# Image Compression Algorithm Using a Fast Curvelet Transform

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Abstract— In this paper, we propose a novel scheme for image compression by the curvelet transform. Curve functions are effective in representing functions that have discontinuities along straight lines. Normal wavelet transforms fail to represent such functions effectively. Modification of the traditional JPEG method based on region-of-interest coding is achieved and used curvelet transform. The modification will be done after the quantization step. In the beginning, the image is subdivided into a block of pixels; the block must be classified as foreground block or background block based on a pre-processing step. Then, keep a certain number of NxN blocks in the top left hand corner for each block and put the rest of our Discrete Cosine Transform (DCT) coefficients with 0. Experimental results show that the compression performance of our method gains much improvement. Moreover, the algorithm works well for declining block effect at higher compression ratios.

*Index Terms*— Curvelet transform, Edge detection, Image Compression and Region of Interest

#### I. INTRODUCTION

**F**ROM early days to now, the basic objective of image compression is the reduction of size for transmission or storage while maintaining suitable quality of reconstructed images. For this purpose, many compression techniques, i.e., scalar/vector quantization, differential encoding, predictive image coding, transform coding have been introduced. Among all these, transform coding is most efficient especially at low bit rate [1].

In the past few years, wavelets and related multi-scale representations pervade all areas of signal processing [2], [3], [4]. The reason for the success of wavelets is the fact that wavelet bases represent well a large class of signals, and therefore allow us to detect roughly isotropic features occurring at all spatial scales and locations.

However, there has been a growing awareness to the observation that wavelets may not be the best choice for presenting natural images recently. This observation is due to the fact that wavelets are blind to the smoothness along the edges commonly found in images. In other words, wavelet cannot provide the 'sparse' representation for an image because of the intrinsic limitation of the wavelet. Hence, recently, some new transforms have been introduced to take advantage of this property. The ridgelet and curvelet transforms [5] are examples of two new transforms, which are

developed to sparsely represent natural images. They are very different from wavelet-like systems that have been developed. Curvelet and ridgelet take the form of basis elements which exhibit very high directional sensitivity and are highly anisotropic. The fast discrete curvelet transform (FDCT) [6], [7] improves upon earlier implementation based upon the first generation of curvelet in the sense that they are conceptually simpler, faster and far less redundant.

Yuancheng Li, et al. [8] proposed a novel scheme for image compression by means of the second generation curvelet transform and support vector machine (SVM) regression. Compression is achieved by using SVM regression to approximate curvelet coefficients with the predefined error. Based on characteristic of curvelet transform, they proposed compression scheme by applying SVM into compressing curvelet coefficients. In their scheme, image is first translated by fast discrete curvelet transform, and then curvelet coefficients are quantized and approximated by SVM, at last adaptive arithmetic coding is introduced to encode model parameters of SVM.

K. Siva Nagi Reddy et al. [9] have proposed algorithm of fast curvelet transform combined with modified SPIHT scheme gave compression ratios as high as 90:1 with very good PSNR. The found to be comparable with conventional wavelet based compression which is more discontinuous with straight line singularity and hence their method further investigation. The fast curvelet with modified SPHIT is low computational complexity and the computational speed of the algorithm is very good than the wavelet based schemes. Experimental results clearly show that their proposed compression technique results in higher quality reconstructed images compared to that of other algorithms operating at similar bit rates for the class of images where edges are dominant with minimum variation in compression ratio.

In this paper, we present a new scheme which provides significant improvement in the compression of the image in terms of CR by fast discrete curvelet transform [10], [11].

In the wavelet transform there is an inability to represent edge discontinuities along the curves. Due to the large or several coefficients are used to reconstruct edges properly along the curves. For this reason, it needs a transform to handle the two dimensional singularities along the sparsely curve. This is the reason behind the birth of Curvelet transform. Here the Curvelet basis elements have wavelet basis and the edge discontinuities and other singularities well than wavelet transform.

The paper is organized as follows: in section II we introduce a brief introduction to the curvelet transform. Section III describes in detail the proposed method of extraction object using curvelets transform. Section IV presented the proposed method. Experimental results are presented in section V, the final section VI is the conclusion.

## II. FAST DISCRETE CURVELET TRANSFORM (FDCT)

Since the theory of the continuous curvelet transform promises an order of magnitude improvement over the wavelet decomposition in many important applications, there have been several implementations of the discrete curvelet transform to operate on digital data.

Two separate digital (or discrete) curvelet transform (DCT) algorithms are introduced in [12]. The first algorithm is the non equispaced FFT Transform [13], where the curvelet coefficients are found by irregularly sampling the Fourier coefficients of an image. The second algorithm is the Wrapping transform, using a series of translations and a wraparound technique. Both algorithms having the same output, but the Wrapping Algorithm gives both a more intuitive algorithm and faster computation time. Because of this, the Unequispaced FFT [14], [15] method will be ignored in this paper with focus solely on the Wrapping DCT method. The data flow diagram of the forward and inverse wrapping FDCT are plotted in Fig. 1. The data are first transformed into the frequency domain by forward FFT. The transformed data are then multiplied with a set of window functions.

The shapes of these windows are defined according to the requirements of the ideal curvelet transform, such as the parabolic scaling rule. The curvelet coefficients are obtained by inverse FFT from windowing data. Since the window functions are zero except on support regions of elongated wedges, the regions that need to be transformed by the inverse FFT are much smaller than the original data. On the wrapping FDCT, the FFT coefficients on these regions are 'wrapped' or folded into rectangular shape before being applied to inverse FFT algorithm. The size of the rectangle is usually not an integer fraction of the size of original data. This process is



Fig. 1. Data flow structure of the FDCT forward and inverse transforms.

equivalent to filtering and subsampling the curvelet subband by rational numbers in two dimensions.

# III. EDGE/OBJECT EXTRACTION USING CURVELET TRANSFORM

## A. Edge detection using curvelet transform (ED-CT)

The edge detection scheme uses the discrete curvelet transform is proposed to extract information about directionality and magnitude of features in the image at selected levels of detail. The edges are then extracted using the 'non-maximal suppression' and 'hysteresis thresholding' steps of the Canny algorithm [16]. The directional information from the curvelets is then further used to connect edge segments that were erroneously separated. Unlike for example the canny algorithm, the edges detected by our scheme are not detected on the single pixel level, but their width is determined by the choice of curvelet detail levels specified in the analysis. The curvelet transform enables a multilevel decomposition of the image so that the magnitudes of the curvelet coefficients signify intensity variations on their level of detail. Hence, edges are detected when intensity variations are large on a selected scale. The edge detection scheme by curvelet transform consisting of the following steps:

*Method 1*: (Edge detection by curvelet transform)

Step1: Read the input image.

Step2: Select the scales and levels for curvelet transform. For the proposed method, 2 scales and 16 directions are selected.

Step3: Apply fast discrete curvelet transform via wrapping function for the input image with the selected number of scales and number of directions.

Step4: Apply the Canny edge detector (algorithm [16]), on the resulting subbands, to extract the edges.

Step5: Using inverse curvelet transform, to map the edges onto the original image.

# B. Object (region of interest (ROI)) extraction using curvelet transform (OE-CT)

In the image coding based on object extraction, images are segmented into the region of interest, which is considered important, and the background, which is less important. By allowing the ROI to be coded with higher fidelity than background, a high compression ratio with good quality in the ROI can be achieved. Therefore, the greatest benefit of ROI coding is its capability of delivering high reconstruction quality over certain spatial regions at high compression ratios.

We introduced the algorithm for object extraction (ROI) based on curvelet transform via wrapping as mentioned above. The input image is entered to curvelet transform procedure with the following parameters: number of scales is 2 and the number of angels is 16. Canny edge detector [16] steps are applied on all the output subbands. The resulting subbands

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which represent strong edge images are converted back to one image with the same size as the original image using the inverse of the curvelet transform via wrapping. The obtained image represent edge image then, post-processing is applied, which using morphological filters to extract objects from the image. The object extraction scheme by curvelet transform consisting of the above steps, and then a morphological filter (suitable to the application) is used to fill in holes and small gaps.

#### C. Post-processing

The output from the scheme described so far is not always what one would like to present as a final output. In particular, one might want to make sure that the edges form a connected loop and remove isolated edge segments. This post-processing has to be adapted to the particular application. Morphological operations are one from the post-processing, where the morphology is a broad set of image processing operations that process images based on shapes. Morphological operations apply a structuring element to an input image, creating an output image of the same size. The most basic morphological operations are dilation, erosion, opening and closing. In a morphological operation, each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbours. By choosing the size and shape of the neighbourhood, we construct a morphological operation that is sensitive to specific shapes in the input image the changes of filters will affect the segmentation results.

# IV. PROPOSED SCHEME

The DCT coefficients in each block are then uniformly quantized with quantization step sizes depending on the DCT coefficient. The step sizes are represented in a quantization matrix called the Q-matrix. Different Q-matrices are typically used for the luminance and chrominance components. This quantization stage determines both the amount of compression and the quality of the decompressed image. Large quantization step sizes give good compression but poor visual performance while small quantization step sizes give good visual performance but small compression.

Four new schemes for the DCT image coding based in pixels classifications are proposed in this section. Two of these schemes are called ED-CT1 and ED-CT2, which provides the image coding based on edge detection. The other two schemes are called OE-CT1 and OE-CT2, which provides the image coding based on object extraction.

In ED-CT methods, we explored modification of the quantized image based on pre-processing; edge detection using curevelet. The modification will be done after the quantization step. The image is subdivided into a block of pixels and then these blocks is classified into edge and non-edge blocks. For each block we shall keep a certain number of NxN blocks in the top left hand corner and put the rest of our DCT coefficients with 0. This would simplify the coding process and improve the compression ratio, but the quality of the

compressed image will be reduced. The first technique ED-CT1 is described as follows: after the classification process, the non-edge blocks are compressed using the DC coefficient only of the DCT coefficients and all significant DCT coefficients are used for the edge blocks. In the second technique ED-CT2, we tried to reduce the number of AC coefficients used to code the edge blocks. This will increase the compression ratio, and fast the coding process. Only the quantized DC coefficient value will be used for non edge blocks.

Also, two image coding approaches (OE-CT1 and OE-CT2) are presented to study the effect of the object-extraction based image coding on the compression quality: These techniques are described as follows: after the classification process, all the background area is compressed using the DC coefficient of one block only. The foreground area is compressed using two techniques. In the first Technique OE-CT1, all coefficients are used in the coding of the foreground blocks. In the second technique OE-CT2, only 70% (choosing experimentally) of the non-zero quantized AC coefficients have been used in the coding of foreground blocks.

#### V. EXPERIMENTAL RESULTS

It is difficult to provide a performance analysis of the proposed new method and we will instead present some experimental results to illustrate its performance. The proposed algorithm is evaluated on grayscale images (Lena and Goldhill with size 512×512, CLAIRE, MTHR\_DOTR, MISS\_AM and AKIYO with size 176×144 and Fruit with size 256×256). As an objective measure of reconstructed image quality, the PSNR (peak-signal-to-noise-ratio) in decibels is used [17], and is defined as:

$$PSNR = 10 \times \log_{10} \frac{255^2}{MSE}$$
$$MSE = \frac{1}{N \times M} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} (x_{i,j} - y_{i,j})^2$$

and  $x_{i,j}$ ,  $y_{i,j}$  are the original and reconstructed image, respectively. We have described a method for image coding based on the discrete curevelet transform, and have seen that the curvelet can be useful for finding edges and elongated structures in images where the edges may not easily be detected using traditional methods. The main advantage of the curvelet transform are that is a multi-scale transform, which enables us to extract edge information from detail levels of our choice and disregard the other levels, and that is gives us directional information at each point which can be used to improve the edge detection.

Fig. 2 shows the input images and results of edge detection and object extraction using curvelet transform from the above algorithm. From Table 1, we can conclude that object extraction with modified JPEG is to be better compression algorithms in terms of visual and computational performance. From the comparison result the better performance for CR is obtained from the ED-CT2 coder as compared with the ED-CT1 compression. It is about 3.6 to 6.04 improvement in CR had arrived from the above ED-CT2 algorithm. And from table 2, the improvement in CR had arrived from the OE-CT2 algorithm about 3.16bpp to 6.57bpp compared to OE-CT1 algorithm and with some image used (like Lena, Fruit and Goldhill) the improvement in the performance of the quality had arrived from the OE-CT1 algorithm about 0.456dB to 0.977dB compared to ED-CT1 algorithm.

Fig. 3 and Fig. 4 present the comparisons between ED-CT1 and ED-CT2 methods in terms of subjective quality for different images. In Fig. 5 and Fig.6, we compare our results for the OE-CT1 scheme to the results achieved using the OE-CT2 scheme.



a) Original image



b) Edge detection



c) Object-extraction

Fig. 2: a) original image, b) results of edge detection using curvelet transform, c) results of object extraction using curvelet transform



Fig. 3: Reconstructed images when using ED-CT1 method



Fig. 4: Reconstructed images when using ED-CT2 method



Fig. 5: Reconstructed images when using OE-CT1 method



Fig. 6: Reconstructed images when using OE-CT1 method

## VI. CONCLUSION

In this paper, we developed and demonstrated a new compression algorithm based on the curvelet transform. Experimental results show that it gains better compression performance than that of existing compression algorithm. The analysis of the results at different compression ratios show that

results from the proposed scheme improves with the increase of compression ratio. At around 3.6 to 6.04 compression, proposed scheme (OE-CT1) shows better results than the JPEG2000. The mean PSNR values indicate this. The proposed recognition scheme uses a block based approach similar to JPEG compression and its pros and cons are similar to JPEG. At high compression ratios, the blocking artifacts reduce the PSNR of the proposed approach. For the same reason JPEG gives poor PSNR compared to JPEG2000 at high compression ratios [18], but is better at lower compression ratios. In future this work can be extended to real time applications for video compression in medical images.

TABLE 1: RESULTS OF THE IMAGE CODING BASED ON EDGE EXTRACTION USING CURVELETS TRANSFORM

Image		Fruit	Goldhill	Lena	CLAIRE	MTHR_DOT	MISS_AM	AKIY O
No. of background block		157	578	373	242	91	193	98
No. of foreground block		867	3518	651	154	305	203	298
PSNR	ED-CT1	38.837	36.2695	37.1959	41.7220	37.6321	42.3790	38.887
	ED-CT2	36.524	34.7551	35.0096	38.5693	35.4100	39.9864	36.366
Compression ratio	ED-CT1	10.211	8.8060	9.8380	15.2273	9.3507	17.6582	10.536
	ED-CT2	14.027	12.4021	13.8840	20.4883	13.3031	23.6998	14.749
MSE	ED-CT1	8.4979	15.3508	12.4019	4.3740	11.2169	3.7599	8.4064
	ED-CT2	14.476	21.7558	20.5174	9.0397	18.7103	6.5230	15.010
bitrate	ED-CT1	0.7835	0.9085	0.8132	0.5254	0.8555	0.4530	0.7593
	ED-CT2	0.5703	0.6451	0.5762	0.3905	0.6014	0.3376	0.5424

TABLE 2: RESULTS OF THE IMAGE CODING BASED ON OBJECT EXTRACTION USING CURVELETS TRANSFORM

Image		Fruit	Goldhill	Lena	CLAIRE	MTHR_DOT	MISS_AM	AKIYO
No. of background Block		9	93	0	230	90	132	48
No. of foreground Block		1015	4003	1024	166	306	264	348
PSNR	OE-CT1	39.654	36.7259	38.1735	41.0182	36.9823	41.9204	35.9306
	OE-CT2	37.125	34.9514	35.7482	38.4092	35.1985	39.8737	34.5914
Compression	OE-CT1	9.7171	8.5372	8.9118	18.7994	9.9150	19.1873	10.7452
ratio	OE-CT2	12.870	11.6683	12.0490	25.3630	13.6276	25.5806	14.3816
MSE -	OE-CT1	7.0417	13.8195	9.9021	5.1435	13.0272	4.1787	16.5966
	OE-CT2	12.603	20.7939	17.3084	9.3790	19.6441	6.6944	22.5912
bitrate	OE-CT1	0.8233	0.9371	0.8977	0.4255	0.8069	0.4169	0.7445
	OE-CT2	0.6216	0.6856	0.6640	0.3154	0.5870	0.3127	0.5563

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