IMAGE DE-NOISING USING DUAL-TREE COMPLEX WAVELET TRANSFORM FOR SATELLITE APPLICATIONS

Dinesh kumar[1] , DVS Nagendra kumar[2],

[1] *Student, Digital electronics and communication engineering ,MGIT ,Telangana , India*

[2] *Senior assistant professor, Electronics and communication , MGIT,Telangana, India*

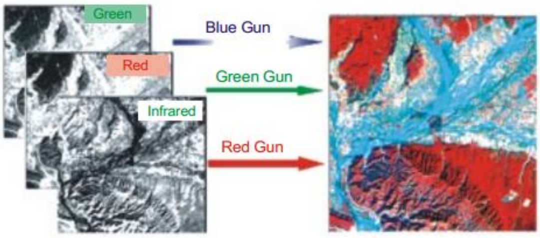
ABSTRACT

This paper presents a unique thanks to cut back noise introduced or exacerbated by image sweetening strategies; especially algorithms supported the random spray sampling technique, however not solely. Multi scale decomposition based on dual-tree complex wavelet transform and edge preservation is presented for SRE of the satellite images. Resolution enhancement schemes (which are not based on wavelets) suffer from the drawback of losing high frequency contents (which results in blurring). A wavelet-domain approach based on dual-tree complex wavelet transform (DT-CWT) and nonlocal means is used for RE of the satellite images. A satellite input image is decomposed by DT-CWT (which is nearly shift invariant) to obtain high-frequency sub bands. The high-frequency sub band and the low-resolution (LR) input image are interpolated using the bi-cubic interpolator. The result's a map of the directional structures gift within the non-enhanced image. Same map is then wont to shrink the coefficients of the improved image. The contracted coefficients and also the coefficients from the non-enhanced image area unit then mixed in keeping with information radial asymmetry. The simulated results will show that technique used in this process provides better accuracy rather than prior methods.

Keywords:-Satellite Resolution Enhancement DTCWT, low-Resolution, Interpolator, Accuracy.

INTRODUCTION:-

Multi-spectral satellite imagery is an economical, precise and appropriate method of obtaining information on land use and land cover since they provide data at regular intervals and is economical when compared to the other traditional methods of ground survey and aerial photography. Classification of multispectral remotely sensed data is investigated with a special focus on uncertainty analysis in the produced land-cover maps. To humans, an image is not just a random collection of pixels; it is a meaningful arrangement of regions and objects. There also exits a variety of images: natural scenes, paintings, etc.



Once the image has been digitized, there are three basic operations that can be performed on it in the computer. For a point operation, a pixel value in the output image depends on a single pixel value in the input image. For local operations, several neighboring pixels in the input image determine the value of an output image pixel. In a global operation, all of the input image pixels contribute to an output image pixel value. These operations, taken singly or in combination, are the means by which the image is enhanced, restored, or compressed. An image is enhanced when it is modified so that the information it contains is more clearly evident, but enhancement can also include making the image more visually appealing. Additionally, matching between primitives can be efficiently computed (e.g., with geometric properties), unlike contour fragments, which require comparisons between individual edge pixels. Finally, as geometric properties are easily scale normalized, they simplify matching across scales.

This has led to the invention of hyper spectral remote sensing techniques to proffer solutions to the mixed pixel problem in remotely sensed imagery. Hyper spectral images have been used in many real applications because of their rich sources of information. Examples of the useful applications of hyper spectral imaging include mineral exploration, urban processes, agriculture, risk prevention, land cover mapping, surveillance system, resource management, tracking wildfires, detecting biological threats and chemical contamination (Hall *et al*. 1991; Ellis 2001; Lacar *et al*. 2001; Zhang *et al*. 2011). These images provide abundant spectral information to identify and differentiate between spectrally similar, but unique materials. They provide potential, detailed and accurate information extraction as compared to other remotely sensed data (Karaka *et al*. 2004). In addition, hyper spectral images provide a high-resolution reflectance spectrum for each pixel in the image (Boardman *et al*. 1995). As a result, large scale land cover maps constructed from remotely sensed data have become important information sources (Boardman *et al*. 1995).

Image enhancement techniques are the algorithms which improve the quality of images by removing blurring and noise, increasing contrast and sharpness of digital medical images. There are many image enhancement approaches (theories) like Contrast stretching, Range compression, Histogram equalization and noise smoothing. A certain amount of trial and error usually is required before a particular image enhancement approach is selected. There is no general theory of image enhancement. When an image is processed for visual interpretation, the viewer is the ultimate judge of how well a particular method works.

Visual evaluation of image quality is a highly subjective process.

LITERATURE SURVEY

Image denoising in steerable pyramid domain based on a local Laplace prior

This paper presents a new image denoising algorithm based on the modeling of coefficients in each subband of steerable pyramid employing a Laplacian probability density function (pdf) with local variance. This pdf is able to model the heavy-tailed nature of steerable pyramid coefficients and the empirically observed correlation between the coefficient amplitudes. Within this framework, we describe a novel method for image denoising based on designing both maximum a posteriori (MAP) and minimum mean squared error (MMSE) estimators, which relies on the zero-mean Laplacian random variables with high local correlation. Despite the simplicity of our spatially adaptive denoising method, both in its concern and implementation, our denoising results achieves better performance than several published methods such as Bayes least squared Gaussian scale mixture (BLS-GSM) technique that is a state-of-the-art denoising technique.

Spectral Clustering Ensemble Applied to SAR Image Segmentation

Spectral clustering (SC) has been used with success in the field of computer vision for data clustering. In this paper, a new algorithm named SC ensemble (SCE) is proposed for the segmentation of synthetic aperture radar (SAR) images. The gray-level cooccurrence matrix-based statistic features and the energy features from the undecimated wavelet decomposition extracted for each pixel being the input, our algorithm performs segmentation by combining multiple SC results as opposed to using outcomes of a single clustering process in the existing literature. The random subspace, random scaling parameter, and Nyström approximation for component SC are applied to construct the SCE. This technique provides necessary diversity as well as high quality of component learners for an efficient ensemble. It also overcomes the shortcomings faced by the SC, such as the selection of scaling parameter, and the instability resulted from the Nyström approximation method in image segmentation. Experimental results show that the proposed method is effective for SAR image segmentation and insensitive to the scaling parameter.

EXISTING METHOD ANALYSIS

The overall assumption in multi-resolution shrinkage is that image information provides rise to thin coefficients within the remodel house. Thus, American state noising is achieved by compression (shrinking) those coefficients that compromise information inadequacy. Such method is sometimes improved by associate degree elaborate applied mathematics analysis of the dependencies between coefficients at totally different scales. Yet, whereas effective, ancient multi-resolution strategies area unit designed to solely take away one explicit style of noise (e.g. mathematician noise).

Discrete Wavelet Transform

Discrete Wavelet transform (DWT) is a mathematical tool for hierarchically decomposing an image. The DWT decomposes an input image into four components labeled as LL, HL, LH and HH [9]. The first letter corresponds to applying either a low pass frequency operation or high pass frequency operation to the rows, and the second letter refers to the filter applied to the columns. The lowest resolution level LL consists of the approximation part of the original image. The remaining three resolution levels consist of the detail parts and give the vertical high (LH), horizontal high (HL) and high (HH) frequencies.

Figure 3 shows three-level wavelet decomposition of an image.

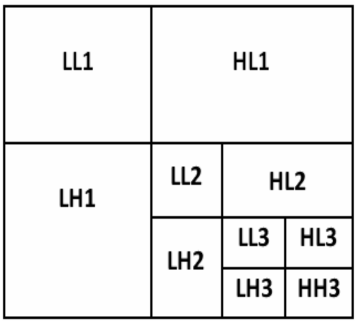
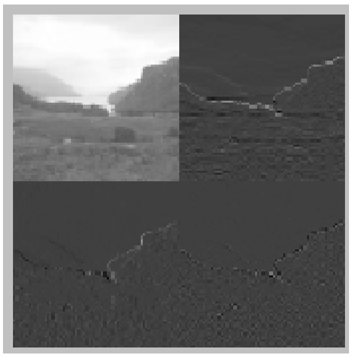
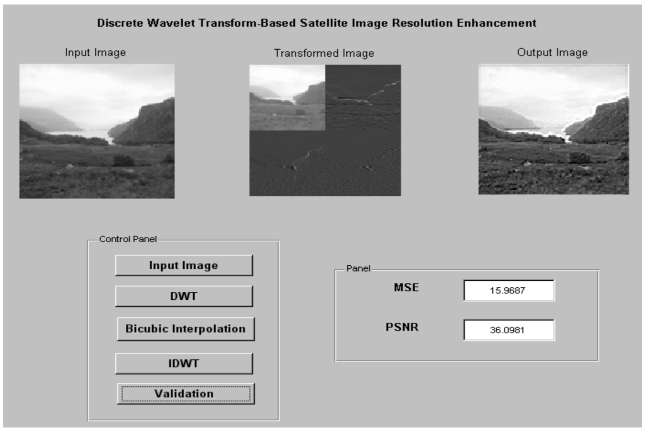


Figure7: Three-level Discrete Wavelet Transform.

The black and white mask from the segmentation step was used to determine which coefficient to select from the transformed image. Typically, discrete multi dimensional wavelet transforms produce a wavelet matrix half the size of the original image using a technique called down-sampling where only half the coefficients are preserved.



In order to maintain the original image size, a discrete wavelet transformation was used which suppresses down-sampling, producing a wavelet matrix the same size as the input matrix. For both levels, the mean and variance of wavelet coefficients for approximations and details were calculated, resulting in a total of 8 features. Features were then normalized to range between 0 and 1.



PROPOSED METHOD ANALYSIS

Image enhancement techniques improve the quality of an image as perceived by a human. These techniques are most useful because many satellite images when examined on a colour display give inadequate information for image interpretation. There is no conscious effort to improve the fidelity of the image with regard to some ideal form of the image. There exists a wide variety of techniques for improving image quality. Image enhancement methods are applied separately to each band of a multispectral image. Contrast ratio has a strong bearing on the resolving power and delectability of an image. Larger this ratio, more easy it is to interpret the image. Satellite images lack adequate contrast and require contrast improvement.

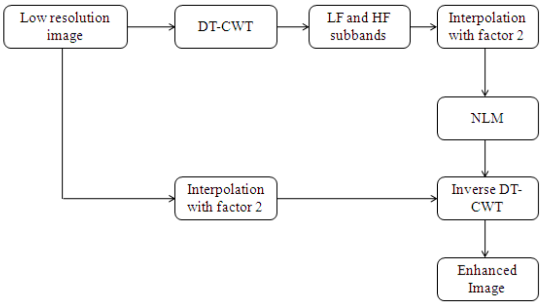


Image Preparation

Digital images of melanoma and benign nevi were collected in JPEG format from different sources totaling 72, half melanoma and half benign. MATLAB's Wavelet Toolbox only supports indexed images with linear monotonic color maps

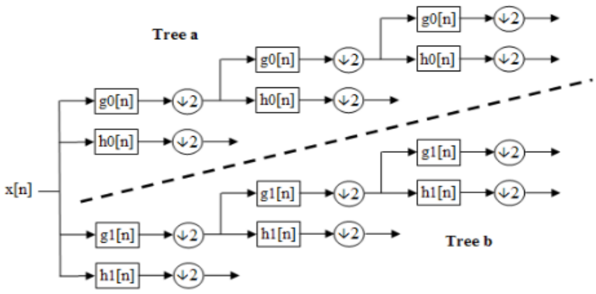
so the RGB images were converted to grayscale images. The next step in the process was to segment the lesion from the surrounding skin. Since a clear color distinction existed between lesion and skin, thresholding was very suitable for this task. A black and white image was produced and its size increased by six pixels all around in order to include the entire border region in the segmented image.

Pre-Processing:-

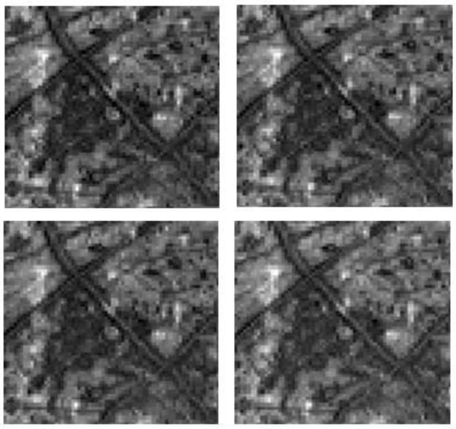
The *L** axis represents *Lightness*. This is vertical; from 0, which has no lightness (i.e. absolute black), at the bottom; through 50 in the middle, to 100 which is maximum lightness (i.e. absolute white) at the top. The *c** axis represents *Chrome* or 'saturation'. This ranges from 0 at the centre of the circle, which is completely unsaturated (i.e. a neutral grey, black or white) to 100 or more at the edge of the circle for very high Chrome (saturation) or 'colour purity'. The *h** axis represents *Hue*. If we take a horizontal slice through the centre, cutting the 'sphere' ('apple') in half, we see a coloured circle. Around the edge of the circle we see every possible saturated colour, or *Hue*. This circular axis is known as *h°* for *Hue*. The units are in the form of degrees° (or angles), ranging from 0° (red) through 190° (yellow), 80° (green), 270° (blue) and back to 0°.

Dual-Tree Complex Wavelet Transforms (DT-CWT)

The dual-tree complex wavelet transform (CWT) is a relatively recent enhancement to the discrete wavelet transform (DWT), with important additional properties: It is nearly shift invariant and directionally selective in two and higher dimensions. It achieves this with a redundancy factor of only 2*d* for *d*-dimensional signals, which is substantially lower than the un decimated DWT.

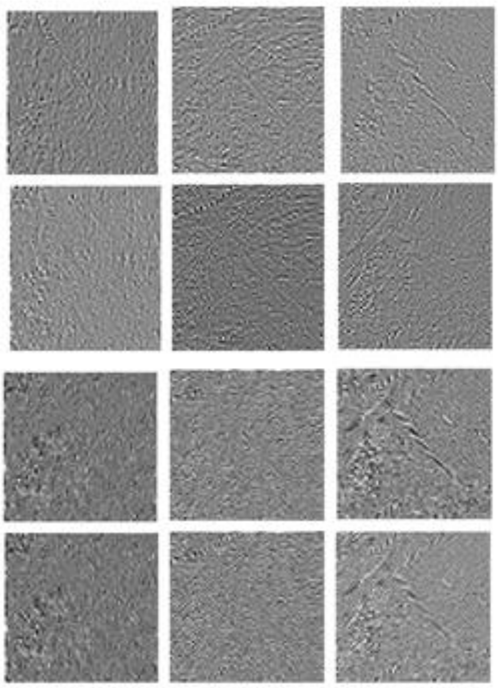


The multidimensional (M-D) dual-tree CWT is non separable but is based on a computationally efficient, separable filter bank (FB).



DTCWT Decomposition: Low frequency Co-Efficient

In the neighborhood of an edge, the real DWT produces both large and small wavelet coefficients In contrast, the (approximately) analytic CWT produces coefficients whose magnitudes are more directly related to their proximity to the edge. The theory behind the dual-tree transforms shows how complex wavelets with good properties can be designed, and illustrates a range of applications in signal and image processing.



DTCWT Decomposition: High frequency Co-Efficient

INTERPOLATION

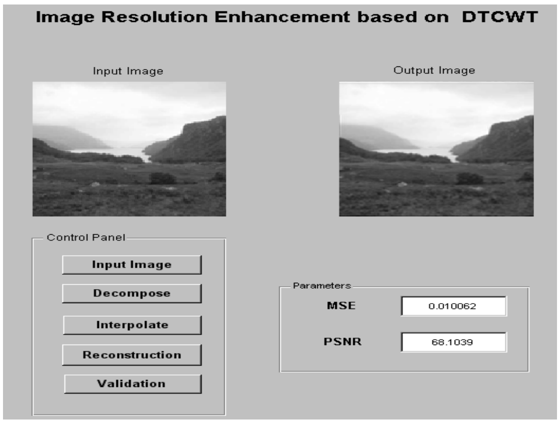
Interpolation is way through which images are enlarged. There are many different types of interpolation methods, each resulting in a different to the final picture. Thus, it is best if the quality, or visible distinction for each pixel, is retained throughout the enlargement process. Thus, one cannot simply have a number of pixels directly represent a single original pixel; this is not sufficient for commercial use. Conspicuous blocks of single color will be visible, and depending on size of enlargement, the original image will be unrecognizable. Cubic Convolution Interpolation determines the grey level value from the weighted average of the 16 closest pixels to the specified input coordinates, and assigns that value to the output coordinates. The image is slightly sharper than that produced by Bilinear Interpolation, and it does not have the disjointed appearance produced by Nearest Neighbor Interpolation. Expectation Maximization (EM) algorithm was used to train the Markov tree model. The algorithm essentially works by finding the set of parameters which would most likely result in the set of observed wavelet coefficients.

Analysis using Filter Banks

Filters are one of the most widely used signal processing functions. Wavelets can be realized by iteration of filters with rescaling. The resolution of the signal, which is a measure of the amount of detail information in the signal, is determined by the filtering operations, and the scale is determined by up sampling and down sampling (sub sampling) operations.

Noise reduction we can do in two steps.

For plain image we have to add some noise and applying filtering concept we have to remove noise. In second step we can remove the noise for existing noisy image.



ADVANTAGES:

- Very economical
- Shrunk with the coefficients provides reduced noise firmly.
- Produces sensible quality output.
- Removing noise while not sterilization the underlying directional structures in the image. Also, verified effective on compression and latent noise delivered to the surface by bar graph exploit.

Quality Measurement:-

The Quality of the reconstructed image is measured in-terms of mean sq. error (MSE) and peak signal to noise magnitude relation (PSNR) magnitude relation. The MSE is commonly known as reconstruction error variance □ q2. The MSE between the initial image f and therefore the reconstructed image g at decoder is outlined as:

$$\textbf{MSE} = \frac{1}{MXN}\sum_{j,k}(f[j,k]-g[j,k])$$

Where the total over j, k denotes the total over all pixels within the image and N is that the variety of pixels in every image.

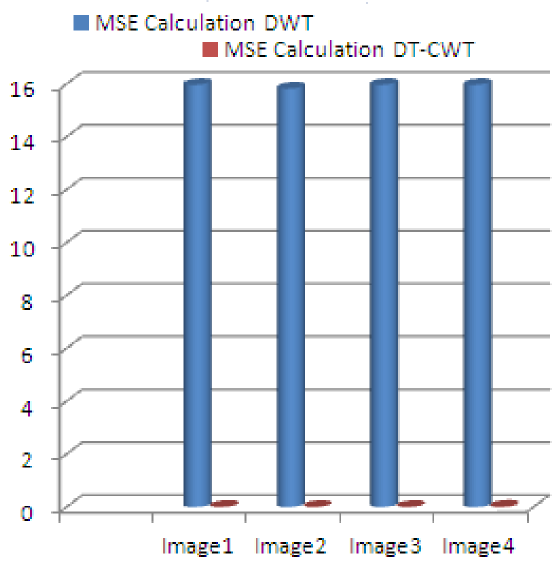
MSE Calculation		
METHOD	DWT	DT-CWT
Image1	15.9687	0.013136
Image2	15.8278	0.010133
Image3	15.9687	0.010062
Image4	15.9684	0.019991

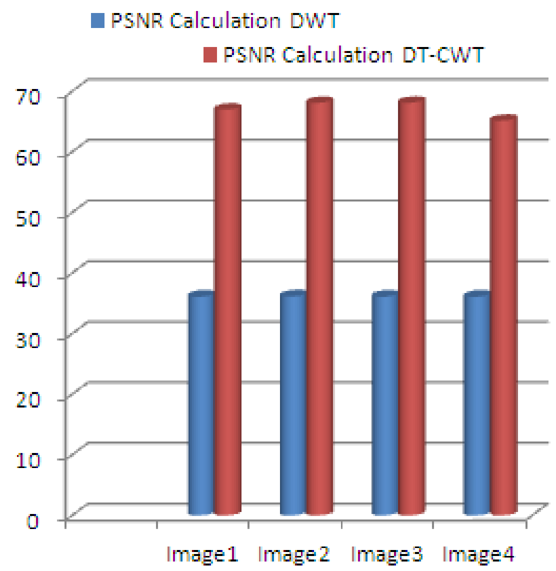
From that the height {signal-to-noise magnitude relation|signal-to-noise|signal/noise ratio|signal/noise|S/N|ratio} is outlined because the ratio between signal variance and reconstruction error variance. The PSNR between 2 pictures having eight bits per pel in terms of decibels (dB) is given by:

$$\textbf{PSNR = 10 log}_{10}\left(\frac{255^2}{MSE}\right)$$

PSNR Calculation		
METHOD	DWT	DT-CWT
Image1	36.0981	66.9461
Image2	36.1366	68.0736
Image3	36.0981	68.1039
Image4	36.0982	65.1224

Generally once PSNR is twenty decibel or larger, then the initial and therefore the reconstructed pictures ar just about in-distinguishable by human eyes.





Conclusion

In Our Project the shape detected guided wrapping and smoothing filters succeeded in enhancing low contrast satellite images. The noise reduction technique supported twin Tree advanced riffle remodel coefficients shrinkage. the most purpose of novelty is delineate by its application in post-processing on the output of a picture sweetening technique (both the non increased image and also the increased one area unit required) and also the lack of assumptions on the distribution of noise. It is presented that dual tree complex wavelet transform better compatible to provide texture and edges of an image from different orientation . It was proved that an low resolution remote sensing image is enhanced to better visual perception by interpolating at high frequency sub bands and it reduces the problem of blocking and ringing artifacts because of its shift invariant property. Here, Edge preservation filtering named as non local means filter also used for This module involves Difference image generation using Image fusion and neural network based segmentation technology.On the opposite hand, the non-enhanced image is meant to be noise-free or laid low with non perceivable noise.

Future Scope:-

This resolution enhancement can further improve with Lenclos based up-sampling and Gabor filtering for texture characterization. Up-sampling reduces the distortion of detailed information and Gabor provides detail, structure components at different orientations using Satellite Images.

REFERENCES

[1] H. Demirel and G. Anbarjafari, "Discrete wavelet transform-based satellite image resolution enhancement," *IEEE Trans Geosci. Remote Sens.*, vol. 49, no. 6, pp. 1997–2004, Jun. 2011.

[2] H. Demirel and G. Anbarjafari, "Image resolution enhancement by using discrete and stationary wavelet decomposition," *IEEE Trans. Image Process.*,
vol. 20, no. 5, pp. 1458–1460, May 2011.

[3] H. Demirel and G. Anbarjafari, "Satellite image resolution enhancement using complex wavelet transform," *IEEE Geosci. Remote Sens. Lett.*, vol. 7, no. 1, pp. 123–126, Jan. 2010.

[4] H. Demirel and G. Anbarjafari, "Image super resolution based on interpolation of wavelet domain high frequency

subbands and the spatial domain input image," *ETRI J.*, vol. 32, no. 3, pp. 390–394, Jan. 2010.

[5] X. Chen, C. Deng, and S. Wang, "Shearlet-based adaptive shrinkage threshold for image denoising," in Proc. Int. Conf. E-Bus. E-Government, Nanchang, China, May 2010, pp. 1616–1619.

[6] J. Zhao, L. Lu, and H. Sun, "Multi-threshold image denoising based on shearlet transform," Appl. Mech. Mater., vols. 29–32, pp. 2251–2255, Aug. 2010. technique for shift invariance and directional filters," in Proc. 8th IEEE Digit. Signal Process. Workshop, Aug. 1998, no. 86, pp. 1–4.

[7] Y. Piao, I. Shin, and H. W. Park, "Image resolution enhancement using inter-subband correlation in wavelet domain," in *Proc. Int. Conf. Image Process.*, San Antonio, TX, 2007, pp. I-445–I-448.

[8] C. B. Atkins, C. A. Bouman, and J. P. Allebach, "Optimal image scaling using pixel classification," in *Proc. Int. Conf. Image Process.*, Oct. 7–10, 2001, pp. 864–867.

[9] A. S. Glassner, K. Turkowski, and S. Gabriel, "Filters for common resampling tasks," in *Graphics Gems*. New York: Academic, 1990, pp. 147–165.

[10] D. Tschumperle and R. Deriche, "Vector-valued image regularization with PDE's: A common framework for different applications," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 27, no. 4, pp. 506–517, Apr. 2005.

[11] A. Gambardella andM.Migliaccio, "On the super resolution of microwave scanning radiometer measurements," *IEEE Geosci. Remote Sens. Lett.*, vol. 5, no. 4, pp. 796–800, Oct. 2008.

[12] A. Buades, B. Coll, and J. M. Morel, "A review of image denoising algorithms,
with a new one," *Multisc. Model. Simul.*, vol. 4, no. 2, pp. 490– 530, 2005.

[13] I. W. Selesnick, R. G. Baraniuk, and N. G. Kingsbur, "The dual-tree complex wavelet transform," *IEEE Signal Prcess. Mag.*, vol. 22, no. 6, pp. 123–151, Nov. 2005.