PAPER

A Contourlet-Based Embedded Image Coding Scheme on Low Bit-Rate*

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SUMMARY Contourlet transform (CT) is a new image representation method, which can efficiently represent contours and textures in images. However, CT is a kind of overcomplete transform with a redundancy factor of 4/3. If it is applied to image compression straightforwardly, the encoding bit-rate may increase to meet a given distortion. This fact baffles the coding community to develop CT-based image compression techniques with satisfactory performance. In this paper, we analyze the distribution of significant contourlet coefficients in different subbands and propose a new contourlet-based embedded image coding (CEIC) scheme on low bit-rate. The well-known wavelet-based embedded image coding (WEIC) algorithms such as EZW, SPIHT and SPECK can be easily integrated into the proposed scheme by constructing a virtual low frequency subband, modifying the coding framework of WEIC algorithms according to the structure of contourlet coefficients, and adopting a high-efficiency significant coefficient scanning scheme for CEIC scheme. The proposed CEIC scheme can provide an embedded bit-stream, which is desirable in heterogeneous networks. Our experiments demonstrate that the proposed scheme can achieve the better compression performance on low bit-rate. Furthermore, thanks to the contourlet adopted in the proposed scheme, more contours and textures in the coded images are preserved to ensure the superior subjective quality.

key words: embedded image coding, contourlet, wavelet, scanning scheme

1. Introduction

With the rapid development of diversified networking technologies, heterogeneity and ubiquity are the major trends of the next-generation network. Because different types of terminals and nodes in heterogeneous networks have different processing, memory and display capabilities, resolution, temporal, and SNR scalability of the coded bit stream are needed. These scalabilities are achievable by realizing progressive transmission and embedding of information in decreasing order of the information content [1]. Embedded image coding (EIC) algorithms have been researched extensively, because it meets heterogeneous networks well [1]–[4]. Efficient representation of visual information lies at the heart of image compression. For 1-D piecewise smooth signals, wavelets have been served as a good representation tool. 1-D wavelet can be easily extended to 2-D sep-

arable wavelet by tensor-product. 2-D wavelet together with its fast transform and convenient tree structures has led to several well-known wavelet-based embedded image coding (WEIC) algorithms, such as EZW [1], SPIHT [2], SPECK [3] and EBCOT [4].

However, 2-D signals are smoothed away from discontinuities across smooth curves [5]. Such signals resemble natural images. The commonly used 2-D separable wavelets obtained by a tensor-product of 1-D wavelets are only good at capturing the discontinuities at edge points, but cannot represent the smoothness along contours well. Thus, more powerful schemes are needed in higher dimensions [5], [6].

In recent years, X-lets have been proposed as the extensions of wavelet that might provide the performance competitive with today's image and video coding standards [7]. For example, as a form of wavelet analysis in the Radon domain, ridgelet [8] by Cands and Donoho achieves the high efficient representation of linear singularities in images. However, ridgelet may not be able to represent edges efficiently since edges in images are typically curved rather than straight [9], [10]. Curvelet [11] by Cands and Donoho can be suited to objects which are smoothed away from discontinuities across smooth curves. Later, the authors proposed the second-generation curvelet [12]. Additionally, bandelet [13], wedgelet [14], and beamlet [15] can represent contours of objects in images efficiently too.

Contourlet transform (CT) [5], [6] is presented by Do and Vetterli as a new image representation method. It may be superior to other X-lets from the compression point of view, since it can efficiently capture the characteristics of both contours and textures in natural images [16]. Of course, CT is also a kind of overcomplete transform with a redundancy factor of 4/3. If it is applied to image compression straightforwardly, it may increase the encoding bit-rate under a given distortion.

Recently, some approaches have been proposed to incorporate CT into image compression. In [17], a low bit-rate image coding scheme using CT was proposed. It uses a scalar quantizer with dead zone which is as large as the other bins to code contourlet coefficients. A coding technique combining CT and wavelet transform (WT) was presented [18], in which the transform is optimized through an iterative projection process to minimize the quantization error. Neither algorithm can produce an embedded bit stream, thus they cannot meet the needs of a heterogeneous network.

In [19], a wavelet-based contourlet transform (WBCT), a critical-sampling transform, is proposed to achieve the em-

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beddability in conjunction with SPIHT, whose coding performance is competitive to WT with SPIHT, especially for a category of images that have a significant amount of textures and oscillatory patterns and therefore are not wavelet-friendly. However, due to the frequency scrambling effect resulting from the downsampling of the high-frequency (HF) subbands in WT, the nonlinear approximation property of WBCT might lead to larger perceptual distortion than contourlet in regions of contours and textures. Meanwhile, the computational complexity of the coding algorithm in [19] will increase quickly due to the repositioning procedure when moving forward along the scales.

The facts that WT incurs frequency scrambling and that CT is more efficient in representing contours and textures motivate us to propose a new contourlet-based embedded image coding (CEIC) scheme on low bit-rate in this paper. Traditional WEIC algorithms are incorporated into the proposed scheme by (1) adopting an adaptive subband coding order scheme, (2) constructing a virtual low-frequency (LF) subband, (3) modifying the coding framework of WEIC algorithms properly, and (4) adopting a high-efficiency significant coefficient scanning scheme for CEIC scheme. Experimental results demonstrate that the proposed scheme can achieve the better compression performance, interestingly even with much lower computing complexity, in comparison with two well-known embedded image coding (EIC) algorithms, which are based on two non-redundant (or critical-sampling) transforms. Furthermore, thanks to the contourlet adopted in the proposed scheme, more contours and textures in the coded images are preserved to ensure the superior subjective quality.

The rest of the paper is organized as follows. Section 2 will present contourlet transform briefly. CEIC scheme is presented in Sect. 3. Section 4 gives experimental results. Section 5 concludes the paper.

2. Contourlet Transform

Contourlet was proposed by Do and Vetterli at 2001. It is a

double filter bank structure for obtaining sparse expansions for typical images with smooth contours. The Laplacian Pyramid (LP) is first used to capture the point discontinuities, and then followed by a directional filter bank (DFB) to link the point discontinuities into linear structures. The overall result is an image expansion using basic elements like contour segments, and thus is named contourlet [6].

Figure 1 shows CT for a 512×512 image. HF images from the LP are fed into a DFB so that directional information can be captured. The CT can be iterated on LF images. It decomposes images into directional subbands at multiple scales. Here, frequency is partitioned into 16 real wedge-shaped frequency bands.

In contrast to the critically sampled wavelet scheme,

Fig. 2 Example of CT for 'Barbara' image. (a) For clear visualization, image is only decomposed into two pyramidal levels, which are then decomposed into 16 directional subbands respectively. Small coefficients are shown in black while large coefficients are shown in white (b) Corresponding sequence numbers of 16 subbands.

Fig. 1 CT for a 512×512 image. (a) Transform flowchart (b) Frequency partitioning.

the LP has the distinguishing feature that each pyramid level generates only one bandpass image (even for multidimensional cases), and this image does not have ‘scrambled’ frequencies. This frequency scrambling occurs in the wavelet filter bank when a highpass channel, after downsampling, is folded back into the LF image, and thus its spectrum is reflected. In the LP, this effect is avoided by downsampling the lowpass channel only [6].

Figure 2 shows the example of CT for ‘Barbara’ image. We noticed that only contourlets that match both location and direction of image contours produce significant coefficients.

3. Contourlet-Based Embedded Image Coding (CEIC) Scheme

3.1 Analysis of Distribution of Significant Contourlet Coefficients in Different Subbands

EIC algorithms demand that the coefficients with larger magnitude (*i.e.* significant coefficients) should be transmitted first because they contain more important information from the rate-distortion point of view. When an image is decomposed into an LF subband and many HF subbands, the numbers of significant coefficients varies with HF subbands. In wavelet domain, there are only three kinds of HF subbands: LH, HL and HH. In general, LH subbands and HL subbands contain much more significant coefficients than HH subbands. Consequently, Zig-Zag scanning is usually adopted in WEIC algorithms to code wavelet coefficients efficiently. However, there are many kinds of HF subbands in contourlet domain (much more than 3), and the numbers of significant coefficients in different HF subbands vary greatly with images. So simply adopting Zig-Zag scanning is not suitable in our CEIC scheme. In order to design an effective coefficient arrangement for CEIC scheme, we must analyze the distribution of significant contourlet coefficients in different subbands first.

Table 1 shows the distribution of significant contourlet coefficients of 4 standard test images (8 bit/pixel (bpp), 512×512) at different thresholds ($threshold1 = 128$, $threshold2 = 64$, $threshold3 = 32$). 4-scale LP and 16 directional decompositions are performed on each image. 16 subbands are sorted in the descending order of the number of significant coefficients above the corresponding threshold. In Table 1, 01-16 are the numbering of 16 subbands corresponding to those in Fig. 2 (b).

We found from Table 1 that although the distribution of significant contourlet coefficients varies with images, the orderliness of distribution at different thresholds is kept for every image. In other words, if a subband has more (significant) coefficients at a higher threshold, it likely has more (significant) coefficients at a lower threshold too.

Therefore, we design an adaptive subband coding order scheme that decides the scanning order of subbands according to *subband significance*, *i.e.*, the number of significant coefficients in the subband. It ensures that the subbands

Table 1 Distribution of significant contourlet coefficients of 4 standard test images at different thresholds.

Image	Threshold1	Threshold2	Threshold3
Barbara	06/04/05/02/	06/04/05/02/	06/04/05/03/
	13/01/03/12/	03/01/13/07/	02/07/01/16/
	09/10/07/16/	16/09/10/12/	13/09/10/12/
	11/14/15/08	11/15/14/08	15/11/14/08
Goldhill	13/04/05/12/	13/04/12/05/	13/04/12/05/
	11/14/16/03/	11/14/16/03/	11/14/16/15/
	06/15/02/10/	10/15/06/02/	03/10/06/02/
	/09/07/01/08	09/07/01/08	01/07/09/08
Mandrill	13/12/14/16/	13/12/14/11/	13/12/14/16/
	04/11/03/06/	16/15/04/10/	11/15/04/10/
	15/09/05/02/	03/06/09/02/	03/06/09/02/
	10/01/07/08	05/01/07/08	05/01/07/08
Fingerprint	13/12/14/16/	13/12/14/11/	13/12/14/11/
	11/15/10/09/	15/16/04/10/	15/16/04/10/
	04/07/01/05/	09/01/07/05/	09/05/03/06/
	02/03/06/08	02/03/06/08	02/07/01/08

contain more (significant) coefficients can be scanned and coded as early as possible, and then results in an efficiently embedded bit-stream. In order to decode correctly, the initialization order of subbands need to be coded as side information, which is of course negligible.

3.2 Construction of Virtual LF Subband

It is well known that the more zero coefficients an algorithm can organize together, the higher compression ratio it can achieve. Zerotrees in EZW and spatial-orientation trees in SPIHT are proposed to effectively organize zero coefficients in the higher bit-planes in order to enhance the compression efficiency.

In contourlet HF images, the size of i th scale is 4 times as that of $(i + 1)$ th, and they are all decomposed into 16 subbands. Clearly, there is the RFC among the HF coefficients through scales, which is similar to the tree structures like zerotree in EZW and spatial-orientation tree in SPIHT.

From the zero trees point of view, the higher a zero tree is, the more zero coefficients it contains. Thus the symbols of the zero trees have higher expression efficiency. In one word, the higher the structure of zero trees is, the better the compact rate-distortion performance it achieves. Therefore, we want to construct a RFC between LF image and HF images in our CEIC scheme, which can make the structure of zero trees higher at the high bit-planes. Thus we can use fewer zero trees (*i.e.* fewer symbols) to represent all zero coefficients at the high bit-planes efficiently, accordingly enhance the compression performance of CEIC scheme. However, the direction correlation is not strong in LF image due to its small size, no further directional decomposition is performed on the contourlet LF image. Therefore we can not construct tree structure between LF image and HF images directly, as there is not such a relationship apparently.

To overcome this problem, a virtual LF subband is constructed in our proposed scheme. It has the same size as the original LF image, but is imaginarily decomposed into 16 subbands like HF images by coefficient rearrangement.

1	5	A	E	(1)	(5)														
9	10	11	12	13	14	15	16	I	J	K	L	M	N	O	P				
2	6	B	F	(2)	(6)														
(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)												
3	7	C	G	(3)	(7)														
4	8	D	H	(4)	(8)														
a	e																		
i	j	k	l	m	n	o	p												
b	f																		
c	g																		
d	h																		

(a)

1	A	(1)						5	E	(5)									
a								e											
2	B	(2)						6	F	(6)									
b								f											
3	C	(3)						7	G	(7)									
c								g											
4	D	(4)						8	H	(8)									
d								h											
9	I	10	J	11	K	12	L	13	M	14	N	15	O	16	P				
(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)												
i	j	k	l	m	n	o	p												

(b)

Fig. 3 The rule of coefficient rearrangement for LF image. (a) Coefficient positions of the original LF image (b) Coefficient positions of the virtual LF image after rearrangement.

Figure 3 shows the rule of rearrangement by an example of LF image with the size 16×16 . 4 groups of coefficients (1-16, (1)-(16), A-P, a-p) are rearranged to explain the rule. On the one hand, the coefficients in the even lines of the original LF image are rearranged to the spatially corresponding positions in the horizontal subbands (*i.e.* the subbands 01-08) of the virtual LF image. On the other hand, the coefficients in the odd lines of the original LF image are rearranged to the spatially corresponding positions in the vertical subbands (*i.e.* the subbands 09-16) of the virtual LF image. The spatial correlation between LF image and HF images is set up easily by the coefficient rearrangement. It is the reason why the virtual LF image is constructed. The coordinates in the virtual LF image (s, t) can be computed by the coordinates in the original LF image (x, y) based on Eq. (1) and Eq. (2). Here, the size of the virtual LF image is defined as $N \times N$.

if $x \bmod 2 = 0$

Fig. 4 Tree structures in two coding schemes. (a) Tree structure in WEIC (b) Tree structure in CEIC. There, the virtual LF image has been decomposed into 16 subbands and RFC is constructed between virtual LF image and HF images.

$$\begin{cases} s = \left(\left\lfloor \frac{x}{8} \right\rfloor + \frac{xN}{16} \right) \bmod \frac{N}{2} \\ t = \left(\left\lfloor \frac{y}{2} \right\rfloor + \frac{yN}{2} \right) \bmod N \end{cases} \quad \begin{cases} 0 \leq s < N, 0 \leq t < N \\ 0 \leq x < N, 0 \leq y < N \end{cases} \quad (1)$$

if $x \bmod 2 = 1$

$$\begin{cases} s = \frac{x + N + 1}{2} \\ t = \left(\left\lfloor \frac{y}{8} \right\rfloor + \frac{yN}{8} \right) \bmod N \end{cases} \quad \begin{cases} 0 \leq s < N, 0 \leq t < N \\ 0 \leq x < N, 0 \leq y < N \end{cases} \quad (2)$$

Because the virtual LF image is imaginarily decomposed into 16 subbands as HF images, it is easy to construct the RFC between LF image and HF images. Therefore, the tree structure becomes higher in our CEIC scheme.

Furthermore, we explore the correlation between the virtual LF image and HF images on four standard test images. Here, the correlation is defined as the consistency between the significance of father coefficient in LF image and the significance of corresponding children coefficients in HF images under the same threshold. Experiment results show that the correlation values are all higher than 0.7, even when the threshold is 64 (*i.e.* high compression ratio). This indicates that there is very high correlation between virtual LF image and HF images.

Based on above analysis, we conclude that the virtual LF image can be used to achieve better compression performance in CEIC scheme.

3.3 Modified Framework of WEIC for Contourlet

Unlike wavelet decomposition, where each scale image except the highest scale only contains 3 kinds of subbands: LH, HL and HH, each scale image in our CEIC scheme contains 16 subbands. In WEIC algorithms, zero-tree and spatial-orientation tree are constructed as shown in Fig. 4 (a). It is apparent that the relationship of wavelet coefficients through scales is not identical with that of contourlet coefficients. So it is difficult to code contourlet coefficients by WEIC algorithms directly in the original structure of contourlet coefficients. In order to overcome this

problem, we organize scales and subbands of contourlet coefficients into a new format.

In the proposed scheme, each scale image, including the virtual LF image, is regarded as a whole firstly and is set in the same direction (e.g. each scale image is set in LF direction of wavelet from high scale to low scale) in order to hold the tree structure. Because the virtual LF image is decomposed into 16 directions too, tree structure can be constructed easily from the virtual LF image to the highest frequency image as shown in Fig. 4 (b).

It is noticeable that the well-known WEIC algorithms such as EZW, SPIHT and SPECK can be easily integrated into our proposed CEIC scheme. The principle of integration for these WEIC algorithms is ilk. So we only discuss the proposed CEIC scheme with respect to SPIHT in detail here. In initialization of SPIHT, all coefficients belonging to the highest scale are added to the list of insignificant pixels (LIP) and only those with descendants are also attached to the list of insignificant sets (LIS) as type A entries in SPIHT. However, in our proposed scheme, the virtual LF coefficients are added to LIP and each subband of the virtual LF image is added to LIS as type A entries in the order described in Sect. 3.1 [20].

By properly modifying, the proposed scheme can easily make use of WEIC algorithms to code contourlet coefficients.

3.4 High-Efficiency Significant Coefficient Scanning Scheme for CEIC

As we all know, image is transformed into two kinds of subbands by contourlet: LF subband and HF subband. LF subband embodies the identity of original image, and HF subband embodies the variance of original image. Obviously, in the same bit-plane, the distortion resulting from the lost of one 1 bit in LF subband is severer than that resulting from the lost of one 1 bit in HF subband, i.e. information of the former is more important than that of the latter in the aspect of reducing distortion. Note that, the motivation behind EIC algorithms is to ensure that bits with more information are coded first. Based on above analysis, we conclude that the significant bits of LF subbands should have been coded before the significant bits of HF subbands are coded in the same bit-plane.

In order to satisfy that information quantity of every coded significant bit is more than that of every uncoded significant bit when bit-stream is truncated randomly, significant coefficient scanning scheme should scan and code significant coefficients not only based on bit-planes from high to low but also based on the same bit-plane from LF subband to HF subband. The new scanning scheme is able to satisfy both demands above.

In addition, the proposed scanning scheme does not need any context-template and can easily be used in CEIC scheme by properly modifying the coding structure of traditional WEIC algorithms, which can improve the ability of compression without the increasing of computational com-

plexity.

Here, we still discuss the proposed CEIC scheme with respect to SPIHT in detail only. In order to explain the new scanning algorithm clearly and directly, we present it in outline below.

Definition in the proposed coding algorithm:

$c(i, j)$: contourlet coefficient of node (i, j) .

$sc(i, j)$: significance of node (i, j) , '1' is defined as significant, '0' as insignificant.

LIP: list of insignificant pixels.

LIS: list of insignificant sets.

RI: refinement information.

SI: sign information.

n : the number of the current bit-plane.

$$S_n(T) = \begin{cases} 1 & \max_{(i,j) \in T} |c(i, j)| \geq 2^n \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

The definitions of $O(i, j)$, $D(i, j)$, $L(i, j)$ are same as that in original SPIHT.

The proposed CEIC scheme with respect to SPIHT:

1) Initialization:

- 1.1) output the number of the highest bit-plane.
- 1.2) add coordinates $(i, j) \in$ genuine LF subband to LIP and set sc of all entries insignificant by '0'.
- 1.3) add each subband of virtual LF image orderly to LIS according to determined subband code order (subband significance) as type A entries.

2) Combining Pass: In the order of high bit-plane to low bit-plane, low band to high band in same bit-plane

- 2.1) for each entry (i, j) in LIP do:
 - if $sc(i, j) = 1$
 - output RI of $|c(i, j)|$
 - else
 - output $S_n(i, j)$
 - if $S_n(i, j) = 1$ then output SI of $c(i, j)$ and set $sc(i, j) = 1$.
- 2.2) for each entry (i, j) in LIS do:
 - 2.2.1) if the entry is of type A then
 - output $S_n(D(i, j))$
 - if $S_n(D(i, j)) = 1$ then
 - for each $(k, l) \in O(i, j)$ do
 - add (k, l) to the end of LIP
 - output $S_n(k, l)$
 - if $S_n(k, l) = 1$
 - output SI of $c(k, l)$ and set $sc(k, l) = 1$
 - else
 - set $sc(k, l) = 0$
 - if $L(i, j) \neq 0$ then move (i, j) to the end of LIS, as an entry of type B, and go to Step 2.2.2); else remove entry (i, j) from LIS.

- 2.2.2) if the entry is of type B then
 output $S_n(L(i, j))$
 if $S_n(L(i, j)) = 1$ then
 add each $(k, l) \in O(i, j)$ to the end
 of LIS as an entry of type A, and re-
 move (i, j) from LIS.

- 3) *Quantization-step update*: decrease quantization-step by 1 and go to Step 2).

Figure 5 presents an example that compares the difference of the scanning order of original scanning scheme and the proposed scanning scheme based on SPIHT. It is easy to

Fig. 5 The comparison of the scanning order of original scanning scheme and the proposed scanning scheme based on SPIHT ($c(i, j)$ is the coefficient of (i, j) , $Threshold = 16$).

know that the proposed scanning scheme scans unknown coefficients, unknown sets, and known significant coefficients simultaneously according to the significance of bits not only from high bit-planes to low bit-planes, but from LF subbands to HF subbands in the same bit-plane.

4. Experimental Results

In this paper, we integrate the well-known SPIHT algorithm into the proposed CEIC scheme to validate the performance, compared with two EIC algorithms: traditional WT with SPIHT [2] and WBCT with SPIHT [19] on low bit-rate. Experiments have been carried out on 4 standard test images (8 bpp, 512×512) at the bit-rates of 0.15 bpp and 0.25 bpp. We used 4-scale decomposition and the 9/7 biorthogonal filters [22] for WT and the filters from Phoong *et al.* [23] for LP and the directional decomposition separately. The output bit stream is not further compressed with any arithmetic coder.

Table 2 Comparison of coding results on three coding algorithms.

Image	Bit-Rate (bpp)	CEIC (dB)	SPIHT (dB)	WBCT (dB)
Barbara	0.15	24.57	23.59	21.41
	0.25	26.74	26.46	24.73
Goldhill	0.15	26.74	25.77	25.22
	0.25	28.04	27.30	27.04
Mandrill	0.15	21.00	19.16	19.05
	0.25	21.74	20.39	19.88
Fingerprint	0.15	23.85	22.35	21.81
	0.25	26.77	26.44	25.06

Fig. 6 The coding results of 'Mandrill' image at 0.25 bpp. (a) Original image (b) CEIC with SPIHT (c) WT with SPIHT (d) WBCT with SPIHT.

Fig. 7 The coding results of 'Barbara' image at 0.25 bpp. (a) Original image (b) CEIC with SPIHT (c) WT with SPIHT (d) WBCT with SPIHT.

Table 2 shows that although the proposed CEIC scheme uses overcomplete transform, it achieves 0.3–1.8 dB PSNR gain over traditional WT with SPIHT, and 1.0–3.2 dB gain over WBCT with SPIHT respectively, both of which are based on non-redundant transform. Figure 6 and Fig. 7 present the visual quality comparison respectively. It is clear that the better subjective quality can be acquired by the proposed scheme with more contours and textures preserved, even when PSNRs are in quality near (see Fig. 7).

We observe that our CEIC scheme has the better performance than two EIC algorithms on low bit-rate since the contourlet transform is more efficient in representing textures and contours. However, our CEIC scheme should have the worse performance when on high bit-rate due to the redundancy of the contourlet transform.

5. Conclusion

This paper has analyzed the distribution of significant contourlet coefficients in different subbands and proposed a contourlet-based embedded image coding scheme on low bit-rate by using an adaptive subband coding order scheme, constructing a virtual LF subband, modifying the coding framework of WEIC algorithms properly and designing a high-efficiency significant coefficient scanning scheme for CEIC scheme. Experimental results show that although the proposed CEIC scheme uses an overcomplete transform, it achieves better compression performance than traditional WT-based SPIHT and WBCT-based SPIHT, both of which

are based on non-redundant transform on low bit-rate. Furthermore, the visual quality of the proposed scheme is superior with more contours and textures.

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