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OBJECT DETECTION OF SPECKLE IMAGE BASE ON CURVELET TRANSFORM

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ABSTRACT
The speckle degrades quality of the image and makes interpretations, segmentation of objects harder. In this paper, we present a method for object detection of speckle image base on curvelet transform. The approximate properties and the high directional sensitivity of the curvelet transform make the new method for object detection of speckle image. We construct a method segmentation that provides a sparse expansion for typical images having smooth contours.

Keywords: object detection, speckle image, curvelet transform.

1. INTRODUCTION
Almost every kind of data contains some kind of noise. Many algorithms have been proposed to solve the problem by wavelet transform. Recently, new X-let multiscale transforms have been developed such as the curvelets, contourlets and bandlets which integrate the concept of directionality and detect objects in an optimal way. Their effectiveness in image processing still remains to confirm.

The discrete curvelet transform is a new image representation approach that codes image edge more efficiently than the wavelet transforms [1]. Indeed, curvelets have useful geometric features that set them apart from wavelets and the likes. So, we use curvelet transform coefficients of the object as a feature.

In this paper, we present a method for object detection of speckle image base on curvelet transform. We use imaginary components of curvelet coefficients to segment the object in the speckle image.

The rest of this paper is organized as follows: in section 2, we review some relevant work and establish the background required for further discussion. Then, we present the algorithm in Section 3. Experimental results are given in section 4, where we demonstrate the performance of the proposed algorithm. In section 5, we present our conclusions, comments and some possible future study directions.

2. BACKGROUND
Before introducing our algorithm, we want to give a short review of relevant work to establish the necessary background.

Denoising is the process of reducing the noise in the digital images that consists of three steps:

1. Transform the noisy image to a new space.
2. In new space, keep the coefficient where the signal to noise ratio is high, reduce the coefficient where the signal to noise ratio is low.
3. Transform the manipulated coefficients back to the original space.

2.1. Curvelets
Curvelets as proposed by E. Cand`es and D. Donoho [1], constitute a relatively new family of frames that are designed to represent edges and other singularities along curves much more efficiently than the traditional wavelet based transforms. The idea of curvelets [1] is to represent a curve as a superposition of functions of various lengths and widths obeying the scaling law width ≈ length^2. This can be done by first decomposing the image into subbands, i.e. separating the object into a series of disjoint scales. Then, each scale is analyzed by means of a local ridgelet transform.

2.2 The ridgelet transform
Ridgelets have been recently applied in image processing. It can be adapted to represent objects with curved edges using an appropriate multiscale localization: at a sufficiently fine scale a curved edges can be considered as almost straight.

The ordinary ridgelet transform can be achieved as follows [3]:

- Compute the 2D FFT of the image.
- Substitute the sampled values of Fourier transform obtained on the square lattice with sampled values on a polar lattice.
- Compute the 1D inverse FFT on each angular line.
- Perform the 1D scale wavelet transform on the resulting angular lines in order to obtain the ridgelet coefficients.

3. THE ALGORITHM OF OBJECT DETECTION
In this section, we introduce our algorithm for object detection of speckle image base on curvelet transform. As mentioned above we are using a two steps algorithm. First, the reducing speckle image algorithm is applied to the curvelet domain. Second, the proposed segmentation algorithm has been done by curvelet transform coefficient.

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3.1 The reducing speckle of image algorithm

The proposed reducing speckle of image algorithm uses the advantage of approximate properties of curvelet transform, described in section 2.

In multiresolution analysis, the noise propagates at the higher level also, but the smoothed manner. For the better removal of noise, thresholding should be done at higher level also. However, the amount of shrinkage should be decrease, moving from lower to higher levels. Here, the level dependent threshold T is,

$$T = \frac{1}{2^{j-1}}\left(\frac{\sigma}{\mu}\right)M$$

where j is number of level at which the shrinkage is applied, M is the median and μ is the mean of absolute wavelet coefficients and σ is the standard deviation.

We decompose the original n x n image into smoothly overlapping blocks of side length L pixels. For an n x n image, we count 2n/L such blocks in each direction. This partitioning introduces a redundancy of four times. In order to get the denoised curvelet coefficient, we use the average of the four denoised curvelet coefficients in the current pixel location.

3.2. The segmentation algorithm

There are many edge detector methods available like the simple such as Prewitt, Sobel or more sophisticated Canny edge detectors to name a few. But they do not exactly fit the purpose that we want to implement. One of the reasons is that all edge detectors when applied to a simple image create many edge points and they may also create edges corresponding to noise. Since the application we intend is compression, detector,…. and we are going to detect only dominant edges available in the image.

The curvelet transform [1] is obtained by filtering and then applying a windowed ridgelet transform [17] to each bandpass image. In R^2, ridgelets are constant along ridge lines $x_1\cos(\theta) + x_2\sin(\theta)$ = const and are wavelets (with a scale s) along the orthogonal direction. In frequency domain, such ridgelet function is essentially localized in the corona $|\omega| \in [2^s, 2^{s+1}]$ and around the angle θ. The ridgelet transform provides a sparse representation for smooth objects with straight edges. In short, the curvelet decomposition is composed of the following steps [1]:

1. Subband decomposition of the object into a sequence of subbands;
2. Windowing each subband into blocks of appropriate size, depending on its center frequency;
3. Applying the ridgelet transform to these blocks; and
4. The motivation behind the curvelet transform is that by smooth windowing, segments of smooth curves would look straight in sub-images; hence they can be captured efficiently by a local ridgelet transform. Subband decomposition is used to keep the number of ridgelets at multiple scales under control by the fact that ridgelets of a given scale live in a certain subband [19]. The window's size and subband frequency are coordinated such that curvelets have support obeying the key anisotropy scaling relation for curves [1, 18]: width ≈length^2.

4. EXPERIMENTAL RESULTS

In this section, we will show the experimental results of our algorithm. We implement segmentation method described in section 3 on several test used in the image processing community. Here, we report the results only for Moon image. Our experimental approach was as follows.

First, we select of parameters. As described in section 3, we determined the parameters for speckle part. Our image with size that is 512 by 512. The speckle noise of certain variance V adds multiplicative noise to image I using

$$I = I + n * I$$

where n is uniformly distributed random noise with zero mean and variance V. Speckle noise n with standard deviation σ = 0.1 is added to the image I.

The method where used to estimate the quality of the denoising method called peak signal-to-noise ratio (PSNR).

$$PSNR = -10\log_{10}\frac{\sum_{i,j}(B(i,j) - A(i,j))^2}{n^2 255^2}$$

where B is the denoised image and A is the noise -free image. PSNR of denoising method is shown in Figure-1.

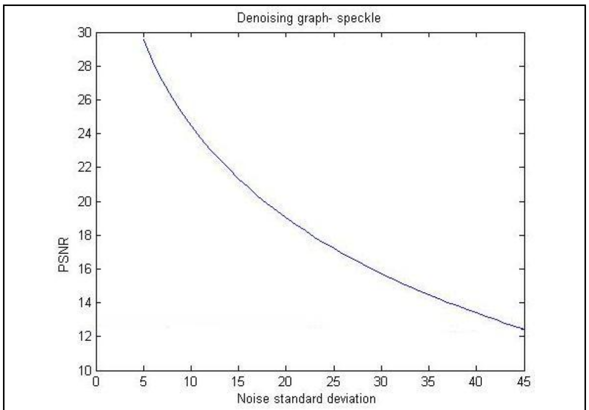

Figure-1. PSNRs of denoising method

For object detection part, the steps decompose an n by n of the original image Im into subbands followed by the spatial partitioning of each subband (block) as

$$\mathrm{Im}(x,y) = c_J(x,y) + \sum_{j=1}^{J} w_j(x,y)$$

where c_J is a coarse or smooth of the original image Im and w_j represents the details of Im at scale 2^{-j}. Then, the ridgelet transform is used to each block of sidelength b pixels. The overlap two vertically adjacent blocks is a

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rectangular array of size b by b/2. In our experiments, for j = 1, it corresponds with the finest scale. We use the '9-7' filters in decomposition. The number of decomposition levels by the filter at finest pyramidal scale is 5, which leads to 32 directions. As we can see, the coefficients in the transform domain are very sparse-significant coefficients are located around edges and in the right directional subbands.

After detecting strong edge points, a simple hysteresis based thresholding has been used for segmentation. The result of the segmentation algorithm described above is shown in Figure-2 for moon.tif image.

	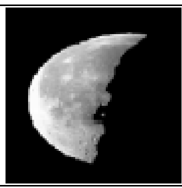	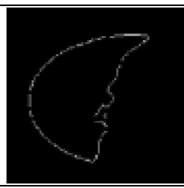
Speckle image	**De-speckle image**	**edge curves**

Figure-2. Moon image and segmentation image.

5. CONCLUSION

In this work, we developed and demonstrated a new algorithm for object detection of speckle image base on curvelet transform. We constructed a method segmentation that provides a sparse expansion for typical images having smooth contours.

Our method is applicable to images taken under a variety of image, improves the mapping between source and reference colors when there is a disparity in size of the chromatic categories, handles achromatic categories separately from chromatic categories. However, if the image is speckled very much, then the estimation ability is reduced because of effect to segmentation. We test our method with several standard images. Our algorithm that allows a user to easily and quickly segment an object in image or video using curvelet transform. Unlike the other method, our algorithm does not rely upon many properties of object such as size, shapes, colors, …

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