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Use Of Curvelet Transform in Digital Image Hiding

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Abstract

Curvelet transform is a multiscale transform in which elements are highly anisotropic at fine scales. In this paper we present digital image hiding using curvelet transform. The curvelet transform, which featured multiscale directional transform can overcome the disadvantage i.e. isotropic and less coefficients and reach better approximation results. Here our work is to reduce the complexity and cost and provide better thresholding function.

Key Terms**—**Curvelets, Curvelet transform, wavelets, digital image hiding, image recovering.

1. Introduction

A. Background

Digital image hiding is a two dimensional numeric representation of image. One important task is that the values of these matrises are adjusted to get clear feature in images. Digital image hiding is the art of hiding information in digital media for various purposes such as annotation, identification, copyright and so on. The main challenge is how to build suitable mathematical models for practical requirements. Taking image denoising as an example, many mathematical models are based on a frequency partition of the image, where components with high frequency are interpreted as noise that have to be removed while those with low frequency are seen as features to be remained. Curvelets, which are going to be reviewed in this paper, can be seen as an effective model that not only considers a multiscale time-frequency local partition but also makes use of the direction of features.

Gibbs phenomenon says that discontinuities destroy the sparsity of Fourier series, we need many, many terms to reconstruct a discontinuity to within good accuracy. Wavelets, because they are localized and multiscale, do much better in one dimension, but because of their poor orientation selectivity, they do not represent higher-dimensional singularities effectively. What makes curvelets interesting and actually motivated their development is that they provide a mathematical architecture that is ideally adapted for representing objects which display *curvepunctuated smoothness*—smoothness except for discontinuity along a general curve with bounded curvature—such as images with edges, for example. The curvelet transform is organized in such a way that most of the energy of the object is localized in just a few coefficients. There is no basis in which coefficients of an object with an arbitrary singularity curve would decay faster than in a curvelet frame. This rate of decay is much faster than that of any other known system, including wavelets. Improved coefficient decay gives optimally sparse representations that are interesting in imageprocessing applications, where sparsity allows for better image reconstructions or coding algorithms.

Let us roughly compare the curvelet system with the conventional Fourier and wavelet analysis. The short-time Fourier transform uses a shape-fixed rectangle in Fourier domain, and conventional wavelets use shape-changing (dilated) but area-fixed windows. By contrast, the curvelet transform uses angled polar wedges or angled trapezoid windows in frequency domain in order to resolve also directional features.

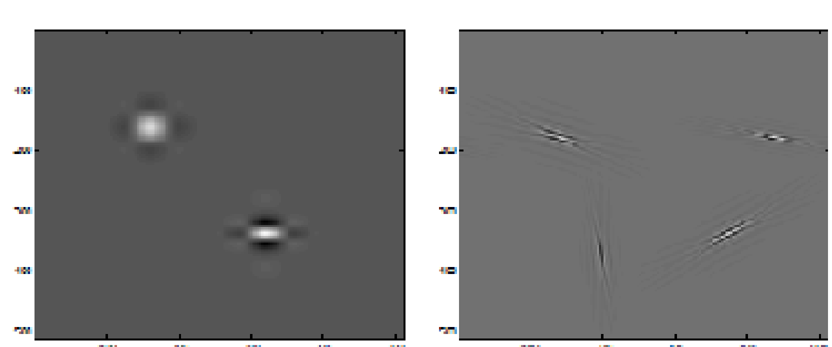

Figure 1 The elements of wavelets (left) and curvelets on various scales, directions and translations in the spatial domain(right). [6]

B. Challenges

B.1 Difference between Wavelets and Curvelets

Wavelets generalize the Fourier transform by using a basis that represents both location and spatial frequency. For 2D or 3D signals, directional wavelet transforms go further, by using basis functions that are also localized in *orientation*. A curvelet transform differs from other directional wavelet transforms in that the degree of localisation in orientation varies with scale. In particular, fine-scale basis functions are long ridges; the shape of the basis functions at scale *j* is 2^{-j} by $2^{-j/2}$ so the fine-scale bases are skinny ridges with a precisely determined orientation.

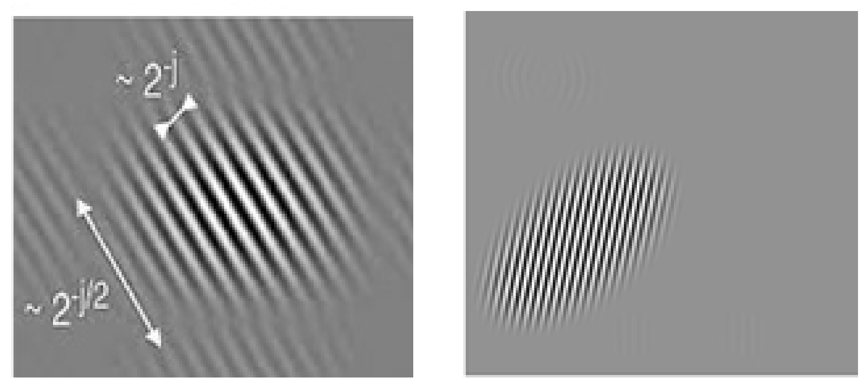

Figure 2 Curvelet transform and Wavelet transform

Curvelets are an appropriate basis for representing images (or other functions) which are smooth apart from singularities along smooth curves, *where the curves have bounded curvature*, i.e. where objects in the image have a minimum length scale. This property holds for cartoons, geometrical diagrams, and text. As one zooms in on such images, the edges they contain appear increasingly straight. Curvelets take advantage of this property, by defining the higher resolution curvelets to be more elongated than the lower resolution curvelets. However, natural images (photographs) do not have this property; they have detail at every scale. Therefore, for natural images, it is preferable to use some sort of directional wavelet transform whose wavelets have the same aspect ratio at every scale.

The major advantage of the curvelet transforms compared to the wavelet is that the edge discontinuity is better approximated by curvelets than wavelets. Curvelets can provide solutions to the limitations that are apparent in wavelet transform and summarized as follows:

- Curved singularity representation,
- Limited orientation (Vertical, Horizontal and Diagonal)
- And absence of anisotropic element (isotropic scaling)

Figure 3 shows the edge representation of wavelet and curvelet curves. More wavelets are required for an edge representation using the square shape of wavelets at each scale, compared to the number of required curvelets, which are of an elongated needle shape. The main idea here is that the edge discontinuity is better approximated by curvelets than wavelets. Curvelets can provide solutions for the limitations (curved singularity representation, limited orientation and absence of anisotropic element) existing in the wavelet transform.

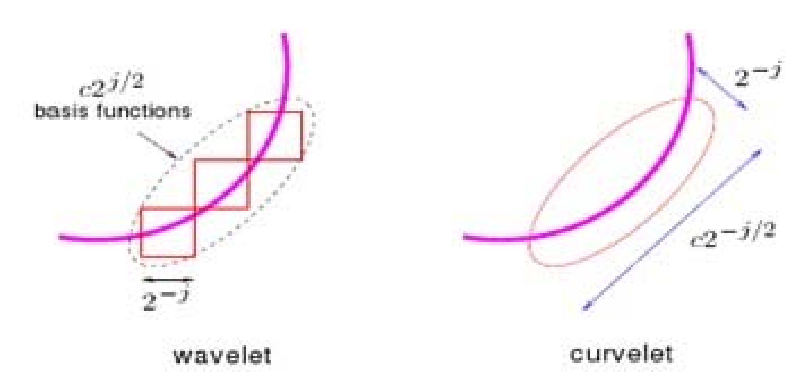

Figure 3 Edge representation of Wavelet curves and Curvelet curves

B.2 Curvelets for what ?

The success of wavelets saw the rapid development of a new field, computational harmonic analysis, which aims to develop new systems for effectively representing phenomena of scientific interest. The curvelet transform is a recent addition to the family of mathematical tools this community enthusiastically builds up. In short, this is a new multiscale transform with strong directional character in which elements are highly anisotropic at fine scales, with effective support shaped according to the parabolic scaling principle length2 ~ width. An important property is that curvelets obey the principle of harmonic analysis stating that it is possible to analyze and reconstruct an arbitrary function $f(x1, x2)$ as a superposition of such templates. One can, indeed, easily expand an arbitrary function $f(x1, x2)$ as a series of curvelets, much like an expansion in an orthonormal basis.

Curvelets partition the frequency plane into dyadic coronae and (unlike wavelets) subpartition those into angular wedges which again display the parabolic aspect ratio. Hence, the curvelet transform refines the scale-space viewpoint by adding an extra element, orientation, and operates by measuring information about an object at specified scales and locations but only along specified orientations.

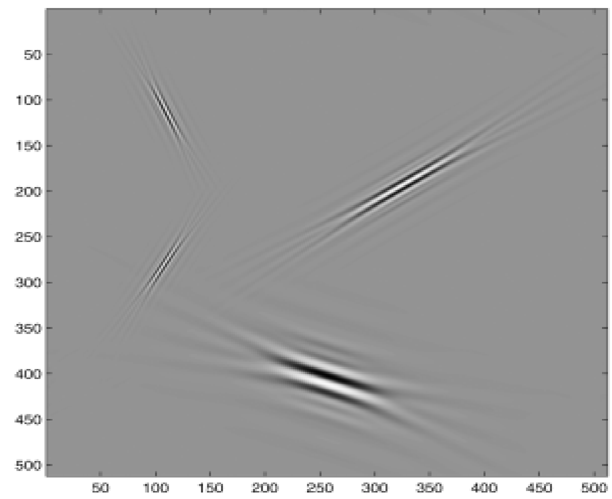

Figure 4 Some curvelets at different scales

II. Related Work

Candes and Donoho proposed curvelet transform which is used for many different applications in image processing, seismic data exploration, fluid mechanics, and solving partial different equations (PDEs). The strength of the curvelet approach is their ability to formulate strong theorems in approximation and operator theory. The discrete curvelet transform is very efficient in representing curve-like edges.

YongHong Zhang proposed Digital Image hiding using curvelet transform where Arnold transform is applied to original image and then curvelet Transform is applied to the original image and the open image, gaining their curvelet coefficients. The curvelet coefficients are then interpolated and fiinally, the image is reconstructed by using Inverse curvelet Transform, and thus get the result image.

The steerable wavelets were built based on directional derivative operators (i.e., the second derivative of a Gaussian),
the steerable wavelets provide translation-invariant and rotation-invariant representations of the position and the orientation of considered image structures. This feature is paid by high redundancy. Both the curvelet and shearlet transforms are (at least theoretically) similarly well suited for approximation of piece-wise smooth images with singularities along smooth curves.

The Gabor wavelets were produced by a Gabor kernel that is a product of an elliptical Gaussian and a complex plane wave. Applications of Gabor wavelets focused on image classification and texture analysis. Gabor wavelets have also been used for modeling the receptive field profiles of cortical simple cells. Applications of Gabor wavelets suggested that the precision in resolution achieved through redundancy may be a relevant issue in brain modeling, and that orientation plays a key role in the primary visual cortex.

Contourlets, as proposed by Do and Vetterli, form a discrete filter bank structure that can deal effectively with piecewise smooth images with smooth contours. This discrete transform can be connected to curvelet-like structures in the continuous domain. Hence, the contourlet transform can be seen as a discrete form of a particular curvelet transform.

Ma et al. applied curvelets for motion estimation and video tracking of geophysical flows and deblurring. Ma and Plonka presented two different models for image denoising by combining the discrete curvelet transform with nonlinear diffusion schemes. In the first model, a curvelet shrinkage is applied to the noisy data, and the result is further processed by a projected total variation diffusion to suppress pseudo-Gibbs artifacts. In the second model, a nonlinear reaction-diffusion equation is applied, where curvelet shrinkage is used for regularization of the diffusion process.

III. PROPOSED METHOD

The proposed system, converts the image into curvelet transform numerical representation and then vice-versa operation is made to get the original image. The work to be done here is to reduce complexity and to obtain better thresholding function so that the isotropic and less coefficients are needed to account for image edge and reach better Approximation Rates. Better thresholding function include edge detection,image denoising and numerical simulation. The curvelet transform is a very young signal analyzing method with good potential. It is recognized as a milestone on image processing and other applications.

A .Digital Image Hiding

Digital Image Hiding is the art of hiding information in digital media for various purposes such as identification, annotation, copyright and so on. This prevents the outside observer from recognizing the presence of hidden information. There are many ways to hide information in images. Any text, image, or anything that can be embedded in a bit stream can be hidden in an image. Here in this paper, as mentioned above, the technique used is curvelet transform which represents the latest research result on multi -resolution analysis. The image will remain hidden until the user performs some action that requires it to be displayed.

The hidden image should be recovered. No two image recovery situations are alike. So, here we use inverse curvelet transform method to recover the hidden image.

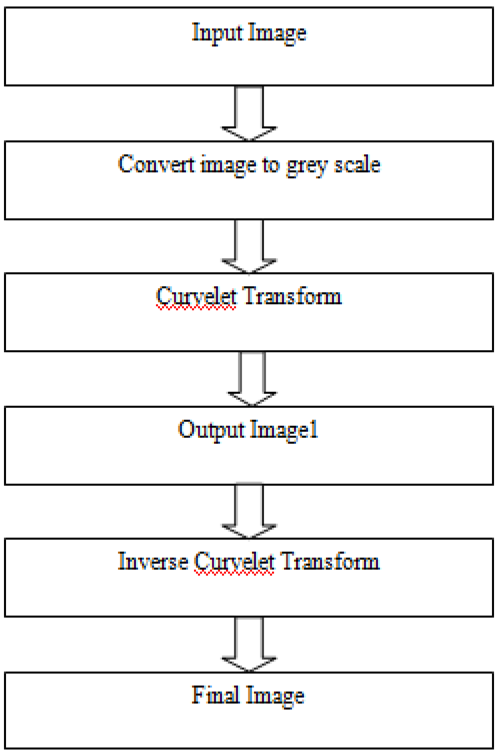

Figure 5 Steps of digital image hiding

A. Input Image:

It means capturing the image and give input to the OpenCV library for further processing. The method for giving input:

By using a webcam
We are using following OpenCV library function for giving input by webcam :

*CvCapture *fc = cvCaptureFromCAM (0);*

B. Convert The RGB Image Into Gray Level:

This step is for converting the colored image (RGB image) into gray level. In order to reduce the processing time, a grayscale image is used on entire process instead of the color image. This is done because it is difficult to work on 3 channel image (color image),so we are converting it into a single channel (gray scale) image.
For converting the RGB image into a gray level image there is a function in opencv library:
CvCvtColor (imgin, imgt1, CV_BGR2GRAY);

C. Curvelet Transform

Energized by the success of wavelets, the last two decades saw the rapid development of a new field, computational harmonic analysis, which aims to develop new systems for effectively representing phenomena of scientific interest. The curvelet transform is a recent addition to the family of mathematical tools this community enthusiastically builds up.

Based on the curvelet transform theory a new implementation for detecting edges will be introduced depending on the fact that the values of curvelet coefficients are determined by how they are aligned in the real image, the more accurately a curvelet is aligned with a given curve in an image; the higher is its coefficient value. Analyzing these coefficients, it can be found that the coefficient in each scale level contains different information. Consequently, by arranging the coefficients of each level and take the most significant part of them, this will enhance the edge information that represents the important part of the image to us. Then, the coefficients are

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reconstructed to get a new image where the edge parts are enhanced. Morphological filters will be applied to remove the undesired noisy pixels.

C.1 Steps of curvelet transform

The Figure.6 shows the steps carried out to convert the image into curvelet transform.

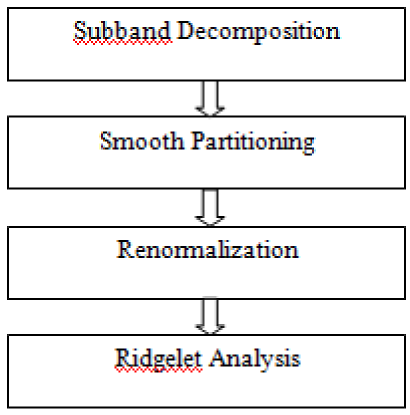


Figure 6 Steps of Curvelet transform

C.1.1 Subband Decomposition:

This step divides the image into severel resolution layers. Each layer contains details of different frequencies:

- P_0 → **Lowpass filter**
- $\Delta_1, \Delta_2, \ldots$ **– Band-pass (high-pass) filters.**

$$f \mapsto (P_0 f, \Delta_1 f, \Delta_2 f, \ldots)$$

So the original image can be reconstructed from the sub-bands

$$f = P_0(P_0 f) + \sum_s \Delta_s(\Delta_s f)$$

Example of **Subband Decomposition**:[4]

$$f \mapsto (P_0 f, \Delta_1 f, \Delta_2 f, \ldots)$$

$P_0 f$ $\Delta_1 f$ $\Delta_2 f$

C.1.2 Smooth *Partitioning*

It is define a collection of smooth window $\mathbf{w_Q(x_1, x_2)}$ localized around dyadic squares:

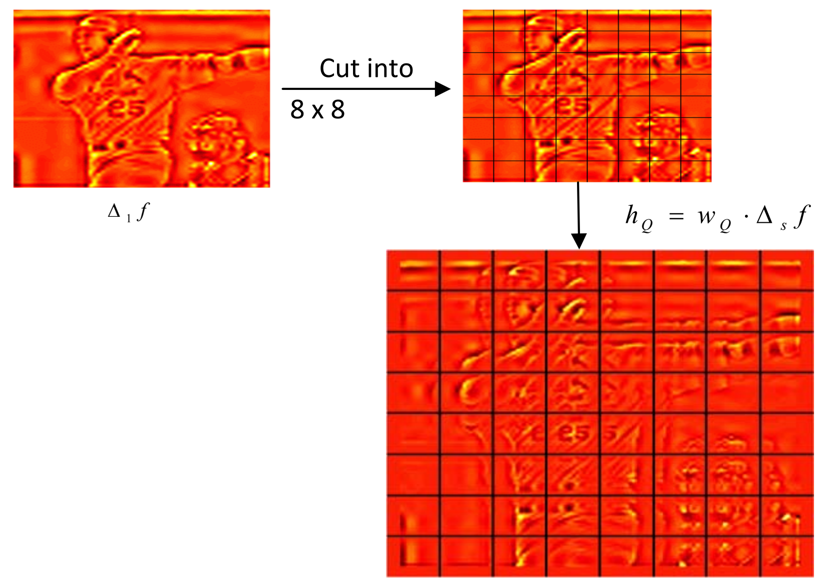
$$Q_{(s,k_1,k_2)} = \left[\frac{k_1}{2^s}, \frac{k_1+1}{2^s}\right] \times \left[\frac{k_2}{2^s}, \frac{k_2+1}{2^s}\right] \in \mathbf{Q}_s$$

Let **w** be a smooth windowing function with 'main' support of size $2^{-s} \times 2^{-s}$. Multiplying a funtion by the corresponding window function $\mathbf{w_Q}$ produces a result localized near Q ($\forall\, Q \in Q_s$). Doning this for all Q at a certain scale, i.e. all Q=Q(s , k_1 , k_2) with k_1 and k_2 varying but s fixed, procedure, we apply this windowing dissection to each of the subbands isolated in the previous stage of the algorithm. And this step produces a smooth dissection of the function into 'squares'.

$$h_Q = w_Q \cdot \Delta_s f$$

Example of **Smooth Partitioning**: [4]

Take the $\Delta_1 f$ part of last example to apply Smooth Partitioning



The image become smooth after multiplying $\mathbf{w_Q}$ function. The partitioning make us more easier to analyze local line or curve singularities.

C.1.3 Renormalization

For a dyadic square Q, let

$$T_Q f(x_1, x_2) = 2^s f(2^s x_1 - k_1, 2^s x_2 - k_2)$$

denote the operator which transports and renormalizes f so that the part of the input supported near Q becomes the part of the output supported near [0,1]×[0,1]. In this stage of the procedure, each 'square' resulting in the previous stage is renormalized to unit scale:

$$g_Q = T_Q^{-1} h_Q$$

C.1.4 Ridgelet Analysis

The ridgelet consturction divides the frequency domain to dyadic coronae $|\xi| \in [2^s, 2^{s+1}]$. In the angular direction, it samples the *s*-th corona at least 2^s times. In the radial direction, it samples using local wavelets.

The ridgelet element has a formula in the frequency domain:

$$\hat{\rho}_\lambda(\xi) = \tfrac{1}{2}|\xi|^{-\frac{1}{2}}\left(\hat{\psi}_{j,k}(|\xi|)\cdot \omega_{i,l}(\theta) + \hat{\psi}_{j,k}(-|\xi|)\cdot \omega_{i,l}(\theta+\pi)\right)$$

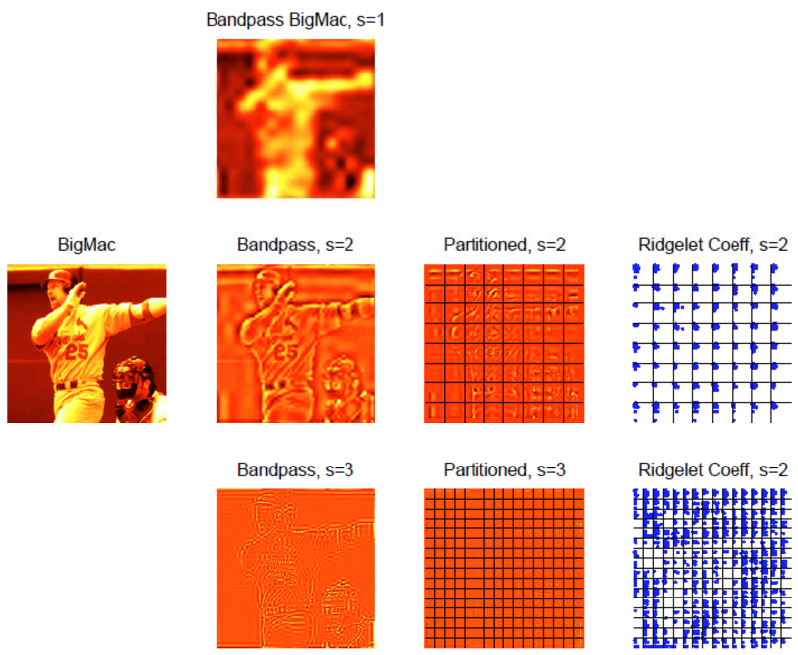
- $\omega_{i,l}$: periodic wavelets for **[**$-\pi, \pi$**)**.
- i : the angular scale , $l \in [0, 2^{i-1}-1]$: the angular location.
- $\psi_{j,k}$: Meyer wavelets for $\Re$.
- j : the ridgelet scale , k : the ridgelet location.

Each normalized square is analyzed in the ridgelet system:

$$\alpha_{(Q,\lambda)} = \langle g_Q, \rho_\lambda \rangle$$

- The ridge fragment has an aspect ratio of $2^{-2s} \times 2^{-s}$.
- After the renormalization, it has localized frequency in band $|\xi| \in [2^s, 2^{s+1}]$.
- A ridge fragment needs only a very few ridgelet coefficients to represent it.

Example of **Ridgelet Analysis: [4]**



D.Output Image

The output image is the image obtained after applying curvelet transform to the image.

Below figure shows an image after applying curvelet transform

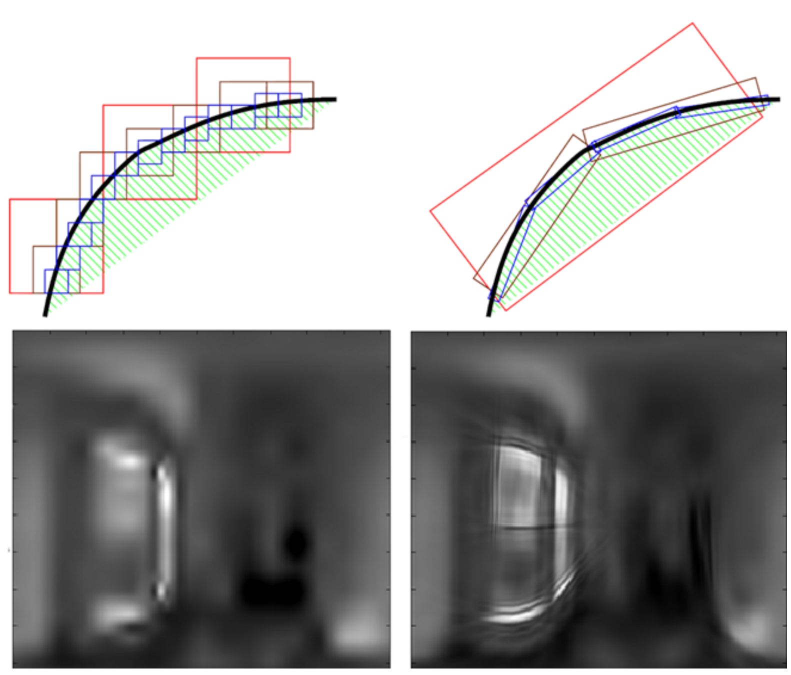


Figure 7 Example of output image after applying curvelet transform

E. Inverse Curvelet Transform

There is also procedural definition of the reconstruction algorithm.Basicly, inverse the procedure of curvelet transform with some mathematic revising:

- Ridgelet Synthesis

Each 'square' is reconstructed from the orthonormal ridgelet system. Summation all the Ridgelet coefficinets with basis:

$$g_Q = \sum_{\lambda} \alpha_{(Q,\lambda)} \cdot \rho_\lambda$$

- Renormalization

Each 'square' resulting in the previous stage is renormalized to its own proper square.

$$h_Q = T_Q g_Q \quad , \quad Q \in Q_s$$

- Smooth Integration

We reverse the windowing dissection to each of the windows reconstructed in the previous stage of the algorithm.

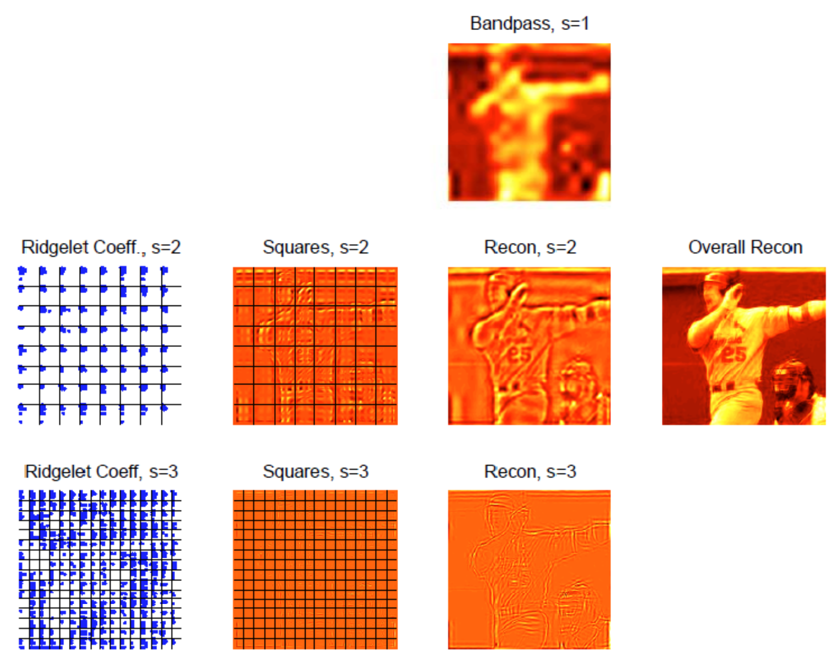
$$\Delta_s f = \sum_{Q \in \mathbf{Q}_s} w_Q \cdot h_Q$$

- Subband Recomposition

We undo the bank of subband filters, using the reproducing formula to summation all the subbands:

$$f = P_0(P_0 f) + \sum_s \Delta_s(\Delta_s f)$$

Example of **Inverse Curvelet Transform**: [4]



IV. CONCLUSION

Here in this paper we present digital image hiding technique using curvelet transform. Images are hidden for safety and security reasons. The curvelet transform, which featured multiscale directional transform can overcome the disadvantage i.e. isotropic and less coefficients are needed to account for edge and reach better approximation rates. We apply four steps of curvelet transform – subband decomposition, renormalization, smooth partitioning and ridgelet analysis to the image. And then inverse curvelet transform is applied to obtain the original image. The computational cost of the curvelet transform is higher than that of wavelet, especially in terms of 3D problems.So a fast message passing inerfaced based parellel implementation can some what reduce the cost.

V. FUTURE SCOPE

The curvelet transform is a very young signal analyzing method with good potential. It is recognized as a milestone on image processing and other applications. The curvelet transform gives better results/performance. Here we have shown that the curvelet transform works well for images containing curve edges but this also can be improved in other application areas such a image denoising and feature detection. Finding optimal value is another interesting research path. When it comes to high resolution image the curvelet transform suffers a drawback, so using very high resolution imagery can also serve as an investigation in the near future.

REFERENCES

[1] YongHong Zhang, "Digital Image hiding using curvelet transform", IEEE Conference 2011.

[2] E. J. CANDÈS and L. DEMANET, Curvelets and Fourier integral operators, *C. R. Math. Acad. Sci. Paris* **336** (2003), 395–398.

[3] E. J. CANDÈS and D. L. DONOHO, New tight frames of curvelets and optimal representations of objects with piecewise *C*2 singularities, *Comm. Pure Appl. Math.*, to appear.

[4] D.L.Donoho; M.R Duncan;, "Digital Curvelet Transform: Strategy, Implementation and Experiments," November,1999

ISSN 2348 – 7968

[5] F. Andersson, M. de Hoop, H. Smith, G. Uhlmann, A multi-scale approach to hyperbolic evolution equations with limited smoothness, Comm. Partial Differential Equations, 33, 988-1017 (2008).

[6] Jianwei Ma and Gerlind Plonka,"A Review of Curvelets and Recent Applications" *IEEE Xplore* (2010)

[7] J. Ma, A. Antoniadis, and F.-X. Le Dimet, "Curvelet-based multiscale detection and tracking for geophysical fluids," *IEEE Trans. Geosci. Remote Sensing*, vol. 44, no. 12, pp. 3626–3637, 2006.

[8] E. Candès and D. Donoho, "New tight frames of curvelets and optimal representations of objects with piecewise singularities," *Commun. Pure Appl. Math.*, vol. 57, no. 2, pp. 219–266, 2004.

[9] J. Ma and M. Hussaini, "Three-dimensional curvelets for coherent vortex analysis of turbulence," *Appl. Phys. Lett.*, vol. 91, no. 18, p. 184101, 2007.

[10] J. Ma, M. Hussaini, O. Vasilyev, and F.-X. Le Dimet, "Multiscale geometric analysis of turbulence by curvelets," *Phys. Fluids*, vol. 21, p. 075104, 2009.

[11] J. Ma and G. Plonka, "Combined curvelet shrinkage and nonlinear anisotropic diffusion," *IEEE Trans. Image Processing*, vol. 16, no. 9, pp. 2198–2206,2007.

[12] E. Candès and F. Guo, "New multiscale transforms, minimum total variation synthesis: Applications to edge-preserving image reconstruction," *Signal Process.*, vol. 82, no. 11, pp. 1519–1543, 2002.

[13] E. Candès, J. Romberg, and T. Tao, "Stable signal recovery from incomplete and inaccurate measurements," *Commun. Pure Appl. Math.*, vol. 59, no. 8, pp. 1207–1233, 2006.

[16] E. Candès and T. Tao, "Decoding by linear programming," *IEEE Trans. Inform. Theory*, vol. 51, no. 12, pp. 4203–4215, 2005.

[17] G. Plonka and J. Ma, "Nonlinear regularized reaction-diffusion filters for denoising of images with textures," *IEEE Trans. Image Processing*, vol. 17, no. 8, pp. 1283–1294, 2008.

[18] G. Plonka and J. Ma, "Curvelet-wavelet regularized split Bregman method for compressed sensing," *Int. J. Wavelets Multiscale Inform. Processing,* to be published.

[19] H. F. SMITH, Wave equations with low regularity coefficients, *Doc. Math.*, Extra Volume ICM 1998, II (1998),
723–730.

[20] Jianwei Ma; Plonka, G.; , "The Curvelet Transform," *Signal Processing Magazine, IEEE* , vol.27, no.2, pp.118-133, March 2010.