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Image Object Extraction Based on Curvelet Transform

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Abstract: Image-object extraction is one of the most important parts in the image processing. Object extraction is the technique of extracting objects from the pre-processed image in such a way that within – class similarity is maximized and between – class similarity is minimized. In this paper, a new method of extracting objects from grey scale static images using Fast Discrete Curvelet Transform (FDCT) via wrapping function is proposed. The motivation of using the curvelet transform in the proposed method is due to the approximate properties and the high directional sensitivity of this transform. An imaginary component of the curvelet coefficients to extract the object in the image is used. Firstly, the Curvelet transform is applied on the input image. Secondly, the Canny edge detector is applied on the edge image in all sub bands in the curvelet domain. Thirdly, the inverse of Curvelet transform is applied and finally; morphological filters are used to extract objects from the obtained binary image. Experimental results of the proposed method are compared with the results of extracting objects in the wavelet domain and the pixel domain. Indeed, the curvelet have useful geometric features that set them apart from the wavelet and the pixel domain.

Keywords: Image Segmentation; Curvelets Transform; Canny Edge Detector; Morphological Filters.

I. INTRODUCTION

Image segmentation is one of the most important pre-processing stages in computer vision. The main idea of image segmentation is to classify similar pixels to one cluster; the clustered pixels have the same attributes such as texture, color and intensity. Many techniques are used for image segmentation. However, until now, there is no fixed technique gives the best segmentation results. The most famous segmentation techniques are edge-based techniques, region-based techniques, clustering based techniques and watershed based techniques. Object extraction is the process of isolating the foreground pixels from the background [1]. Our work is related to extracting objects from images by detecting edges based on the second generation of the curvelet transform (FDCT).

Many researchers have been recently interesting in using curvelets transform in object extraction using different methods. G. Xiuhua et al. [2] extracted texture features of pulmonary nodules of CT images using curvelets transform by establishing prediction model of support vector machine (SVM). They proved that the SVM model can diagnose early stage of lung cancer effectively, reduces the difficulty of distinguishing characteristics of pulmonary nodules and improve accuracy rate diagnose of early stage of lung cancer. S.S. Kumar and R.S. Moni [3] diagnosis liver diseases using fast discrete curvelet transform. They segmented liver from CT image using adaptive threshold detection then extracted the tumour from the liver using fuzzy-c mean (FCM) clustering. The textural information about the tumour is obtained using fast discrete curvelet transform (FDCT). They compared the results with the same algorithm using the wavelet transform, and they showed that the results obtained using FDCT improve the classification rate of liver tumours from CT scans. H. Shan and J. Ma [4] proposed a new approach of curvelet transform called curvelet-based geodesic snake for image segmentation with multiple objects which extend the curvelet based parameter snake for single object to the geometric snake of multiple object segmentation. As a result, this algorithm can treat images of multiple objects that contain weak edges and strong noise. The obtained results are compared with the traditional GAC and proved the strong of this algorithm.

The main idea of the proposed work is to extract objects from images based on the curvelet transform, which treat the singularities and the curve of the edges accurately. The resulting edges are processed using a morphological filter to extract objects.

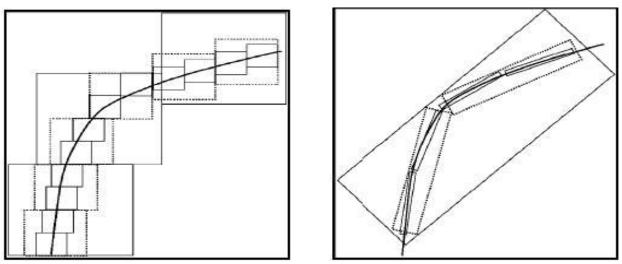
This paper is organized as follows: in the following section, a brief introduction to the curvelet transform is introduced. Section 3 describes in detail the proposed method of extraction object using the curvelet transform. Experimental results are presented in section 4. The final section concludes the results.

II. FAST DISCRETE CURVELET TRANSFORM (FDCT)

Curvelet transform is developed to overcome the limitation of wavelet and Gabor transforms. Although, wavelets are widely used in image processing, but it failed to handle randomly oriented edges of the object and the singularities of the object. Gabor filters overcome the limitation of wavelet transform and deal with the oriented edges, but it loses the spectral information of the image. Curvelet transform is used to overcome these problems of the wavelet and Gabor filters. It can obtain the complete spectral information of the image and handle with the different orientations of the image edges as shown in Figure 1. The initial approach of curvelet transform implements the concept of discrete ridgelet transform [10].

Since its creation in 1999 [7], ridgelet based curvelet transform has been successfully used as an effective tool in image denoising [8], image decomposition [11], texture classification [12], image deconvolution [13], astronomical imaging [14] and contrast enhancement [15], etc. However, ridgelet based curvelet transform is not efficient as it uses complex ridgelet transform [10]. In 2005, Candès et al. proposed two new forms of curvelet transform based on different operations of Fourier samples [9], namely, unequally-spaced fast Fourier transform (USFFT) and wrapping based fast curvelet transform. Wrapping based curvelet transform is faster in computation time and more robust than ridgelet and USFFT based curvelet transform [5].

The idea of curvelets [5] 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 a local ridgelet transform.



(a) (b)

Fig. 1: Comparison between wavelet in (a) and curvelet in (b).

The newly constructed and improved version of the curvelet transform is known as Fast Discrete Curvelet Transform (FDCT). The new constructed version is faster, simpler and less redundant than the original curvelet transform, which based on Ridgelets. As mentioned, according to Cand'es et al. in [5] two implementations of FDCT are proposed:

1. Unequally spaced Fast Fourier Transform (USFFT).
2. Wrapping Function.

Both implementations of FDCT differ mainly in choosing the spatial grid that used to translate curvelet at each scale and angle. Both digital transformations return a table of digital curvelet coefficients indexed by scale, orientation and location parameters.

The new implementation of curvelet transform, based on wrapping of Fourier samples, takes a 2D image as input in the form of a Cartesian array $f[m,n]$, where $0 \le m < M, 0 \le n < N$ and *M,N* are dimensions of the array. As illustrated in equation (1) the output will be a collection of curvelet coefficients $c^D(j,l,k_1k_2)$ indexed by a scale *j*, an orientation *l* and spatial location parameters k_1 and k_2.

$$c^D(j,l,k_1k_2) = \sum_{\substack{0\le m<M \\ 0\le n<N}} f[m,n]\varphi^D_{j,l,k_1k_2} \qquad (1),$$

where $\varphi^D_{j,l,k_1k_2}[m, n]$ is the curvelet waveform. This curvelet approach implements the effective parabolic scaling law on the subbands in the frequency domain to capture curved edges within an image more effectively. Curvelets exhibit an oscillating behaviour in the direction perpendicular to their orientation in the frequency domain.

Wrapping based curvelet transform is a multi-scale pyramid which consists of different orientations and positions at a low frequency level. Basically, multiresolution discrete curvelet transform in the spectral domain utilizes the advantages of fast Fourier Transform (FFT). During FFT, both the image and the curvelet at a given scale and orientation are transformed into the Fourier domain. At the end of this computation process, we obtain a set of curvelet coefficients by applying inverse FFT to the spectral product. This set contains curvelet coefficients in ascending order of the scales and orientations. The complete feature extraction process using one single curvelet is illustrated in Figure 2 (a).

Cand'es et al. [10] describe the discrete curvelet transform as follows:

Curvelet transform = IFFT [FFT (Curvelet) x FFT (Image)], and the product from the multiplication is a wedge.

The following steps of applying wrapping based fast discrete curvelet transform via frequency wrapping:

1. Apply the 2D fast Fourier transform (FFT) and obtain Fourier samples $\hat{f}[n_1,n_2], \quad -n/2 \le n_1,n_2 < n/2.$
2. For each scale *j* and angle *l* form the product $\tilde{U}_{j,\ell}[n_1,n_2]\hat{f}[n_1,n_2]$. Where $\tilde{U}$ is the "Cartesian" window.
3. Wrap this product around the origin and obtain
$$f_{j,\ell}[n_1,n_2] = W(\tilde{U}_{j,\ell}\hat{f})[n_1,n_2], \qquad (2)$$
Where, the range for n_1 and n_2 is $0 \le n_1 < L_{1,j}$ *and* $0 \le n_2 < L_{2,j}$ (for θ in the range $(-\pi/4, \pi/4)$).
4. Apply the inverse 2D FFT to each $\hat{f}_{j,\ell}$, hence collecting the discrete coefficients $c^D(j,\ell,k)$.

This set contains curvelet coefficients in ascending order of the scales and orientations. Clearly, this algorithm has computational complexity O (n^2 log n).

There is a problem in applying inverse FFT on the obtained frequency spectrum. The frequency response of a curvelet is a trapezoidal wedge which needs to be wrapped into a rectangular support to perform the inverse Fourier transform. The wrapping of this trapezoidal wedge is done by periodically tiling the spectrum inside the wedge and then collecting the rectangular coefficient area in the origin. Through this periodic tiling, the rectangular region collects the wedge's corresponding fragmented portions from the surrounding parallelograms. For this wedge wrapping process, this approach of curvelet transform is known as the 'wrapping based curvelet transform'. The wrapping is illustrated in Figure 2 (b). As shown in Figure 2 (b), in order to do IFFT on the FT wedge, the wedge has to be arranged as a rectangle.

The idea is to replicate the wedge on a 2-D grid, so a rectangle in the center captures all the components a, b, and c of the wedge. Wedge wrapping is done for all the wedges at each scale in the frequency domain, so we obtain a set of subbands or wedges at each curvelet decomposition level. These subbands are the collection of the discrete curvelet coefficients.

III. THE PROPOSED METHOD

In this section, our algorithm for image object extraction based on curvelet transform via wrapping technique is introduced. Comparing the obtained results with the results obtained from the same approach in the wavelet domain ensures the high performance of the proposed algorithm.

The proposed object extraction algorithm can be summarized as follows:

Step1: Read the input image.
Step2: Select the number of scales and angles as input parameters.
Step3: Apply fast discrete curvelet transform via wrapping function on the input image.
Step4: Calculate edges in the sub-bands using the Canny [6] edge detector algorithm.
Step5: Apply the inverse curvelet transform.
Step6: Use a morphological filter to extract the objects.
Step7: Return the binary objects back to the original objects.

Figure 3 shows the block diagram of the proposed method. It is known that the morphological operations are dilation, erosion, opening and closing. In a morphological operation, each pixel on the output image is extracted based upon a comparison of the corresponding pixel in the input image with its neighbours. By choosing the size and shape of the neighbourhood, we can construct a morphological operation that is sensitive to specific shapes in the input image.

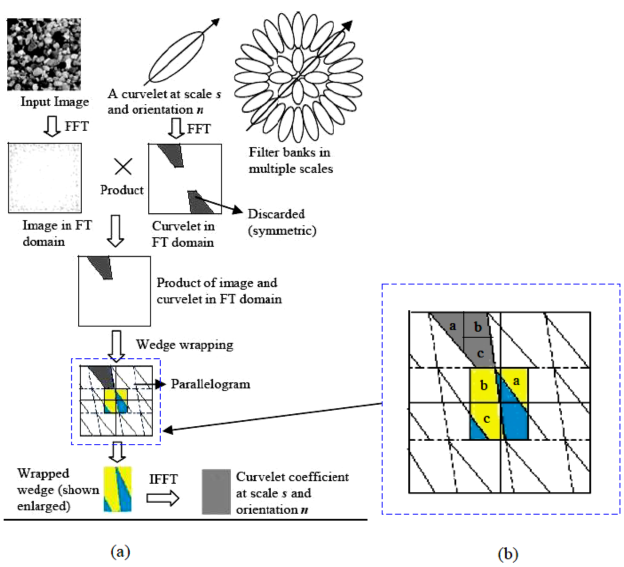


Fig.2 Fast discrete curvelet transform

IV. SIMULATION RESULTS

In this Section, different images are used to demonstrate the performance of the proposed algorithm. Goldhill and Fruit images of size (256x256), Cameraman image of size (512x512) and one frame of Claire, Akiyo, Miss-AM and Mother & daughter video sequence of size (144x176) are used in the simulation results. As an illustration example, we consider the number of scales=2 and the number of angles=16. The results of the proposed approach is introduced in a comparison form with the results of the same approach of edge detector in the wavelet domain and the results of direct applying the Canny edge detector on the current images in the pixel domain.

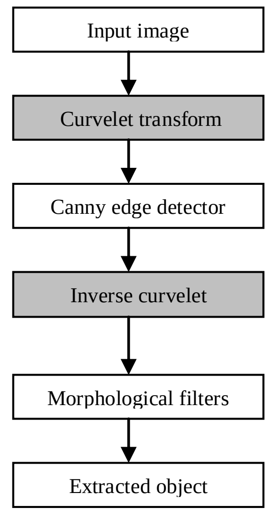


Fig. 3 The block diagram of the proposed method

In Figure 4 and Figure 5, we can see clearly that all the methods can detect the edges, but the proposed method provides the best result. The obtained edges from the proposed algorithm are very strong. However, the result using the edge detection approach in the wavelet domain is noisy, not smooth and the extracted objects are not clear. Numerically, we measured the performance of the proposed algorithms using the accuracy (s) tests. In the simulation results, a prior known segmentation object (reference object) is used in calculating the accuracy (s) of the segmented object and is represented by A_{ref}.

$$S = \left| \frac{A \cap A_{ref}}{A \cup A_{ref}} \right|,$$

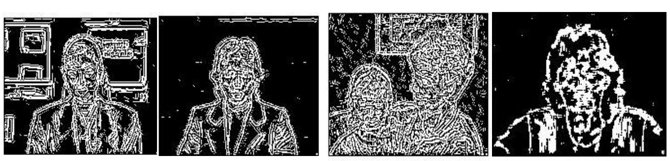
where A represent the object extracted using the proposed algorithm. The results of the accuracy measurement S for the proposed approach and the same approach using the wavelet transform are illustrated in table 1. Clearly, the accuracy of the extracted objects using the proposed method has higher accuracy than the extracted objects using the same approach in the wavelet domain. Object extraction accuracy using the proposed method in the curvelet and in the wavelet is shown in Figure 6. Finally, to measure the performance of the proposed algorithm the spatial accuracy measurement is used. The error ratio of the segmented image is measured by taking missing foreground pixels and added background pixels into account. Not only, the number of error pixels is considered but also the number of wrong pixels location is considered. The spatial accuracy is measured by the absolute spatial quality measure (SQM) defined by:

$$SQM = \sum_{d=1}^{D_{fg\max}} w_{MF}(d).Card(R_d \cap E^C) + \sum w_{AB}(d).Card(R_d^c \cap E)$$

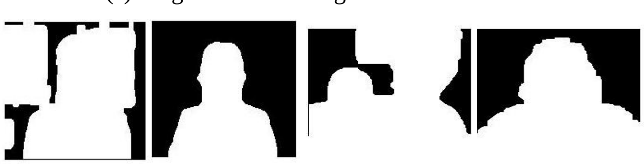
Where, E is the estimated segmentation mask, R the reference mask, (c) indicates the complement of the set, and Card(s) is the cardinality operator for the set S. R_d is the set of pixels situated at a distance d from the reference mask. $W_{MF}(d)$ and $W_{AB}(d)$ are weighting factors. The results of SQM for the proposed method are illustrated in Table 2. Clearly, the obtained values of SQM of the proposed method are less than that achieved using the same approach in the wavelet transform. Moreover, the object extraction based on canny method [6] in the curvelet domain and in the pixel domain is shown in Figure 6. The accuracy and the SQM comparison of the results of the proposed method and the canny method in the pixel domain are illustrated in Table 3. Also, recent improved image segmentation have been presented [16-17].

(a) Original images

(b) Edge detection of the proposed method using Curvelet transform.

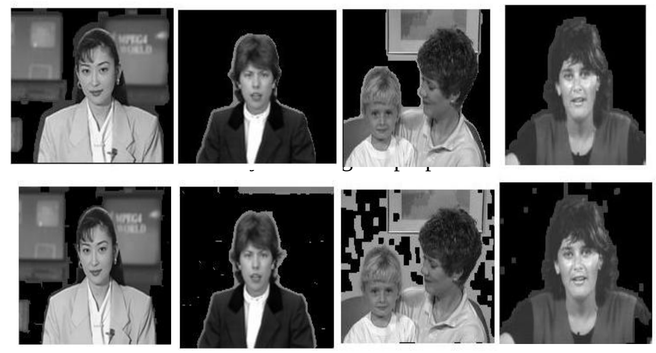


(c) Edge detection using Wavelet transform.



(d) Object extraction using the proposed method in binary.

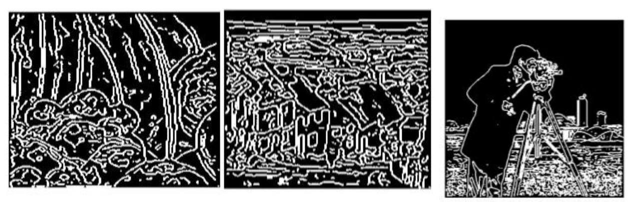
(e) Object extraction using wavelet transform in binary.



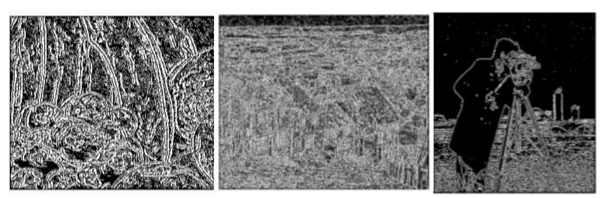
(g) Extracted objects using Wavelet transform.

Fig. 4 Object Extraction using the proposed method and the Wavelet transform for one frame from Claire, Akiyo, Moth & dot and Miss AM sequence respectively.

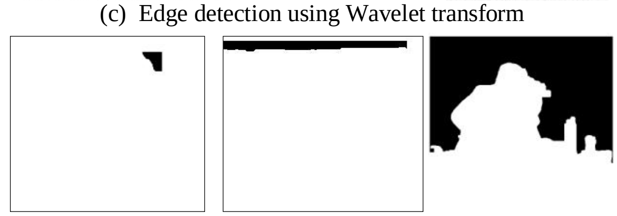
(a) Original images



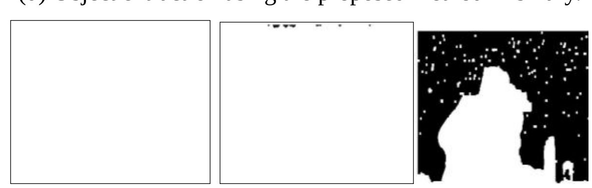
(b) Edge detection of the proposed method using Curvelet transform.



(c) Edge detection using Wavelet transform



(d) Object extraction using the proposed method in binary.



(e) Object extraction using wavelet transform in binary.

(f) Extracted objects using the proposed method.

(g) Extracted objects using Wavelet transform.

Fig. 5 Object Extraction using the proposed method and Wavelet transform for Fruit, Goldhill and cameraman image.

TABLE 1: Object extraction accuracy

image	Quality of measurement (s)	
	Proposed method using Curvelets	**Wavelets**
Claire	96.93 %	85.55 %
Akayio	91.34 %	77.28 %
Miss_AM	93.38 %	86.45 %
Mthr&dot	93.28 %	83.49 %
Goldhill	98.35 %	90.74 %
Fruit	99.27 %	96.03 %
Cameraman	97.63 %	88.10 %

TABLE 2: SQM error measure of the proposed method and the object extraction in the wavelets domain.

image	SQM error	
	Proposed method using Curvelets	**Wavelets**
Claire	-0.1404	-0.6747
Akayio	-0.4054	-1.0021
Miss_AM	-0.2965	-0.6143
Mthr&dot	-0.2924	-0.7791
Goldhill	-0.0724	-0.4219
Fruit	-0.0314	-0.1760
Cameraman	-0.1107	-0.5464

(a) (b) (c)

Fig. 6 (a) original Image, (b) object extraction in the curvelet domain, (c) edge detection based on canny method in the pixel domain

TABLE 3: the accuracy and the SQM error measure of the proposed method and canny method in the pixel domain.

Image	Canny method in the Curvelet domain		Canny method in the pixel domain	
	Accuracy	**SQM**	**Accuracy**	**SQM**
Cameraman	97.63	-0.1107	96.24	-0.1637
Miss_AM	93.38	-0.2965	87.42	-0.5339

V. CONCLUSION

The paper has presented a new algorithm for extracting objects from the image based on the curvelet transform. A comparison study has been introduced between the object extraction in the wavelet domain and the proposed algorithm.

The simulation study shows that using the curvelet transform in extracting object is superior to the application of traditional method. The results of the proposed method achieved accuracy from 91.34% to 99.27% higher than the same method in the wavelet domain. Moreover, the spatial error measured by SQM is less than all the error measured of the traditional image segmentation methods.

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