Non sub sampled Contourlet Transform Application in image Denoising

[1]Anshuj jain,[2]Dr.Sanjeev Gupta,[3]Dr Laxmi Singh

[1]Research Scholar, [2]Profesor,[3]Assistant Professor

[1,2,3]Department Electronics & Communication Engineering,

[1,2,3]Rabindranath Tagore University, Bhopal, India.

Abstract—Modern technology depends on image or video to understand the things absolutely. These images are collected through the various different sensors. The sensing strategy and capabilities, for multidimensional (MD) signals such as images, videos, multispectral images, brightness fields and biomedical data volumes have become omnipresent. Multidimensional filter banks and the related constructions gives a unified structure and efficient computational. These filters also include configuration, demonstration, and processing of these multidimensional data sets. In this work covers non sub sampled Contourlet transform (NSCT) and its application for noise reduction. This work, an image trous algorithm is used which is based on Nonsubsampled Contourlet Transform (NSCT) coefficient histogram matching. . The one-dimensional transforms has limitation, such as the Fourier and wavelet transforms, we follow a "factual" two dimensional transform that can capture the essential geometrical construction that is the key in visual information to subside the limitations. The most significant thing to explore the geometry in images comes from the discrete nature of the data. We create a discrete-domain multi-resolution and multidirectional expansion using non-separable filter banks. This structure is a consequence in a flexible multi-resolution, local and directional images development using contour segments and hence it is named the Contourlet Transform.The Nonsubsampled Contourlet Transform (NSCT) has been built up and its applications have been studied. Here the construction proposed is based on a nonsubsampled pyramid structure and nonsubsampled directional filter banks. The result is a variable multiscale, multidirectional, and shift invariant image decomposition that can be efficiently implemented. Next to the interior of the proposed scheme is the non separable two-channel nonsubsampled filter bank (NSFB) [1]. Discussion is based on use of the less stringent design condition of the NSFB to design filter that lead to a NSCT with better frequency selectivity and regularity when compared to the Contourlet transform. We evaluate the performance of the NSCT in image Denoising application.. Firstly, in the NSCT domain the original image is decomposing. Secondly, the NSCT coefficient histograms of the original image in corresponding sub-band are adaptively mapped to those of the reference image via histogram matching after threshold Denoising. Finally, the superior image is reconstructed from the modified coefficients via inverse NSCT. Investigational results express that the proposed adaptive algorithm efficiently improves slight features while suppressing noise compared with presented algorithms.

Keywords: NSCT, NSFB, filter banks, Nonsubsample, Contourlet transform.

Introduction: Image processing is a method to modernize an image into digital structure and perform a number of operations on it, in organizes to achieve a superior image or to extract some valuable information from it. It is a category of signal dispensation in which key is image, like video framework or photograph and output may be illustration or characteristics linked with that image. Generally Image Processing system includes treating images as two dimensional signals while applying already set signal processing methods to them. It is among quickly growing technologies today, with its applications in various aspects of a business [2][3]. Image Processing forms central part investigate area within engineering and computer science disciplines too.

Image processing basically includes the following three ladders.

1. Importing the image with optical scanner or by digital photography.

2. Analyzing and manipulating the image which includes data compression and image development and spotting patterns that are not to human eyes like satellite photographs.

3. Output is the last stage in which result can be altered image or report that is based on Image Analysis.

Contourlet Transform: Contourlet transform is a combination Laplacian pyramid and directional filter bank. In other word the Contourlet transform uses a double filter bank structure to get the smooth contours of images. In this double filter bank, the Laplacian pyramid (LP) is first used to capture the point discontinuities, and then a directional filter bank (DFB) is used to form those point discontinuities into linear structures[7][8]. The Contourlet transform is a multidirectional and multiscale transform that is constructed by combining the Laplacian pyramid with the directional filter bank (DFB) proposed. The pyramidal filter bank structure of the Contourlet transform has very little redundancy, which is important for compression applications [10]. However, designing good filters for the Contourlet transform is a difficult task. In this work, we propose an over complete transform that we call the Nonsubsampled Contourlet transform (NSCT). Our main motivation is to construct a flexible and efficient transform targeting applications where redundancy is not a major issue (e.g., Denoising)[5][6]. The NSCT is a fully shift-invariant, multiscale, and multidirectional expansion that has a fast implementation.

The proposed construction takes to a filter-design problem that to the best of our knowledge has not been introduced elsewhere. The design problem is much less demanding than that of Contourlet. This enables us to design filters with better frequency selectivity thereby achieving better sub band decomposition. Using the mapping approach we can provide a framework for filter design that ensures good frequency localization in addition to having a fast implementation through ladders steps. The NSCT has proven to be very efficient in image Denoising as we show in this work.

Nonsubsampled Contourlet Transform: Fig. 1(a) displays an overview of the proposed NSCT. The structure consists in a bank of filters that splits the 2-D frequency plane in the sub bands illustrated in Fig1 (b).

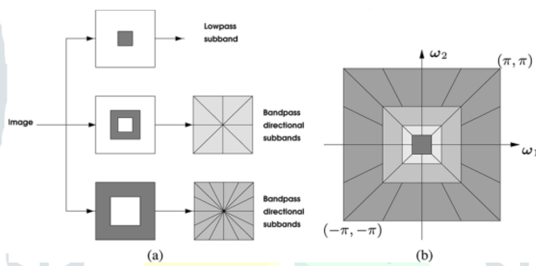


Fig.1. Nonsubsampled Contourlet transforms. (a) NSFB structure that implements the NSCT. (b) Idealized frequency partitioning obtained with the proposed structure.

Our proposed transform can thus be divided into two shift-invariant parts:

1) A nonsubsampled pyramid structure that ensures the multiscale property and
2) A Nonsubsampled DFB structure that gives directionality.

History-The two types of methods used for Image Processing are Analog and Digital Image Processing.

Fundamental of Analog Image Processing: Analog Image Processing refers to the alteration of image through electrical means. The most common example is the television image. The television signal is a voltage level which varies in amplitude to represent brightness through the image.

Fundamental of Digital Image Processing: Digital Image Processing usually refers to the processing of a 2-dimensional (2-D) picture signal by a digital hardware. The 2-D image signal might be a photographic image, text image, graphic image (including synthetic image), biomedical image (X-ray, ultrasound, etc.), satellite image, etc[12][13]. In a broader context, it implies processing of any 2-D signal using a dedicated hardware, e.g. an application specific integrated circuit (ASIC) or using a general-purpose computer implementing some algorithms developed for the purpose.

Problem Identification

In this work, our main aim of the thesis is how to reduce the noise from the image through nonsubsampled counterlet transform. By studying the above literature and the result found that the proposed technique gives far better results in the parameters in comparison with the existing methods of image processing such as curvelets/Fourier/wavelet is transformations.

Proposed Algorithm: Nonsubsampled Contourlet convert is a implement to find the frequency domain for decomposition and then we find the noise section in the image by analyzing the frequency part then eliminate these noisy components by De-correlation of the noisy image with the estimated noise part. In Matlab, we use the Matlab tool like the image processing tools, signal processing tools & Matlab compiler.

a. Non-sampled Contourlet transform: The Contourlet transform is a real 2-D image representation using cascade of Laplacian pyramid (LP) and a directional filter bank (DFB). The Contourlet transform can efficiently capture the intrinsic geometric structures such as contours in an image and can achieve better expression of image than the wavelet transform. Moreover, it is easily adjustable for detecting fine details in any orientation along curvatures, which results in more potential for effective analysis of images. However the Contourlet transform is lack of shift-invariance due to the down sampling and up sampling, In2006, Cunha et al. proposed the nonsubsampled Contourlet transformation (NSCT), which is a fully shift-invariant, multi-scale, and multi-direction expansion that has better directional frequency localization and a fast implementation. NSCT consists of two filter banks, i.e. the nonsubsampled pyramid filter bank (NSPFB) and the nonsubsampled directional filter bank (NSDFB) which split the 2-D frequency plane in the sub bands. The NSPFB provides nonsubsampled multi-scale decomposition and captures the point discontinuities. The NSDFB provides nonsubsampled directional decomposition and links point discontinuities into linear structures.

The different part is non sub sampled Contourlet removes the process of sub sampling. It is made up of a non sub sampled pyramid and a non sub sampled directional filter bank. Non sub sampled Contourlet can provide shift-invariant and higher redundancy besides of most of the excellent property which Contourlet can provide. Expanding basis function set can represent image information more flexible and more completely when certain amount of redundancy is admitted. Pyramid filters and DFB in non sub sampled Contourlet is non sub sampled, which derives two profits: the first, higher redundancy ensure the integrity of information and visual features in each sub-band which is transformed from original image by non sub sampled Contourlet. The second, according to multi-sample Theory, there's no frequency spectrum mixing in low-pass sub-band by non sub sampled Contourlet, which can provide stronger direction decision. Suppose any signal in R^m can be expressed by linear combination of $N \times 1$ basis vector, and suppose these basis are standardized orthogonal. Let Vector

$$\{\varphi_i\}_{i=1}^{N} \epsilon R^N$$

be a column vector. to form a $N \times N$basis matrix

$$\Psi = [\Psi_{1,} \Psi_2, \dots\dots\dots\dots\dots.. \Psi_N]$$

Any time-domain signal x which is real, finite and discrete with one dimension can be expressed

as:

x=$\Psi\Theta = \sum_{i=1}^{N} \theta_i \Psi_i$ ………. (1)

Where vector is coefficient of x which is sparsely represented (decomposed) in basis Ψ.

X and Θ are equal expresses of same signals, x is spatial express of the signal, and Θ is the express of signal. In Ψ-domain especially, if the non-zero number in vector Θ is K, it's called k-sparse. If Θ is sorted and attenuated with power law in basis Ψ, x is compressible [14]. Generally speaking, signal is not sparse itself, but when it is transformed (like wavelet transform), the coefficients can be considered sparse. For example, when a signal is transformed by wavelet transform, we can reserve k bigger components of the coefficients, and set other n-k components to zero(because their contribution to signal reconstruction is very small),and then obtain approximate reconstructed data by inverse wavelet transform. Thus x can be considered K-sparse in wavelet basis Ψ.

Let T be linear transformed by measurement matrix Φ⍰$R^{M \times N}$

Where measurement times M<<N, we can obtain measure result

Y=Φx=ΦΨΘ …………(2)

Where=$\{y_i\}_{i=1}^{M}$ is considered as linear projection. The dimension of y is much lower than the dimension of x. When x is reconstructed by y, it can be exactly reconstructed with a high probability from measurement results by solving the optimal problem of $l_0$norm.

$\tilde{x} = \arg min \|x\|_0$ s.t. y = Φx ………..(3)

The problem of solving l0 norm is a NP-hard problem,

So we can change the problem to

$\tilde{x} = \arg min \|x\|_1$s.t. y = Φx ………… (4)

Wherel_1 : the optimal problem with smallest norm. Algorithms like Match Pursuit, Orthogonal Match Pursuit, Gradient Projection, Chain Pursuit etc. are current solutions. In original CS algorithm of image processing, a N×N image was firstly transformed by certain transform, like DCT transform, or wavelet transform, then a measurement matrix F was formed,(measurement matrix could be random Gaussian matrix which obeys (0,1/N) distribution, or ±1 Bernoulli matrix[15]. namely Noise let, etc.)All of the wavelet transform coefficients are measured by F, and then M×N measurement coefficients are obtained. When recovering image, original image can be recovered by F and M×N measurement coefficients with OMP algorithm. During the research, it is found that in original CS algorithm, wavelet decomposition level has significant impact on reconstruction results. The less the decomposition level is, the worse the reconstruction results is. With the increase of the decomposition reconstruction effects will be improved. That's because original image could be decomposed to low-frequency sub-band and high-frequency

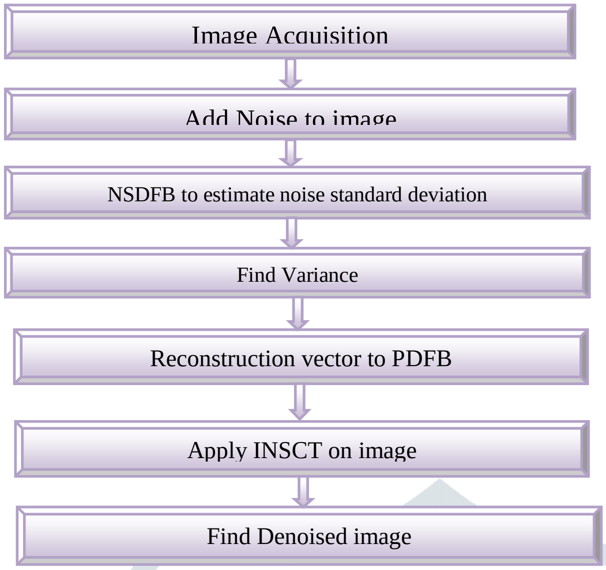
Sub-band by wavelet decomposition. High-frequency sub-band can be considered sparse, but low-frequency sub-band is the approach signal of original image under different scales, it cannot be considered sparse. When measurement matrix F is multiplied by low-frequency and high-frequency coefficients together, the correlation among low-frequency approximate components coefficients will be damaged, which will deteriorate reconstruction results. When the number of wavelet decomposition level is 1, the reconstruction image is completely different from its origin. So, the wavelet decomposition level should be as large as possible. Even so, the recovered image quality is less than satisfactory. In this paper the CS algorithm is based on NSCT. The method of CS algorithm based on NSCT is as following:

1. Decomposing the N×N size image by NSCT, getting the coefficients of high-frequency and low-frequency sub-bands [19].
2. Selecting suitable value of M to get the measurement matrix F which is M × N / 2 size and Gaussian distribution, measuring the high-frequency sub-band coefficients.
3. Using OMP algorithm [19] to reconstruct the high-frequency sub-band coefficients, and combining the low-frequency sub-band coefficients to do inverse transformation of NSCT to get the recovery image.

Steps for apply in Matlab simulation:-

1. Save the all target images and programme related methods.
2. Write a programme in Matlab for finding the disparity using Matlab tools.
3. Input the values of image size & select the method &save it.
4. Run the programme then find the result if we get any error then removes it. And again runs it.
5. Save &compile the programme in Matlab.
6. We get the final result and find better Denoising image trough best methods.

Flowchart of Denoising Process



RESULT AND DISCUSSION: In this work I have discussed about results obtain by implementing the algorithm and Denoised images obtained using NSS Contourlet transform with increases sampled rate. The diagrammatical representations used in our test wavelet, Contourlet, Nonsubsampled transform. Here I have taken four images like barbare, Lena, pepper and zoneplate. By applying Denoising process through each method one by one in these images and by comparing results with previous works we have found the best result in proposed method. I have compared results in three type's representation; i.e. diagrammatical representation, tabular representation and graphical representation. Through these types of representation I found the best method for the removal of noise from images. Here we show our result and compression of all parameter through barbare image.These representations are as follows:-

Digramitical Representation Barbara In this figure we compare the all methods.firstly we take original barbar image in first image after that add noise in this image we see in second figure then find denoise resuilt throgh wavelet in third image ,in fourth image find denoising result trogh contourlet transform,in fifth image we see the previous result and in last image we get the our proposed result.then find in each image SNR in increasing order

Figure 5.1 (A) Original image, (B) Noisy image (16.11db), (C) Denoise using wavelete (35.27db), (D) Denoise contourlet(SNR=36.03db), (E) In previous method denoise using NSS counterlet transform (SNR=29.83db), (F) in proposed method denoise using NSS counterlet transform(SNR=39.75db)

Tabular Representation

Tabular respresentation shows the comparison of performance parameters like MEAN, MSE, VARIENCE, UIQI, PSNR AND SNR for methods like wavelet,contourlet of base paper and our's result.we can find which method is best for denoising images

Method	MEAN (%)	MSE (%)	VAR (%)	UIQI	PSNR
Wavelet	45.86	00.11	05.05	1.1915	35.27
Counterlet	45.86	00.14	05.07	1.1892	36.03
Prev. NSCT	45.87	00.15	04.42	4.7865	29.83
Proposed NSCT	45.87	00.14	04.42	4.7729	39.75

Table 5.1 Tabular representation of comparative analysis of different methods by different parameters

Graphical representation shows the different result in some previous method base paper and our's result.Blue colour shows the wavelet transform method,red colour shows contourlet transform,green colour represent base paper result and last ond violet colour represent our's result.through these representation we get the best method of denoising.

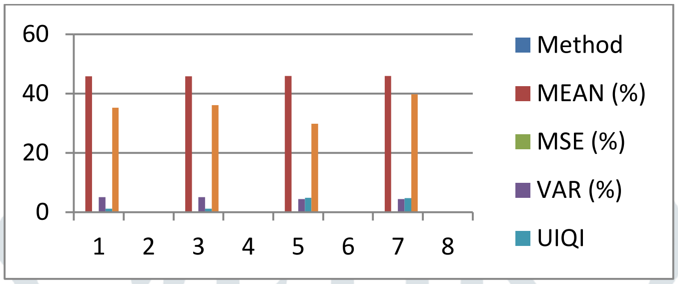


Figure:-5.1.2 Graphical representation of comparative analysis of different methods by different parameters

Conclusion: We have developed a completely shift-invariant description of the Contourlet transform, the NSCT. The design of the NSCT is reduced to the design of a nonsubsampled pyramid filter bank and a nonsubsampled fan filter bank. We exploit this new less stringent filter-design difficulty using a mapping approach, thus provision with requires for 2-D factorization. We also developed a lifting/ladder structure for the 2-D NSFB. This structure, when coupled with the filters designed via mapping, provides a very efficient noise performance that under some additional circumstances can be reduced to 1-D filtering operations. Applications of our proposed transform in image Denoising and enhancements were studied. In Denoising, we studied the performance of the NSCT when coupled with a hard thresholding estimator and a local adaptive reduction. For hard thresholding, our results indicate that the NSCT provides better performance than competing transform such as the NSWT and Contourlet. Concurrently, our local adaptive reduction results are competitive to other Denoising methods. In particular, our results show in previous method fairly simple estimator in the NSCT field yields comparable performance to high-tech Denoising methods that are more sophisticated and complex. In image denoising, the results obtained with the NSCT are better-quality to those of the NSWT both visually and with respect to purpose measurements

Future Scope: The research finding made out of this thesis has opened several research directions, which have a scope for further investigations. The design of the NSCT is reduced to the design of a nonsubsampled pyramid filter bank and a nonsubsampled fan filter bank. In image denoising, the results obtained with the NSCT are better-quality to those of the NSWT both visually and with respect to purpose measurements. In this work we deal on nonsubsampled contourlet transform and taken general image for denoising. Next work can be extending for the time basis images. Along this by increasing the level of denoising work can be precede so that result improve the performance parameter.

References

1. S.Mitra and R. Sherwood, "Digital ladder networks," IEEE Trans. Aud Electroacoust., vol. AU-21, no. 1, pp. 30–36, Feb. 1973.
2. J. H. McClellan, "The design of two-dimensional digital filters by transformation," in Proc. 7th Annu. Princeton Conf. Information Sciences and Systems, 1973.

3. P. J. Burt and E. H. Adelson, “The Laplacian pyramid as a compact image code,” IEEE Trans. Commun., vol. 31, no. 4, pp. 532–540, Apr. 1983.
4. J. G. Daugman, “Uncertainty relation for resolution in space, spatial frequency, and orientation optimized by two-dimensional visual cortical filters,” J. Opt Soc. Amer. A, vol. 2, no. 7, pp. 1160–1169, Jul. 1985.
5. E. P. Simoncelli, W. T. Freeman, E. H. Adelson, and D. J. Heeger, “Shiftable multiscale transforms,” IEEE Trans. Inf. Theory, vol. 38, no. 2, pp. 587–607, Mar. 1992
6. J. Kovaˇcevic´ and M. Vetterli, “Nonseparable multidimensional perfect reconstruction filter banks and wavelet bases for ,” IEEE Trans. Inf. Theory, vol. 38, no. 2, pp. 533–555, Mar. 1992.
7. R. H. Bamberger and M. J. T. Smith, “A filter bank for the directional decomposition of images: Theory and design,” IEEE Trans. Signal Process., vol. 40, no. 4, pp. 882–893, Apr. 1992.
8. M. J. Shensa, “The discrete wavelet transform: Wedding the à trous and Mallat algorithms,” IEEE Trans. Signal Process., vol. 40, no. 10, pp. 2464–2482, Oct. 1992.
9. P. P. Vaidyanathan, Multirate Systems and Filter banks. Englewood Cliffs, NJ: Prentice-Hall, 1993.
10. D. B. H. Tay and N. G. Kingsbury, “Flexible design of multidimensional perfect reconstruction FIR 2-band filters using transformation of variables,” IEEE Trans. Image Process., vol. 2, no. 4, pp. 466–480, Oct. 1993.
11. T. Cooklev, T. Yosbida, and A. Nishihara, “Maximally flat half-band diamond-shaped FIR filters using the Bernstein polynomial,” IEEE Trans. Circuits Syst. II, vol. 40, no. 11, pp. 749–751, Nov. 1993.
12. M. Vetterli and J. Kovaˇcevic´, Wavelets and Subband Coding. Englewood Cliffs, NJ: Prentice-Hall, 1995.
13. R. R. Coifman and D. L. Donoho, “Translation invariant de-noising,” in Wavelets and Statistics, A. Antoniadis and G. Oppenheim, Eds. New York: Springer-Verlag, 1995, pp. 125–150.
14. S.-M. Phoong, C. W. Kim, P. P. Vaidyanathan, and R. An sari, “A new class of two-channel biorthogonal filter banks and wavelet bases,” IEEE Trans. Signal Process., vol. 43, no. 3, pp. 649–661, Mar. 1995.
15. W. Sweldens, “The lifting scheme: A custom-design construction of biorthogonal wavelets,” Appl. Comput. Harmon. Anal., vol. 3, no. 2, pp. 186–200, 1996.