laplacian pyramid provides a multiscale decomposition of an image of the $L^2(\mathrm{R}^2)$ space. On applying the Laplacian, set of band pass filtered images are generated that can be expressed in to series of increasing resolution as follows:

$$L^2(R^2) = V_{jo} \oplus (_{j=jo} \oplus W_j) \tag{1}$$

V_{j0} and W_j refer to an approximate subspace in multiresolution analysis, which is defined at the scale $2j0$, whereas W_j consists of the “added details” which is defined up to the finer scale $2j-1$ [2,14]. The spanning factor at each subspace in the Laplacian is defined by the frame $\{\mu_n(t)\}_{n\epsilon Z^2}$. The DBF (Directional bank filter) determines the impulse response in the 2^l direction with the shift, which is described as follows:

$$\{g_k^l\left[.-S_k^{(l)}n\right]\}_{0\leq k<2^l, n\in Z^2} \quad (2)$$

The horizontal and vertical mask depends upon the following matrix.

$$S_k^{(l)}=\begin{bmatrix}2^{l-1} & 0\\ 0 & 2\\ 2 & 0\\ 0 & 2^{l-1}\end{bmatrix}\begin{matrix}0\leq k<2^{l-1},\\ 2^{l-1}\leq k<2^l,\end{matrix} \quad (3)$$

When the DFB is applied on the detail subspace W_j towards the direction 2^{l_j} , the final result after each level is accumulated as:

$$W_j=\oplus_{k=0}^{2_j^l-1}W_{j,k}^{(l_j)} \quad (4)$$

At each level, the resultant image is spanned by a frame with the ratio 4/3.The spanning frame $\rho_{j,k,n}^{(l_j)}(t)$ is given as:

$$\rho_{j,k,n}^{(l_j)}(t)=\sum_{m\epsilon Z^2}g_k^{l_j}\left[m-S_k^{l_j}n\right]\mu_{j,m}(t) \quad (5)$$

The factor $2^{j+l_{j-1}}\times 2^j$ defines a rectangular grid on the subspace$W_{j,k}^{l_j}$.The spanning frame with the shift function is given as:

$$\rho_{j,k,n}^{(l_j)}(t)=\rho_{j,k,}^{(l_j)}\left[t-2^{j-1}S_k^{l_j}n\right] \quad (6)$$

The index ‘j’, ‘k’ and ‘n’ defines the scale, direction and location respectively in the above equations.

In the Contourlet transform, the Laplacian pyramid has fixed scale at each decomposition level that performs the multi-resolution analysis. Preservation of edges and enhancement of important feature in an image has been the primary concern in denoising process. In order to achieve the more resolution in the estimated image, the nonsubsampled Contourlet transform is proposed in image enhancement process. In this method, multi-scale pyramid structure is imposed with directional filter bank that introduces the shift invariant process and removes aliasing in the image enhancement process.

As mentioned before, the noise image is passed through the multiscale pyramid that decomposes the image into various sub bands. On the basis of local statistics property, the noise variance is calculated, which then classify the edges from the noise. The nonsubsampled pyramid decomposes the image using two fan filters. The H0(z) refers to the low pass filter, while the other filter is defined by H1(z) =1-H0(z). The synthesis filter is defined by G0(z) =G1(z)=1.The perfect reconstruction is found using the *Bezout identity*.

H0 (z) G0 (z) +H1 (Z) G1 (Z) =1 (7)

PCA (principle component analysis) transforms correlated variables in an image into a set of uncorrelated ones. It also identifies the orders on which the data points exhibit the most variation. PCA uses the fewer dimension and can estimate the best approximation of the original data points. The data below a particular threshold is discarded and some important principle components are taken to reconstruct the particular image. The variation among the images is characterized by associated Eigen values. These vectors determine the projected image on a space by using linear combinations of the *M* vectors.

$$K_n = \sum_{k=1}^{M} v_{nk}\Phi_k = Av_n, n = 1,......, M \quad (8)$$

The vectors μ_k and scalars λ_k are the eigenvectors and Eigen values, respectively, which are determined using the covariance matrix given below:

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n\Phi_n^T \qquad where\ \Phi = \mathrm{A} - \mathrm{mean}\left(\mathrm{A}^{\mathrm{T}}\right) \quad (9)$$

Where the matrix $A = [\Phi_1\Phi_2...\Phi_M]$. A is the input image's column vector.

The proposed algorithm is based on to use the PCA based image fusion in which the coefficient of Contourlet and nonsubsampled Contourlet are taken to reconstruct the estimated image. The process highlights the important edges and enhances the hidden feature of the image. The process of image fusion is described as followed:

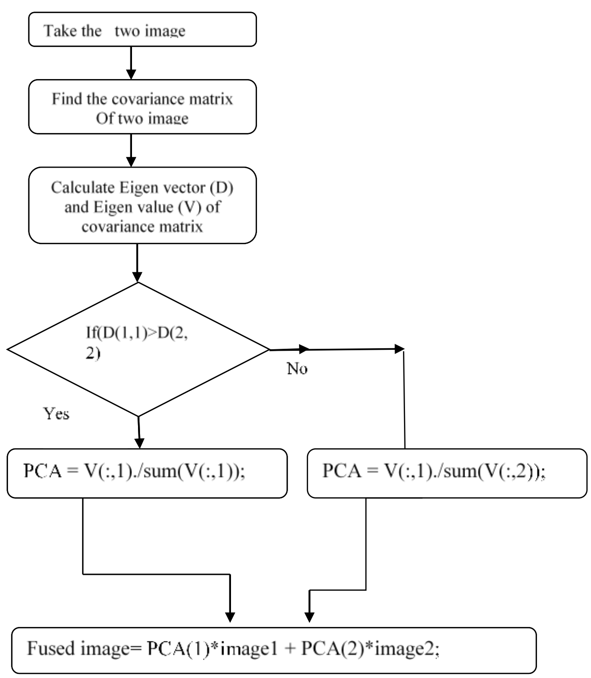


Figure 3.1: Block diagram of proposed method.

In the above process, it uses the principle component of the two images. The pixels of two images are fused to reconstruct the pixels in estimated image in which the weight of each pixel is calculated on the basis of Eigen value. In the next section, the results using the method is calculated and compared with the other multiscale transform techniques[15].

IV. RESULTS AND DISCUSSION

In this section, the simulation results through the proposed method are calculated on some standard dataset. The results are shown qualitatively and quantitatively. In order to evaluate the result quantitatively, the parameter mean square error and PSNR are taken.
The mean square error(MSE) and peak signal to noise ratio(PSNR) are given as follows:

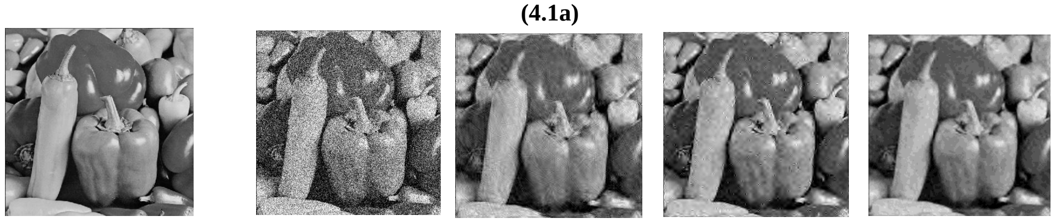
$$MSE = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}[I(i,j) - K(i,j)]^2 \quad (10)$$

$$PSNR = 10 \times log_{10}(\frac{255^2}{MSE}) \quad (11)$$

Where, I and K are the original and reconstructed images.

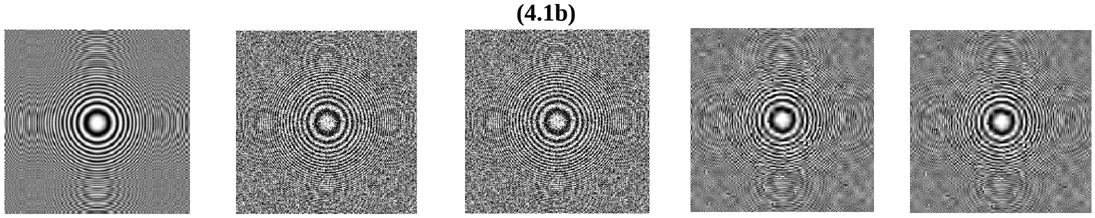
Original Image | Noisy Image=11dB | 24.14dB(Contourlet) | 33.8dB(non sub sampled Contourlet) | 37.65dB Proposed method (PCA Based fusion of Contourlet NSCT

(4.1a)



Original Image | Noisy Image=13dB | 25dB (Contourlet) | 33.21dB (non sub sampled Contourlet) | 34.08dB Proposed method (PCA Based fusion of Contourlet and NSCT)

(4.1b)



Original Image | Noisy Image=9dB | 14.12dB (Contourlet) | 20.24dB(non sub sampled Contourlet) | 21.42dB Proposed method(PCA Based fusion of Contourlet and NSCT)

(4.1c)

Fig. 4.1 Comparison of the denoised results on images Lena, peppers and Zone plate with respect to PSNR.

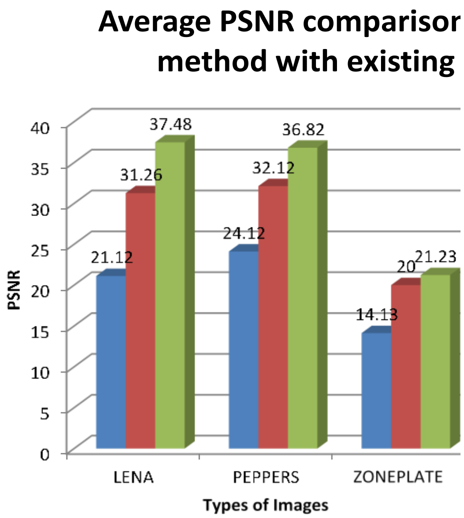


Figure 4.2: Average noise comparison between proposed method and other method

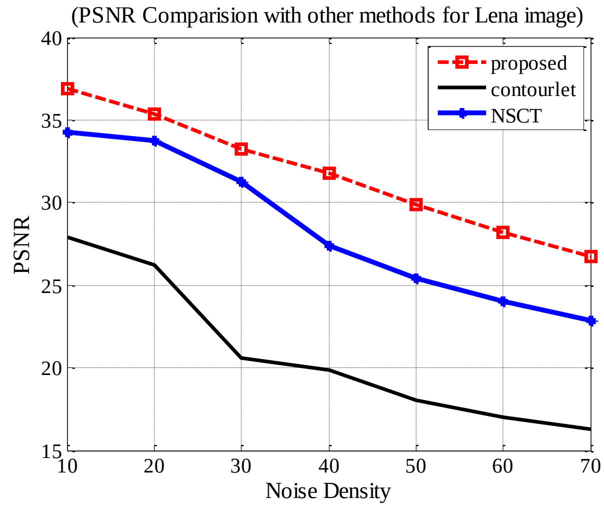


Figure 4.3: Variation of PSNR with increasing noise density level

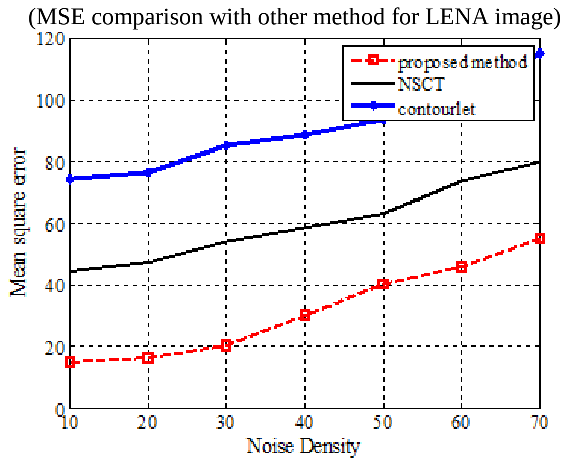


Figure 4.4: Variation of MSE with increasing noise density level.

Table 1 Variation of PSNR with increasing noise density level on LENA image

Noise level	Contourlet	NSCT	Proposed method
10	27.2	34.2	37.12
20	26.2	33.3	35.23
30	22.4	32.2	33.42
50	19.1	24.4	29.21

Table 2 Variation of PSNR with increasing noise density level on PEPPERS image

Noise level	Contourlet	NSCT	Proposed method
10	28..32	34.65	36.22
20	27.42	33.87	34.87
30	25.65	32.24	33.41
50	22.71	23.87	28.87

In Figure 4.1 , it can be seen that the proposed method has achieved better visual image quality than the other methods. The PSNR of Lena image is found as 36.18 dB, which is better than other two denoising method.

Figure 4.3 represents the variation of PSNR with increasing noise density, while the figure 4.4 represents the variation of MSE with respect to increasing noise density.

Table 4.1 represents the PSNR value calculated on LENA image, while the Table 4.2 represents the PSNR value calculated on PEPERS image. The above data depicts that the PCA based method has recovered the image better than the NSCT and Contourlet method. Since the weight, which is decided by the principle component is found suitable to estimate the correct pixels in the image.

CONCLUSION AND DISCUSSION

In this work, we use the fusion techniques to estimate the denoised image. Though, Contourlet and NSCT is good image denoising techniques, but in order to enhance the weak edges, the coefficient at that level should be improved. Using the Principle component analysis, we have recalculated the coefficient and reconstructed the pixels at that place. In this work, we also studied about the multiscale transform method, which is well suited to reform the contour, curve and in an image. Experimental analysis shows that the proposed method efficiently reduces the noise and enhances the edges in an image.

REFERENCES

1. Kazubek, Marian. "Wavelet domain image denoising by thresholding and Wiener filtering." *IEEE Signal Processing Letters* 10, no. 11, 324-326 (2003).
2. Do, Minh N., and Martin Vetterli. "The contourlet transform: an efficient directional multiresolution image representation." *IEEE Transactions on image processing* 14, no. 12, 2091-2106 (2005).
3. Bi, Xue, and Xiangdong Chen. "NSCT-NLmeans based CS reconstruction for noisy image." In Image and Signal Processing (CISP), 2014 7th International Congress on, pp. 174-178. *IEEE*, (2014).
4. Li, Ying, Jie Hu, and Yu Jia. "Automatic SAR image enhancement based on nonsubsampled contourlet transform and memetic algorithm." *Neurocomputing* 134, 70-78 (2014).
5. Yang, Ou, and Hong Bo. "Image De-Noising Algorithm Using Adaptive Bayes Threshold by Subband Based on Nonsubsampled Contourlet Transform." InIntelligent System

Design and Engineering Applications (ISDEA), 2013 Third International Conference on, pp. 832-835. *IEEE*, (2013).

6. Al Jumah, Abdullah, Mohammed Gulam Ahamad, and Syed Amjad Ali. "Denoising of medical images using multiwavelet transforms and various thresholding techniques." *Journal of Signal and Information Processing* 4, no. 1, 24 (2013).
7. Eslami, Ramin, and Hayder Radha. "The contourlet transform for image denoising using cycle spinning." In Signals, Systems and Computers, 2004. Conference Record of the Thirty-Seventh Asilomar Conference on, vol. 2, pp. 1982-1986. *IEEE*, (2003).
8. Sajedi, Hedieh, and Mansour Jamzad. "Adaptive steganography method based on contourlet transform." In Signal Processing, 2008. ICSP 2008. 9th International Conference on, pp. 745-748. *IEEE*, (2008).
9. Da Cunha, Arthur L., Jianping Zhou, and Minh N. Do. "The nonsubsampled contourlet transform: theory, design, and applications." *IEEE transactions on image processing* 15, no. 10, 3089-3101 (2006).
10. Sethunadh, R., and Tessamma Thomas. "Image denoising using SURE-based adaptive thresholding in directionlet domain." *Signal & Image Processing* 3, no. 6, 61 (2012).
11. Zhou, Jianping, Arthur L. Cunha, and Minh N. Do. "Nonsubsampled contourlet transform: construction and application in enhancement." In Image Processing, 2005. ICIP 2005. IEEE International Conference on, vol. 1, pp. I-469. *IEEE*, (2005).
12. Lu, Yue M., and Minh N. Do. "A mapping-based design for nonsubsampled hourglass filter banks in arbitrary dimensions." *IEEE Transactions on Signal Processing* 56, no. 4, 1466-1478 (2008).
13. da Cunha, Arthur L., Jianping Zhou, and Minh N. Do. "Nonsubsampled contourilet transform: filter design and applications in denoising." In Image Processing, 2005. ICIP 2005. IEEE International Conference on, vol. 1, pp. I-749. *IEEE*, (2005).
14. Do, Minh N., and Martin Vetterli. "Contourlets: a directional multiresolution image representation." In Image Processing. 2002. Proceedings. 2002 International Conference on, vol. 1, pp. I-I. *IEEE*, (2002).
15. Naidu, V. P. S., and J. R. Raol. "Pixel-level image fusion using wavelets and principal component analysis." Defence Science Journal 58, no. 3 (2008): 338.