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A novel direction-adaptive wavelet based image compression

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Abstract

Directional wavelet can effectively capture the directional dependence in images. However, the computational complexity is high. Based on the image statistics estimated by the structure tensor, a novel directional lifting image coder locally adapting the filtering directions to image content is presented. Before performing wavelet transform (WT), the proposed algorithm detects all the image blocks in a given image to decide whether the block is homogenous or not. For homogeneous block, the conventional 2-D discrete WT is used. This will considerably reduce the computational complexity and the number of bits needed to code the directional information. On the other hand, heterogeneous block is decomposed using directional lifting wavelet transform, which can effectively capture the directional dependence in the selected image and improve the coding gain of the image coder. Experimental results have shown that, compared to some existing methods, the proposed scheme has a better performance in terms of peak signal to noise ratio (PSNR) and subjective quality.

Keywords: Image compression; Structure tensor; Direction-adaptive lifting; Directional wavelet; Wavelet transform

1. Introduction

Discrete Wavelet Transform (DWT) has become one of the most important tools in image analysis and coding over the last two decades [1–6]. Thanks to its super performance, DWT is adopted as the heart of the JPEG2000 image compression standard. Unfortunately, the DWT lifting scheme is usually only applied in horizontal and vertical directions. This prevents the DWT transform from effectively capturing the dependence in other directions and therefore distributing the energies of such edges into several subbands. The reason is that image representation in separable orthonormal bases such as Fourier, local cosine or wavelets cannot take advantage of the geometrical regularity of image structure. Standard wavelet bases are optimal to represent functions with piecewise singularities. However, they fail to capture the geometric regularity because of their isotropic support.

Many new schemes, such as curvelets [7], contourlets [8], bandlets [10,11], and wedgelets [9], have emerged, trying to overcome the limitation of standard wavelets. But all of them suffer from problems such as computational complexity, filter design involved in, and so forth. Therefore, they are not commonly used in compression. Directionlets [12,21] provide more computational and filter design simplicity as compared with the above wavelet transforms. However, in this method, independent processing of image blocks fails to exploit the correlation across block boundaries, and may produce block artifacts. Several other directional approaches that also use lifting scheme [13–15,20], [22] were recently proposed. A separable directional lifting-based wavelet transform that is directionally adaptive has been proposed in [13]. An implementation based on separable standard wavelets and satisfying both the directionality and anisotropy, has been proposed in [14,15]. Moreover, the implementation extends the range of directions. In segmentation driven direction-adaptive discrete wavelet transform (SD-DADWT) [22], the adaptation of the directional

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wavelet bases is performed on the segments describing the natural geometry of the image. Whereas, adaptive lifting scheme [20] adapts the filtering directions to the orientations of image features and the statistic properties of image signal. These implementations achieve better coding gains through adaptive directional lifting. However, they suffer from high computational complexity. The reason is that before performing directional adaptive wavelet transform, they first predict and update all candidates' directions, and then decide which direction is the best.

We propose a new direction-adaptive lifting wavelet transform scheme which partitions the image to be compressed into nonoverlapping blocks. The motivation is based on the following two phenomena:

(1) Some blocks have little directional information. For these blocks, using horizontal and vertical directions lifting transform will considerably reduce the computational complexity for wavelet transform and avoid the coding bit for directional information.
(2) For heterogeneous blocks with many edges and contours, using neighboring pixel to directionally predict the current pixels will increase the prediction accuracy. This will effectively capture the directional dependence in image and increase the coding gain of the image coder.

The rest of the paper is organized as follows. Section 2 describes the structure tensor and how to estimate the heterogeneous and homogeneous property of each block. Section 3 presents our results along with their analysis. The conclusions are finally described in Section 4.

2. Direction-adaptive wavelet transform

Three critical problems must be solved in the proposed algorithm. (1) How to decide the subimage (block) size. (2) How to avoid the block artifacts which result due to partitioning the image to be compressed into nonoverlapping blocks. (3) How to decide the direction of wavelet transform and the corresponding model (using directional lifting wavelet transform or using conventional horizontal/vertical lifting wavelet transform) in each block due to great variation in image objects and textures. In the following section, we will explain our solution, focusing on the analysis of directional lifting and wavelet transform model selection. The first problem was solved through an optimized method which will be described in detail in Section 2.3. Meanwhile we use adjacent block's pixels to predict the current block's boundary pixels. This will solve the block artifacts problem. For the third problem, we use the structure tensor to adaptively estimate the homogeneous property of each nonoverlapping block, and then decide on the direction and corresponding model of the selected wavelet transform.

2.1. Local homogeneous analysis using structure tensor

Structure tensor has been widely used in local coherence estimation [16,17]. In image processing, structure tensor is defined for a 2D neighborhood $I(x, y)$ by

$$ST = \begin{bmatrix} I_{11} & I_{12} \\ I_{12} & I_{22} \end{bmatrix}, \tag{1}$$

$$G = \begin{bmatrix} I_x \\ I_y \end{bmatrix}, \tag{2}$$

where $I_{11} = I_x^2$, $I_{12} = I_x I_y$, $I_{22} = I_y^2$, I_x, I_y represent the image gradient in the horizontal and vertical directions, respectively.

In our experiment, a 3×3 Sobel gradient is used to estimate the gradient. Using Eq. (3), we can easily compute the eigenvalues λ_1, λ_2 of the matrix ST:

$$\lambda_{1,2} = (I_{11} + I_{22} \pm \sqrt{(I_{11} - I_{22})^2 + 4I_{12}^2})/2. \tag{3}$$

From the analysis of gradient structure tensor, we can have an insight into the following properties.

Anisotropy: Confidence measure is the confidence of structure orientation estimation, defined as

$$\alpha = (\lambda_1 - \lambda_2)/(\lambda_1 + \lambda_2). \tag{4}$$

If $\lambda_1 \approx \lambda_2$, then $\alpha = 0$, and the structure is isotropic. If $\lambda_1 \gg \lambda_2$, then $\alpha = 1$, and the structure is linear or anisotropic.

Coherence C: Local structure is estimated from λ_1 and λ_2. Homogeneous regions are characterized by $\lambda_1 \approx \lambda_2 \approx 0$, edges by $\lambda_1 \gg \lambda_2 \approx 0$. Structure coherence measures the coherence within a window, defined by $C = |\bar{\lambda}_1 - \bar{\lambda}_1| = \sqrt{(\bar{I}_{11} - \bar{I}_{22})^2 + 4\bar{I}_{12}^2}$, where $\bar{I}_{11}$, $\bar{I}_{22}$, $\bar{I}_{12}$ is the average value in one block. Large value of C means the block (subimage) is heterogeneous.

2.2. Adaptive block's homogeneous estimating

Based on the aforementioned structure tensor, we estimate the homogeneous property of block. In order to get the homogeneous information adaptively, the image to be compressed is partitioned into nonoverlapping blocks with initial size equal to 32×32. For the image to be compressed, the structure tensor is used to get the global threshold using

$$cthreshold = \frac{\sum_{i=1}^{N} \sum_{j=1}^{M} C_{i,j}}{N \times M}, \tag{5}$$

where $C_{i,j}$ is the coherence coefficient in a given block and $N \times M$ is the total block numbers of the image. After that, for each block, the following equation is used to estimate

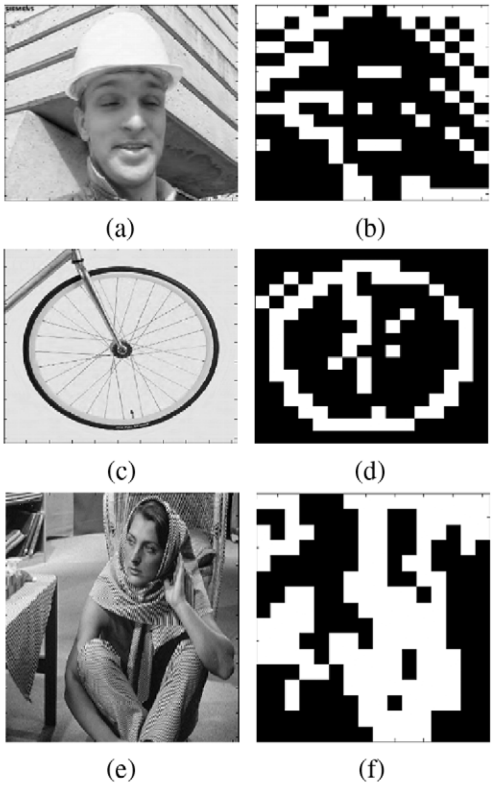

Fig. 1. Original images and directional map of test images: (a) Foreman, (b) corresponding directional map of Foreman, (c) Bike, (d) corresponding directional map of Bike, (e) Barbara, and (f) corresponding directional map of Barbara.

the homogeneous property:

$$CH = \begin{cases} 1, & C \geqslant cthreshold, \\ 0, & C < cthreshold, \end{cases} \tag{6}$$

$CH = 1$, this means that the block is heterogeneous and it contains rich directional information. Therefore, wavelet adaptive filtering should be used. This will effectively capture the dependence along the directions in the image. $CH = 0$, this means that the block is homogeneous and the wavelet used to decompose it needs not to be directional. Only using conventional horizontal and vertical directions lifting transform can effectively decrease the correlation among the pixels in the block. This will reduce the computational complexity and the number of bits needed to code the directional information.

In order to verify our method, we use Barbara, Foreman, and Bike to test the directional block selection.

In Fig. 1, the white blocks represent the heterogeneous block in the original image. The black blocks correspond to the homogeneous blocks in the original image. From Fig. 1, we can see that it is easy to effectively estimate the blocks' heterogeneous feature. For example in Fig. 1(e), the floor area in the Barbara is more homogeneous than other regions. Correspondingly, the black blocks in Fig. 1(f) are concentrated on the floor part in the original image.

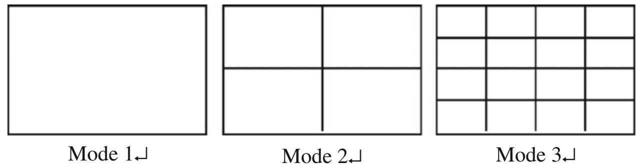

Fig. 2. The three partition block modes.

2.3. Adaptive direction and block mode prediction scheme

After adaptively estimating the heterogeneous and homogeneous features of each block, 11 candidate directions (out of the heterogeneous blocks) were used to estimate which direction is the best. To reduce the overhead bits needed to signal the direction, we made a block-wise selection rather than pixel-wise selection. Also, the block size must be adaptive. During our experiments, the block size was further categorized into three modes (illustrated in Fig. 2): 32×32 block (mode 1), 16×16 block (mode 2), and 8×8 block (mode 3). For each 32×32 block, the optimized R-D algorithm is used to estimate the best block-partition mode and transform direction. In the first direction-adaptive lifting (corresponding to the vertical lifting in the traditional lifting scheme), the criterion is based on the minimal value of the following cost function:

$$E = \sum_{m} \sum_{n} |h(m, n)| + \lambda_v R_v, \tag{7}$$

where $h(m, n)$ are the coefficients for high frequency subband after the first direction-adaptive lifting, R_v are the bits needed to code the directional information and the corresponding block mode. λ_v is the Lagrangian multiplier with value of 20.

After the first direction-adaptive lifting, we get the low subband signal $l(m, n)$ and high subband signal $h(m, n)$. We perform the second directional lifting on the $l(m, n)$ subband (corresponding to the horizontal lifting in the traditional lifting scheme). The block mode and direction may be different from the first lifting. The criterion is based on the following function:

$$E = \sum_{m} \sum_{n} |lh(m, n)| + \lambda_h R_h, \tag{8}$$

where $lh(m, n)$ are the coefficients for lh high frequency subband after performing two-step direction-adaptive lifting. R_h and λ_h remain the same as given in Eq. (7).

To further increase the efficiency of the prediction step, each 32×32 block may be further partitioned into four 16×16 blocks or 16 8×8 blocks. Based on the minimal values from Eqs. (7) and (8), the best block-partition for each block and the best direction for each sub-block are then selected.

The prediction scheme is illustrated by Fig. 3. For all the 11 candidate directions, we use the 9/7-M wavelet to perform

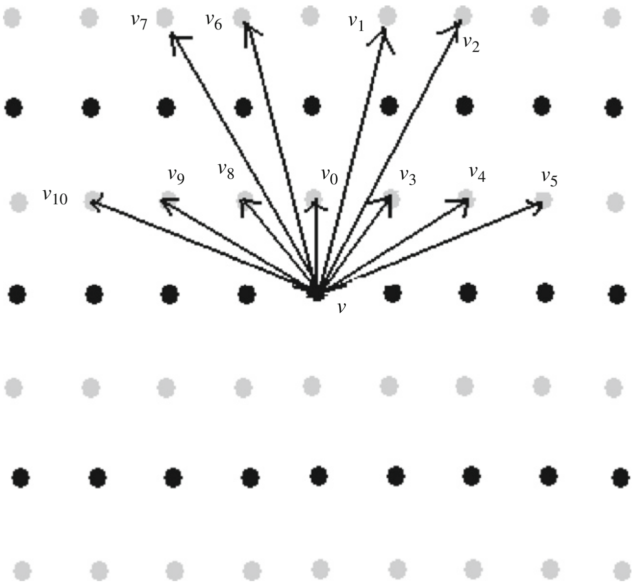

Fig. 3. The diagram of prediction directions.

the directional lifting between the gray solid pixels and black pixel such as (v, v_0), (v, v_1) and so on. The main purpose of predicting directions (v, v_1), (v, v_2), (v, v_3), (v, v_4), (v, v_5), (v, v_6), (v, v_7), (v, v_8), (v, v_9), and (v, v_{10}) are to improve the spatial prediction accuracy.

Note that we only do the direction selection for the 32×32 mode. This is because we store the temporary results in the process of estimating each candidate's direction. So from the temporary results, we can get the optimal directions for modes 2 and 3. Once the optimal direction is selected, we use the 9/7-M wavelet to perform the directional lifting. Its lifting scheme is as follows:

$$\begin{cases} d_l = d_l^0 + \frac{1}{16}((s_{l+2}^0 + s_{l-1}^0) - 9(s_l^0 + s_{l+1}^0)), \\ s_l = s_l^0 + \frac{1}{4}(d_l + d_{l-1}) + 1/2, \end{cases} \tag{9}$$

where s_l and d_l represent low and high frequency subbands, respectively.

2.4. Directional information coding

Directional information is used to predict and update the lifting direction, and must be lossless encoded. We use the block in the top and left of the current block to predict the lifting direction of the current block which is illustrated in Fig. 4. Here, c is the current block's direction being coded $(1 \leqslant c \leqslant 11)$; a and b are the directions of adjacent block used to predict the current block's direction.

Let the prediction direction p equals the minimal value of a and b. If c is equal to p, which means the prediction direction is equal to the real lifting direction, we encode it with only one bit; otherwise we encode it with 5 bits in the form of $1xxxx$, where $xxxx$ is the binary representation of c. For example, if c is equal to 8, $xxxx$ is represented by 1000.

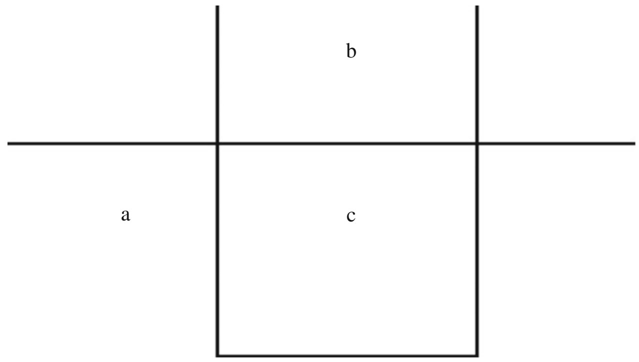

Fig. 4. The sketch map of the direction prediction.

In summary, we generalize our algorithm as follows:

(1) Partition the original image into many nonoverlapping blocks, the initial size of each block is 32×32.
(2) For each block, use Eqs. (1)–(6) to adaptively decide the lifting model (normal horizontal/vertical lifting or directional lifting).
(3) For homogeneous block, use conventional horizontal/vertical 9/7-M lifting wavelet to perform the required wavelet transform.
(4) For heterogeneous block, use 9/7-M directional lifting along the selected optimal direction decided by Eqs. (7) and (8) to perform the required directional lifting.
(5) Encode the direction and block mode of each block and place it at the head of total bitstream.
(6) For lossy compression, use SPIHT [18] algorithm to encode the wavelet coefficients, while for lossless compression, use arithmetic coder [19] to encode the wavelet coefficients.
(7) When decoding, do the inverse process.

3. Experimental results and comparisons

In the experiments, six schemes (9/7-M wavelet, DA-DWT method, directionlets, adaptive lifting, segmentation driven direction adaptive (SD-DADWT), and the present scheme) were used on several natural images. The algorithms were implemented on AMD DualCore Turion 64X2 TL-56, 1.8 GHz personal computer with 2 G memory using Matlab. The images used during our experiments are 512×512 pixels wide with 8-bit gray levels.

3.1. Lossy compression experiment

Results from the first experiment, as depicted in Tables 1–3, evaluate the time computational complexity of our method and peak signal to noise ratio (PSNR) with DA-DWT for different images Barbara, Building, and Bike. Here, BN represents block numbers needed by the

Table 1. Comparison of performance for Barbara.

Method	Threshold	$\frac{1}{18}$	$\frac{1}{6}$	$\frac{1}{4}$	$\frac{2}{5}$	$\frac{1}{2}$	$\frac{5}{9}$	$\frac{3}{5}$	$\frac{5}{7}$	$\frac{4}{5}$
Our method	BN	212	185	166	146	129	122	113	106	97
	Times (s)	3.90	3.62	3.43	3.20	3.03	2.96	2.88	2.74	2.61
	Overhead bit (bpp)	0.0214	0.0205	0.0190	0.0182	0.0176	0.0172	0.0163	0.0157	0.0148
	PSNR	30.13	30.11	30.13	30.13	30.11	30.12	30.11	30.04	30.00
DA-DWT	PSNR	30.10								
	Times (s)	4.15								

Table 2. Compression performance comparison for Building.

Method	Threshold	$\frac{1}{30}$	$\frac{1}{6}$	$\frac{1}{5}$	$\frac{1}{3}$	$\frac{1}{2}$	$\frac{3}{5}$	$\frac{9}{13}$	$\frac{6}{7}$	$\frac{6}{5}$
Our method	BN	170	162	158	144	133	129	124	117	104
	Times (s)	3.45	3.37	3.26	3.14	3.05	2.97	2.90	2.83	2.67
	Overhead bit (bpp)	0.0241	0.0234	0.0233	0.0228	0.0222	0.0220	0.0218	0.0207	0.0179
	PSNR	27.41	27.41	27.40	27.38	27.36	27.36	27.32	27.29	27.17
DA-DWT	PSNR	27.34								
	Times (s)	4.16								

Table 3. Compression performance comparison for Bike.

Method	Threshold	$\frac{1}{16}$	$\frac{1}{7}$	$\frac{4}{11}$	$\frac{9}{14}$	$\frac{13}{14}$	$\frac{7}{6}$	$\frac{7}{5}$	$\frac{11}{6}$	2
Our method	BN	178	168	149	119	90	70	62	50	45
	Times (s)	3.48	3.37	3.12	2.79	2.46	2.24	2.10	1.88	1.82
	Overhead bit (bpp)	0.0180	0.0178	0.0167	0.0146	0.0122	0.0102	0.0088	0.0068	0.0059
	PSNR	35.15	35.10	34.81	34.41	33.77	33.48	33.33	32.96	32.83
DA-DWT	PSNR	35.11								
	Times (s)	4.14								

directional lifting wavelet transform in the first level decomposition. Overhead bit is used to code the directional information and block mode information, and time represents the time needed for the forward wavelet transform. From Tables 1–3, we can see that when maintaining similar performance in terms of PSNR, the computational complexity of our method is only 75% of that of DA-DWT. The reason is that according to our algorithm, some blocks (subimage) directly use the normal lifting wavelet. This reduces the computational complexity and the number of overhead bits for directional information and block mode coding.

From Tables 1–3, we can see that as the threshold become larger, the blocks needed for directional lifting become smaller. Also, the time needed for the wavelet transform, and overhead bits coded for the directional information and block mode decreased. This is because larger threshold means more blocks are estimated to be homogeneous, which may decrease the computational complexity of wavelet transform and bits needed for directional information and block mode coding.

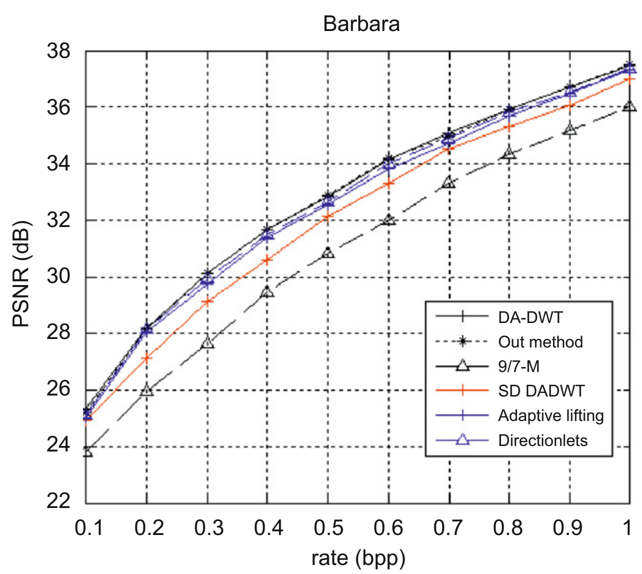

Fig. 5. The PSNR versus bpp curve for Barbara.

In order to further verify the performance of the proposed method, compression performance curves (at different bit rates) corresponding to the six schemes are shown in Figs. 5–7. From Fig. 5, we can see that our algorithm is better than the one using 9/7-M wavelet. Thus, for Barbara, a gain of up to 2 dB can be obtained. Compared to DA-DWT method, the proposed algorithm maintains similar image compression performance in terms of PSNR at different bit rates. Also, Figs. 5–7 show that when using SPIHT to encode the wavelet coefficients, our method is a little better than adaptive lifting scheme and directionlets. Basically, all the three methods, that is adaptive lifting, directionlets, and the one we hereby present, have similar performance at low bit rates. From Figs. 5–7, we can notice that our method outperforms SD-DADWT (for about 0.8 dB) for the three test images in Fig. 8.

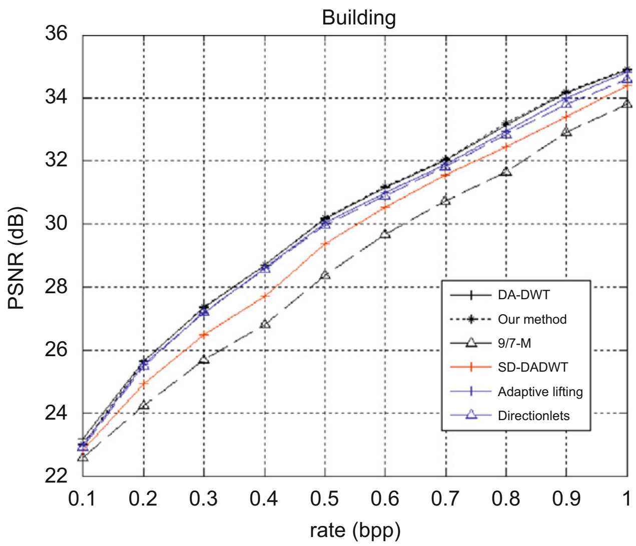

Fig. 6. The PSNR versus bpp curve for Building.

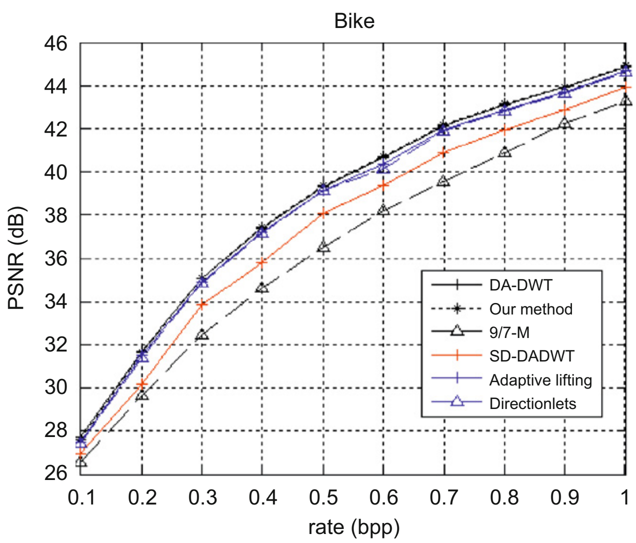

Fig. 7. The PSNR versus bpp curve for Bike.

Part of the Barbara image is shown in Fig. 9, along with the reconstructions at 0.3 bpp. The subjective quality from the proposed method around the arm and along the stripes on the fabrics in Barbara is significantly better than that from the 9/7-M scheme. These results show that, compared to conventional 9/7-M approach, the proposed method is better in handling sharp image features. Compared to the DA-DWT method, reconstruction image with our method has similar visual quality. However, the computational complexity is less with our method than with DA-DWT scheme (Tables 1–3). When compared with directionlets, our method has better subjective quality. This can be verified by comparing Fig. 9(c) and (e). Some block effect remains in Fig. 9(e).

Considering the Building and Bike test images, the original and the reconstruction test images using four methods (9/7-M, the DA-DWT, directionlets, and our method) are shown in Figs. 10 and 11. We can see that our method outperforms the 9/7-M wavelet and has similar performance with DA-DWT method, with lower computational complexity. Some local effects for directionlets shown in Fig. 10(e) are not as good as those shown in Fig. 10(c).

3.2. Lossless compression experiment

In this part, we compare the performance of three methods (9/7-M, DA-DWT, and our method) using lossless compression. During our experiment, wavelet coefficients are encoded using an arithmetic coder [19]. Results are shown

(a) (b) (c)

Fig. 8. Original test images: (a) Barbara, (b) Building, and (c) Bike.

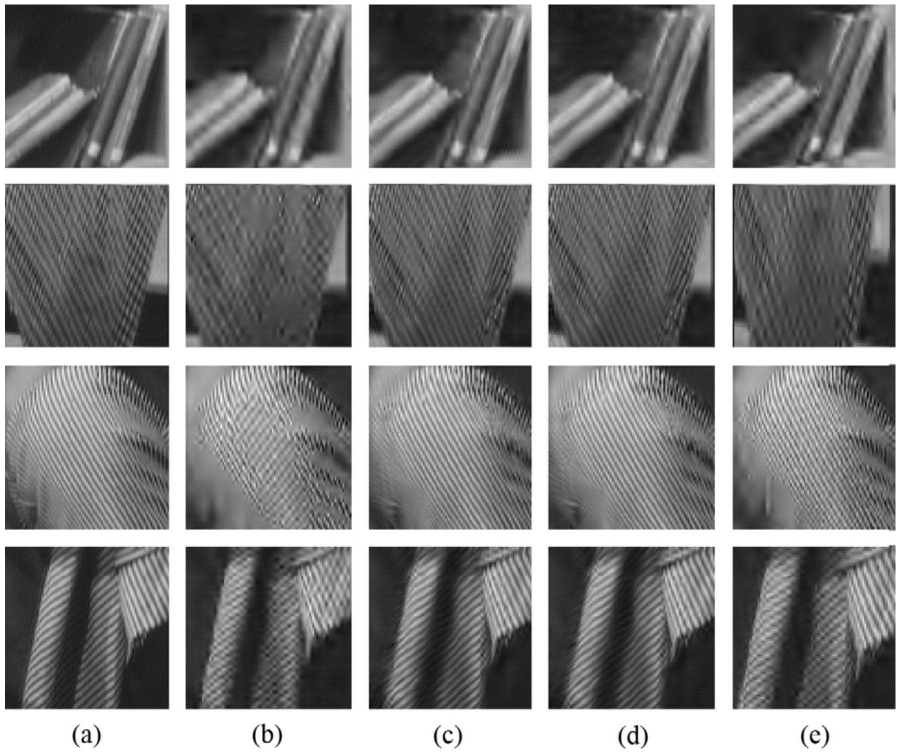

Fig. 9. Local effects of Barbara at 0.3 bpp. (a) Original Barbara image; (b)–(e) reconstruction image using 9/7-M wavelet, our method, DA-DWT, and Directionlets, respectively.

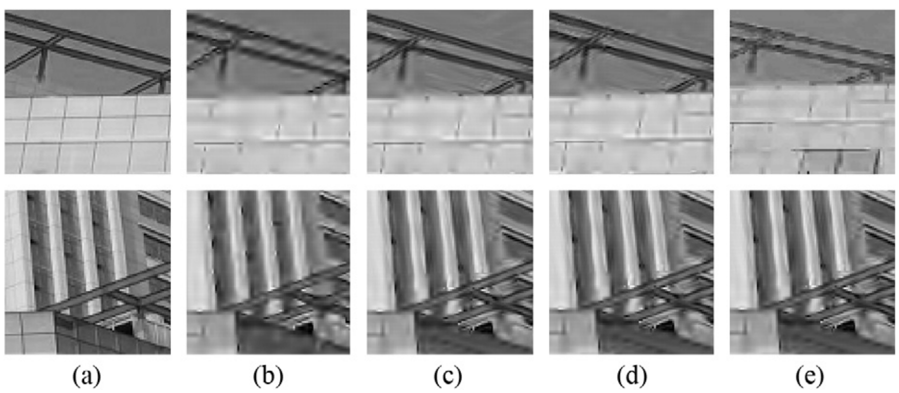

Fig. 10. Local effects of Building at 0.3 bpp. (a) Original building image; (b)–(e) reconstruction image by 9/7-M wavelet, our method, DA-DWT, and Directionlets, respectively.

in Tables 4 and 5. In this experiment, the directional information is considered. The overhead bits are added at the head of the total bitstream. From the result, we can see that although the directional lifting wavelet needs some additional bitstream, the proposed directional lifting always outperforms the conventional 9/7-M wavelet. For Barbara, a performance of up to 0.2 bpp can be achieved in different decomposed levels. This is because the directional lifting can effectively capture the directional dependence in the Barbara image. Compared to DA-DWT method, the performance is fairly the same; but the computational complexity is reduced. The reason is that DA-DWT performs directional lifting wavelet transform for all the pixels in the image; while our method only does it in heterogeneous block which is estimated by structure tensor.

4. Conclusion

In this paper, a new image coding method based on adaptively selecting directional lifting or normal horizontal/vertical lifting is presented. In our algorithm, image is partitioned into many nonoverlapping blocks. For each block, structure tensor is used to decide which of directional

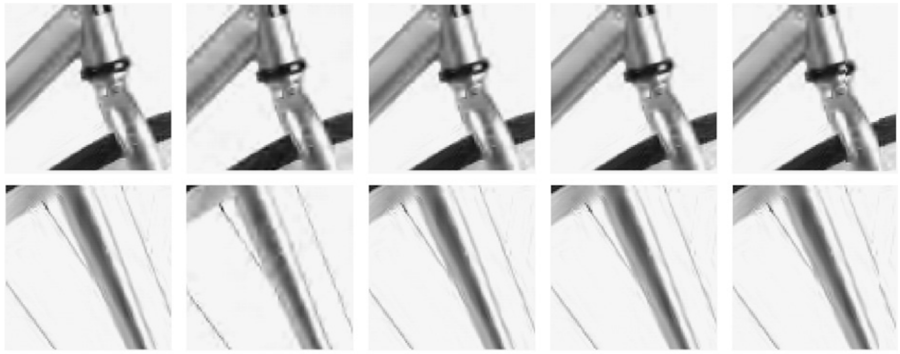

Fig. 11. Local effect of Bike at 0.3 bpp. (a) Original Bike image; (b)–(e) reconstruction image by 9/7-M wavelet, our method, DA-DWT, and Directionlets, respectively.

Table 4. Comparison of performance for Barbara.

Decomposition level	2	3	4	5
Normal 9/7-M (bpp)	4.8712	4.7753	4.7486	4.7360
DA-DWT (bpp)	4.6579	4.5663	4.5423	4.5223
Our method (bpp)	4.6935	4.6001	4.5793	4.5651

Table 5. Comparison of performance for Bike.

Decomposition level	2	3	4	5
Normal 9/7-M (bpp)	3.2281	3.2328	3.2289	3.2140
DA-DWT (bpp)	3.0684	3.0753	3.0780	3.0668
Our method (bpp)	3.0707	3.0768	3.0792	3.0683

lifting wavelet transform or horizontal/vertical lifting should be used. It is worth mentioning that the directional lifting though much more complex than the horizontal/vertical lifting can effectively capture the directional dependence.

Theoretical analysis and experimental results prove that the proposed method is more powerful than the normal 9/7-M wavelet method. It outperforms it both using lossy and lossless compressions. Compared to the DA-DWT method, the proposed algorithm can reduce the computational complexity of wavelet transform, while maintaining similar compression performance in terms of PSNR. Compared to some other existing methods, our method outperforms them in terms of PSNR.

In the future, we will further analyze image statistic characteristics and use proper threshold to adaptively estimate the directional information. If that works, better results could be obtained.

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