Available Online at www.ijcsmc.com

International Journal of Computer Science and Mobile Computing

A Monthly Journal of Computer Science and Information Technology

ISSN 2320–088X

IJCSMC, Vol. 3, Issue. 4, April 2014, pg.1240 – 1250

RESEARCH ARTICLE

An Efficient Directional Multiresolution Image Representation using Contourlet Transform

[1]Ankita Sharma
M.Tech Scholar
Deptt. Of CSE
MIST Bhopal(M.P.)

[2]Prof. Abhay Kumar
[3]Assoc. Professor Rahul Deshmukh
Deptt. Of CSE
MIST Bhopal(M.P.)

Abstract-The limitations of commonly used separable extensions of one-dimensional transforms, such as the Fourier and wavelet transforms, in capturing the geometry of image edges are well known.A "true" two dimensional transform that can capture the intrinsic geometrical structure that is key in visual information. The main challenge in exploring geometry in images comes from the discrete nature of the data. Thus, unlike other approaches, such as curvelets, that first develop a transform in the continuous domain and then discretize for sampled data, our approach starts with a discrete-domain construction and then studies its convergence to an expansion in the continuous domain. Specifically, a discrete-domain multiresolution and multidirection expansion using non-separable filters, in much the same way that wavelets were derived from filter banks. This construction results in a flexible multiresolution, local, and directional image expansion using contour segments, and thus it is named the contourlet transform. The discrete contourlet transform has a fast iterated filter bank algorithm that requires an order N operations for N-pixel images. Furthermore, we establish a precise link between the developed filter bank and the associated continuous domain contourlet expansion via a directional multiresolution analysis framework. We show that with parabolic scaling and sufficient directional vanishing moments, contourlets achieve the optimal approximation rate for piecewise smooth functions with discontinuities along twice continuously differentiable curves. Finally, we show some numerical experiments demonstrating the potential of contourlets in several image processing applications.

Key Terms—Sparse representation, wavelets, contourlets, filter banks, multiresolution, multidirection, contours, geometric image processing

I. INTRODUCTION

The proficient illustration of pictorial information lies at the core of many image processing tasks, which includessegmentation ,denoising, compression,feature extraction, and inverse solutions of short comings .Proficiency of a representation shows the ability to capture important information about an object of interest with a small description. For content-based image retrieval system , image compression and image segmentation , the use of an effectivedemonstrationdenotes the solidity of the compressed file or the directory entry for each image in the image database.

Wavelets have been recognized as the correct tool for representing the one-dimensional piecewise smooth signals,because wavelets provide an optimumillustration for these signals in a certain sense [1], [2]. In addition, the wavelet representation is responsive to efficient algorithms; in particular it leads to fast transforms and convenient tree data structures. These are the key reasons for the success of wavelets in many signal processing and communication applications; for example, the wavelet transform was adopted as the transform for the new image-compression [3].

However, natural images are not cumulative heaps of one dimensional piecewise smooth scanes; the break points (i.e. edges) are typically placedbesideeven(smooth) curves (i.e. contours) owing to even boundaries of physical objects. Thus, natural images haveessential and fundamental geometrical structures which are vital features in visual information system. As a consequence of a discreteaddition from one-dimensional bases, wavelets in two-dimensional are good for separating the breaking points at edge points, but will not visible the evenness along the contours. In addition, separable wavelets can capture only limited directional information an important and unique feature of multidimensional signals. These disappointing behaviors indicate that more powerful representations are needed in higher dimensions[4].

II. RELATED WORK

The curvelet transform is hybrid transform which was created originallyin the continuous domain [4] with multiscale filtering and ridgelet transform [9] on each bandpass image using a block of image partition. After it , the authorsE. J. Cand`es and D. L. Donoho proposed the second generation curvelet transform [5] that was well-defined directly via frequency partitioning dispossessed of using the ridgelet transform. Both curvelet creations require a rotation operation and correspond to a two dimensional frequency partition based on the polar coordinate. This createsthe curvelet construction trivial in the continuous domain but bases the putting into practice for discrete images sampled on a rectangular grid to be very fascinating. In precise, potential critical sampling seems challenging in such discretized constructions the cause for this difficulty, it rely on the typical rectangular sampling grid enacts a prior geometry to discrete images; e.g. strong bias toward horizontal and vertical directions. This fact motivates the development of a directional multiresolution transform like curvelets, but directly in the discrete domain, which results in the contourlet construction described in this paper.

Furthermore,here advantage from the deep-rootedfamiliarity in transform coding when applying contourlets to image compression (e.g. for bit allocation).Numerous other well-known systems that provide multiscale and directional image representations include: Two- Dimensional Gabor wavelets [15], the cortex transform [16], the steerable pyramid [17], 2-D directional wavelets [18], brushlets [19], and complex wavelets [20]. The keydissimilarities between these systems and the contourlet construction is that the previous approaches do not agree for a different number of directions at each scale while achieving approximately critical sampling. In addition, our construction employs iterated filter banks, which makes it computationally well-organized, and there is a precise association with continuous-domain expansions.

In a more recent work [25], developed a critically sampled contourlet transform, which call CRISP-contourlets, using a combined iterated nonseparable filter bank for both multiscale and directional decomposition.It would like to point out that the decoupling of multiscale and directional disintegration stages offers a simple and flexible transform, but at the cost of a small redundancy (up to one third of , which comes from the Laplacian pyramid). Accoring to Xiao feng Li et. al. (2012)[32],the NSCT has been proposed by Cunha and Do [6,7] , to remove the aliasing of frequency from contourlet and improve its selective directionand shift-invariance. The NSCT gives a complete shift-invariant and multiscale representation, similar to the redundant wavelet transform, with a quickoperation. Here, briefly introduce the construction of the NSCT. For the filter design, refer from the [6]. The contourlet transform employs Laplacian pyramids (LPs) [10,11], for multiscale decomposition, and directional filter banks for directional decomposition [12].

Xue Bi et. al.[33] proposed their work as image is broken into one multiple level,and it is then decomposed into eight directionalsubbands.Small coefficients are darked,while large coefficients are colored white, here see a small number of large coefficients.Thus the contourlet transform successfully gave the sparse directional subbands for images. The contourlets achieve the optimal nonlinear approximation behavior for section wise plane function,which is different from smooth contours.The decay rates of approximation error for images by different basis of parameters, where ,let x is the original image, $m$denotes the index of the m-largest coefficients of image ,and xm is the m-term approximation of image$x$.

The tunable-Q contourlet-based multi-sensor image fusion the contourlet transform(CT) outpaces wavelet transforms for image representation, but it developes aliasing components outside of the preferred pass band section [15]. By employing the nonsubsampled CT (NSCT) overcome the aliasing components.So result of nonsubsampling,requires huge data processing and suffers too high computational complexity, Haijiang wang,et.al [34]. In order to achieve an antialiasing transform with realistic computational complexity,it developed a innovative version of the CT that uses a new multiscale pyramid structure in lieu of the Laplacian pyramid of the CT. The basic of antaliasing CT is sharply restricted in the frequency domain and provides it with more desirable de-noising and fusion results than the CT [15] [19].

F. Luisier et. al. [35]Linear expansion of thresholds (LET) is parametrizing the errorneous image probability density function and then deriving the corresponding estimator, it directly parametrize the estimator. More precisely, it describe the denoising process F as a linear combination of k possibly non-linear processing Fk, i.e.

$$F(y) = \sum_{k=1}^{K} a_k F_k(y)$$

Since the effective part of the processing is usually a thresholding performed in a transform-domain, it have coined the above formulation of the denoising process a linear expansion of thresholds (LET).

Mingwei Chui et. al. [31] described in their paper that ,an improved image denoising method based on a nonlinear thresholding function with adaptive bayes threshold in nonsubsampled contourlet transform domain. For removing the shortcomings of the same threshold, the noise deviation of the different sub-band are estimated based on the coefficients of different directions and level sub-bands in NST domain, and the thresholds of every sub-band is estimated by bayesian threshold method.

After deciding the thresholds, a nonlinear thresholding function was chosen to overcome the shortcomings of the soft and the hard thresholding function.The simulation results show that removal of Gaussian white noise more effectively, and get a higher PSNR value and keep image texture and detail information more clearly, which also has a better visual effect.

III. THEORY DISCUSSION

With the rise in the number of image pixels per unit area of a chip, modern image capturing devices are ever more sensitive to noise.So,camera manufacturers,depend on image denoising algorithms to reduce the effects of such noise artifacts in the resultant image. Recently denoising methods use different approaches to address the problem. Image denoising signal is used to remove the additive noise while holding as much as possible the important signal features. Denoising images corrupted by Gaussian noise using wavelet techniques is very effective because of its ability to capture the energy of a signal in few energy transform values and represent them as group of pixels as shown in figure 1. Wavelet transform is good at energy compaction, the small coefficient are more likely due to noise and large coefficient due to important signal feature.

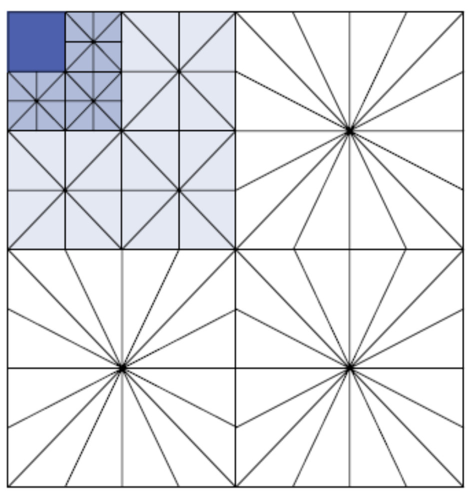


Figure:1.An illustration of wavelet-based contourlet transform[33].

So, Wavelet based denoising methods are important in the area of image noise reduction. Over the last decade, it has been commonly used in images denoising.

NST transformationis linear in nature, so it have two parts of coefficients: original image coefficient and noise coefficient. The coefficients of original image is large and dense, while the coefficients of noise is small and sparse. Therefore,to arrange with them, a proper threshold method required. The image signal can be recovered after reconstruction with the new image and noise coefficients. The basic principle of the reducing threshold denoising algorithm in NST domain is comparing NST sub-band coefficients with the thresholds, the image and noise coefficient which is less than the threshold is set to zero, while the greater one retained or modified. So threshold based denoising mainly involves two key factors: the estimation of thresholds and the choice of function for thresholding.

The threshold is estimated by the adaptive bayesian threshold (ABT) method, and a nonlinear thresholding function is chosen to deal with NST sub-band coefficients. The threshold estimation is one core of the shrinking threshold denoising algorithm. There are many threshold selection methods exist, like VisuShrink, SURE and Bayesian threshold estimation methods. Bayesian threshold estimation is follow Bayes standards, set the ideal threshold getting in the condition of Bayes minimal risk is:

$$T = \arg\min r_{bayes}$$

Where r_{bayes} is the Bayesian risk function. It is very difficult to solve the analytical expressions. So the approximate solution usually is calculated by numerical methods in the simulation

$$T = \frac{\sigma^2}{\delta}$$

Whereσ^2 is estimating the noise variance, and δ is the signal variance estimation. The estimate noise varianceσ^2 and the estimated signal variance δ can be deduced by equation

$$\sigma^2 = \left(median(w_{i,j})\middle|0.6745\right)^2$$

$$\delta^2 = max\left(\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} w_{i,j}^2 - \sigma^2, 0\right)$$

Where $w_{i,j}$is the lowest frequency coefficient(pixel value) after the transformation,M×N is the size of image.In Bayesian threshold estimation, the noise σ^2 variance is estimated as a same value in each directional and each level sub-bands. However, NST is not an orthogonal transform, the noise variance of sub-bands in each directional and each level are different in the NSCT domain. So, the noise variance of every sub-band signal for image is estimated independently. The noise variances are estimated based on the sub-band image coefficients of each directional and each level.For the NSCT sub-band $S_{m,n}$ (m is the level and n is the direction), its noise variance $\sigma^2{}_{m.n}$ is obtained by above equation and $w_{i,j}$ is the coefficients of sub-band $S_{m,n}$

$$\sigma^2{}_{m.n} = \left(\frac{median\left(|w_{i,j}|\right)}{0.6745}\right)^2$$

Then,the threshold $T_{m,n}$ of sub-band $S_{m,n}$ is estimted by equation.The most common thresholding functions are the hard thresholding function and the soft-thresholding function. The hard threshold denoising is as follow:

$$\widehat{w}_{i,j} = \begin{cases} w_{i,j}, |w_{i,j}| \geq T \\ 0, \quad |w_{i,j}| < T \end{cases}$$

The soft threshold denoising method is as follows:

$$\widehat{w}_{i,j} = \begin{cases} sign(w_{i,j})(|w_{i,j}| - T), |w_{i,j}| \geq T \\ 0, \qquad |w_{i,j}| < T \end{cases}$$

Where T is the threshold, $w_{i,j}$ is the coefficient of the original signal,$\widehat{w}_{i,j}$ is the coefficient of the restore signal. The soft and hardthreshold denoising methods are to compares the threshold with the decomposition coefficient of the original signal. In these methods, the nonimportant coefficients are set to zero. In hard thresholding, the important coefficients remain unchanged. In soft thresholding, the important coefficients are reduced by the absolute threshold value. However, there is deviation between the coefficients and the original ones. So, a nonlinear thresholding function is applied in the NSCT domain for denoising. The thresholding function is as follows:

$$\widehat{w}(i,j) = \begin{cases} sign(w(i,j))\left(|w(i,j)| - \propto_{i.j} * T_{m,n}\right), & |w(i,j)| \geq T_{m,n} \\ 0, & |w(i,j)| < T_{m,n} \end{cases}$$

Where $T_{m,n}$ is the threshold of sub-band $S_{m,n}$, $w(i,j)$ *and* $\widehat{w}(i,j)$ is the original and denoised coefficients of sub-band $S_{m,n}$,the weighted factor $\propto_{i.j}$ in the coefficient $w(i,j)$ is defined as :

$$\propto_{i.j} = \frac{\boldsymbol{T_{m,n}}}{\left(|\boldsymbol{w(i,j)}|.\boldsymbol{exp}(|\boldsymbol{w(i,j)}| - \boldsymbol{T_{m,n}})\right)}$$

The specific procedure of proposed denoising method based on adaptive Bayes threshold and nonlinear thresholding function .

IV. PROPOSED SOLUTION

Wavelet transform is an efficient image denoising algorithm, but it shortages shift and orientation invariance,and directional selectivity is poor. Aiming at the inadequacies, put forward a kind of Real two-dimension signal sparse representation method: Contourlet transform, which has multiresolution,local time-frequency and the opposite directions.So the contourlet transform is used for images denoising, better performance. The reason for this is because the typical rectangular-sampling grid imposes a prior geometry to discrete images; e.g. strong bias toward horizontal and vertical directions. This approache is typically require an edge-detection stage, followed by an adaptive representation.By contrast, wavelets representations are fixed transforms. This feature allows them to be easily applied in a wide range of image processing tasks.This fact motivates development of a directional multiresolution transform like wavelets, but directly in the discrete domain, which results in the contourlet construction.

The proposed contourlet filter bank and its associated continuous-domain frames in previous sections provide a framework for constructing general directional multiresolution image representations. Since the goal is to develop efficient or sparse expansions for images having smooth contours, the next important issues are: what conditions should it impose on contourlets to obtain a sparse expansion for that class of images; and how can it design filter banks that can lead to contourlet expansions satisfying those conditions. Here trying to match the form of a smooth probability density function, and preferably one that is easy to workwith. (Though as computing power becomes better and better, researchers are becomingless concerned with ease of computation.) while Joint probability density function described as, X and Y are jointly continuous if there exists a function f(x, y)defined for all real x and y so that for every set C of pairs of real numbers.One of the most common probability density functions is theGaussian distributionalso known as the normal distribution, or somewhat infamously as the bell curve.

The Gaussian probability density function for a random variable withmean and standard deviation

$$PSNR\ in\ dB = 10\ Log_{10}\left(\frac{255^2}{MSE}\right)$$

In contourlet filter bank construction,we replaced the probability density function by the cumulative density function,the image vector constructed on basis of cumulative weight of each vector then convert it to vector to cumulative density function bank which yields deterministic and exact results.

Steps for Proposed methodlogy for Image representation

Step 1. Take the input image.

Step 2. Do Multiscale and directional decomposition of input Image(Which is DFB).

2.1 Do Multiscale Analysis of Input Image

2.2 Do Multidirection Analysis of Input Image

Step 3.Apply the contourlet expansion on Multiscale and multidirection analyzed Image

3.1 Do the Parabolic scaling.

3.2 Do the Directional vanishing based on cumulative density by calculating the weight vector of image.

3.3 Do the Contourlet approximation

Step 4. Take Contourlet efficient Image.

V. EXPERIMENTAL RESULTS

The synthetically speckled images are generated by multiplying the noise-free ground truth image with a speckle noise simulated by passing a complex Gaussian random process through a 3 × 3 averaging filter, since a short-term correlation is sufficient to account for real speckle noise, and thentaking the magnitude of the filtered output. Furthermore, a number of noisy images with different levels of speckle noise are generated by changing the standard deviation of the complex Gaussian random process. The proposed approach is compared with Frost filter which is adaptive weiner filter despeckling approache.

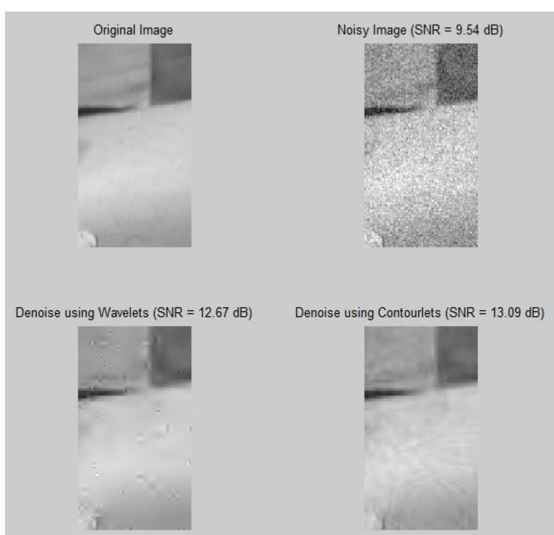


Figure1. Results with barbara Image

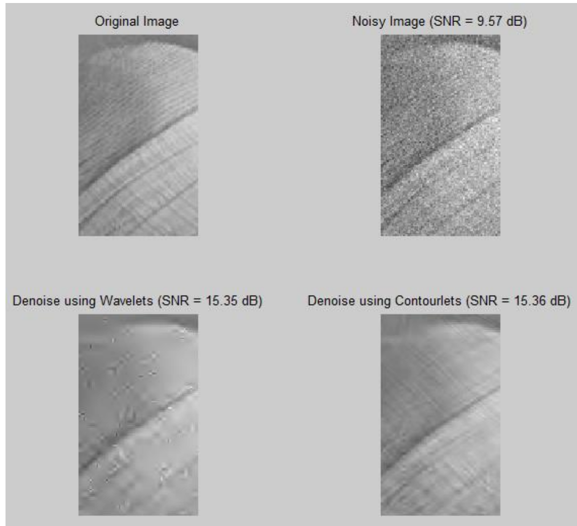
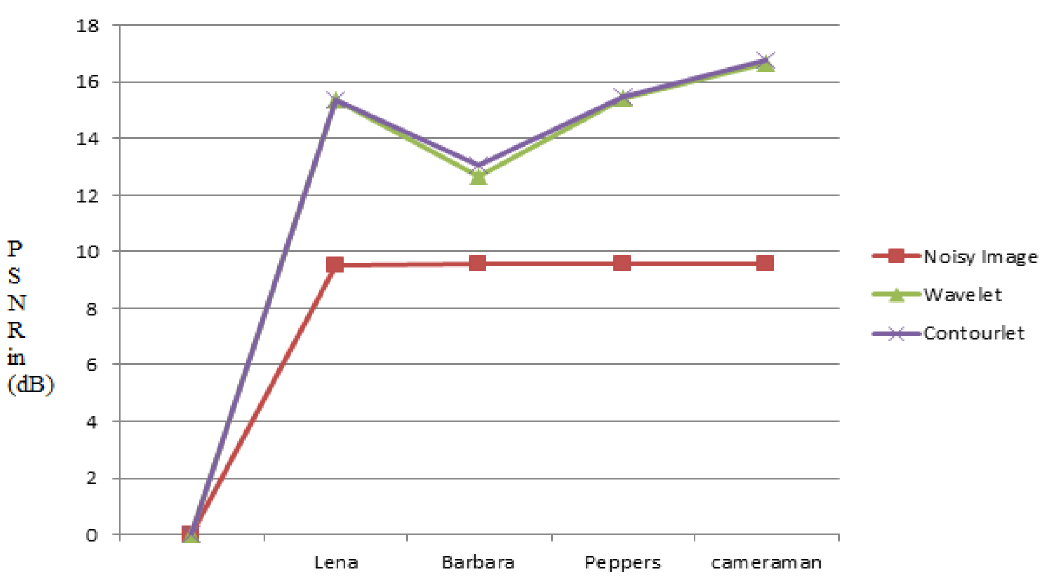


Figure2. Results with Lena Image.

Table 1 : Experimental result Analysis

S.No.	Test Images	Noisy Image representation (dB)	Wavelet Representation (dB)	Contourlet Representation (dB)
1	Lena	9.54	15.35	15.36
2	Barbara	9.55	12.67	13.09
3	Peppers	9.57	15.44	15.49
4	Camera man	9.55	16.64	16.78



VI. CONCLUSION

The wavelet transform has been widely used in different scientific applications including signal and image processing. This increasing success, which has been characterised by the adoption of some wavelet-based schemes, is due to features inherent to the transform, such as time-scale localisation and multiresolution capabilities. The basic concepts of the wavelet transform have been introduced. First, the historical development of the wavelet transform and its advent to the field of signal and image processing were reviewed. Then, its features and the mathematical foundations behind it were reviewed. To ease the understanding of the wavelet theory, the related notations and terms, such as the scaling function, multiresolution, filter bank and others were described and then briefly explained.

The developed filter bank has a detailedassociation with the associated continuous-domain contourlet expansion. This connection is defined via a directional multiresolution analysis that provides successive refinements at both spatial and directional resolution. With parabolic scaling and sufficient directional vanishing moments,with cumulative density function and the contourlet is shown to achieve the optimal approximation rate for piecewise smooth images with smooth contours.

REFERENCES

[1] D. L. Donoho, M. Vetterli, R. A. DeVore, and I. Daubechies, “Data compression and harmonic analysis,” IEEE Trans. Inform. Th., vol. 44, no. 6, pp. 2435–2476, October 1998.

[2] S. Mallat, A Wavelet Tour of Signal Processing, 2nd ed. Academic Press, 1999.

[3] A. Skodras, C. Christopoulos, and T. Ebrahimi, “The JPEG 2000 still image compression standard,” IEEE Signal Processing Magazine,vol. 18, pp. 36–58, Sep. 2001.

[4] E. J. Cand`es and D. L. Donoho, “Curvelets – a surprisingly effectiveonadaptive representation for objects with edges,” in Curve and SurfaceFitting, A. Cohen, C. Rabut, and L. L. Schumaker, Eds. Saint-Malo:Vanderbilt University Press, 1999.

[5] ——, “New tight frames of curvelets and optimal representations of objects with piecewise C2 singularities,” Commun. on Pure and Appl. Math., pp. 219–266, Feb. 2004.

[6] D. H. Hubel and T. N. Wiesel, “Receptive fields, binocular interaction and functional architecture in the cat’s visual cortex,” Journal of Physiology, no. 160, pp. 106–154, 1962.

[7] B. A. Olshausen and D. J. Field, “Emergence of simple-cell receptive field properties by learning a sparse code for natural images,” Nature, pp. 607–609, 1996.

[8] M. Vetterli and J. Kovaˇcevi´c, Wavelets and Subband Coding. Prentice- Hall, 1995.

[9] E. J. Cand`es and D. L. Donoho, “Ridgelets: a key to higher-dimensional in termittency?” Phil. Trans. R. Soc. Lond. A., pp. 2495–2509, 1999.

[10] E. L. Pennec and S. Mallat, “Sparse geometric image representation with bandelets,” IEEE Trans. Image Proc., vol. 14, pp. 423–438, Apr. 2005.

[11] A. Cohen and B. Matei, "Compact representation of images by edge adapted multiscale transforms," in Proc. IEEE Int. Conf. on Image Proc., Special Session on Image Processing and Non-Linear Approximation, Thessaloniki, Greece, Oct. 2001.

[12] D. L. Donoho, "Wedgelets: nearly-minimax estimation of edges," Ann. Statist., vol. 27, pp. 859–897, 1999.

[13] M. B. Wakin, J. K. Romberg, H. Choi, and R. G. Baraniuk, "Ratedistortion ' optimized image compression using wedgelets," in Proc. IEEE Int. Conf. on Image Proc., Rochester, New York, Oct. 2002.

[14] R. Shukla, P. L. Dragotti, M. N. Do, and M. Vetterli, "Rate-distortion optimized tree structured compression algorithms for piecewise smooth images," IEEE Trans. Image Proc., vol. 14, pp. 343–359, Mar. 2005.

[15] J. Daugman, "Two-dimensional spectral analysis of cortical receptive field profile," Vision Research, vol. 20, pp. 847–856, 1980.

[16] A. B. Watson, "The cortex transform: Rapid computation of simulated neural images," Computer Vision, Graphics, and Image Processing, vol. 39, no. 3, pp. 311–327, 1987.

[17] E. P. Simoncelli, W. T. Freeman, E. H. Adelson, and D. J. Heeger, "Shiftable multiscale transforms," IEEE Transactions on Information Theory, Special Issue on Wavelet Transforms and Multiresolution Signal Analysis, vol. 38, no. 2, pp. 587–607, March 1992.

[18] J. P. Antoine, P. Carrette, R. Murenzi, and B. Piette, "Image analysis with two-dimensional continuous wavelet transform," Signal Processing, vol. 31, pp. 241–272, 1993.

[19] F. G. Meyer and R. R. Coifman, "Brushlets: A tool for directional image analysis and image compression," Journal of Appl. and Comput. Harmonic Analysis, vol. 5, pp. 147–187, 1997.

[20] N. Kingsbury, "Complex wavelets for shift invariant analysis and filtering of signals," Journal of Appl. and Comput. Harmonic Analysis, vol. 10, pp. 234–253, 2001.

[21] P. V. C. Hough, "Methods and means for recogninzing complex patterns," U.S. Patent 3069654, 1962.

[22] M. N. Do and M. Vetterli, "Pyramidal directional filter banks and curvelets," in Proc. IEEE Int. Conf. on Image Proc., Thessaloniki, Greece, Oct. 2001.

[23] 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, April 1983.

[24] R. H. Bamberger and M. J. T. Smith, "A filter bank for the directional decomposition of images: Theory and design," IEEE Trans. Signal Proc., vol. 40, no. 4, pp. 882–893, April 1992.

[25] Y. Lu and M. N. Do, "CRISP-contourlet: a critically sampled directional multiresolution image representation," in Proc. SPIE Conf. on Wavelet Applications in Signal and Image Processing, San Diego, Aug. 2003.

[26] M. N. Do and M. Vetterli, "Framing pyramids," IEEE Trans. Signal Proc., pp. 2329–2342, Sep. 2003.

[27] M. Vetterli, "Multidimensional subband coding: Some theory and algorithms," Signal Proc., vol. 6, no. 2, pp. 97–112, February 1984.

[28] S.-I. Park, M. J. T. Smith, and R. M. Mersereau, "Improved structures of maximally decimated directional filter banks for spatial image analysis,"IEEE Trans. Image Proc., vol. 13, pp. 1424–1431, Nov. 2004.

[29] M. N. Do, "Directional multiresolution image representations," Ph.D. dissertation, Swiss Federal Instituteof Technology, Lausanne, Switzerland, December 2001,http://www.ifp.uiuc.edu/˜minhdo/publications.

[30] R. R. Coifman, Y. Meyer, and M. V. Wickerhauser, “Wavelet analysisand signal processing,” in Wavelets and their Applications, M. B. R. et al, Ed. Boston: Jones and Barlett, 1992, pp. 153–178.

[31] A. L. Cunha and M. N. Do, “Bi-orthogonal filter banks with directional vanishing moments,” in Proc. IEEE Int. Conf. Acoust., Speech, and Signal Proc., Philadelphia, Mar. 2005.

[32] Xiao feng Li , Jun Xu, Jijun Luo, Lijia Cao, Shengxiu Zhang,"Intensity image denoising for laser active imaging system using nonsubsampled contourlet transform and SURE approach",Science direct ,Optik 123 (2012) 808– 813

[33] Xue Bi n, Xiang-dong Chen a, YuZhan c, BinLiu ,"Image compressed sensing based on wavelet transform in contourlet domain",Science direct ,Signal Processing91(2011)1085–1092

[34]Haijiang wang, QinkeYang ,n, RuiLi, "Tunable-Q contourlet-basedmulti sensorimagefusion",www.elsevier.com/locate/sigpro,Signal Processing93(2013)1879–1891.