I.J. Information Technology and Computer Science, **2010, 2, 25-32**
Published Online December 2010 in MECS (http://www.mecs-press.org/)

32Still Image Compression Algorithm Based on Directional Filter Banks

Chunling Yang, Duanwu Cao and Li Ma
School of Electronic and Information Engineering, South China University of Technology, Guangzhou, China
Email: eeclyang@scut.edu.cn, eedwcao@gmail.com, maryhp6@163.com

***Abstract*—Hybrid wavelet and directional filter banks (HWD) is an effective multi-scale geometrical analysis method. Compared to wavelet transform, it can better capture the directional information of images. But the ringing artifact, which is caused by the coefficient quantization in transform domain, is the biggest drawback of image compression algorithms in HWD domain. In this paper, by researching on the relationship between directional decomposition and ringing artifact, an improved decomposition approach of HWD(IHWD) is proposed to reduce the ringing artifact. In addition, the IHWD algorithm and directional weighting model is applied into the JPEG2000 coding framework, and a new still image compression algorithm IJPEG2000 is proposed. The experimental results show that IJPEG2000 has better performance than JPEG2000 whether on objective evaluation method or on subjective visual feeling.**

***Index Terms*—Image compression, wavelet transform, directional filter banks(DFB), hybrid wavelet and directional filter banks(HWD)**

I. Introduction

JPEG2000 is a new generation still image compression standard based on wavelet transform. It has many advantages, such as a better compressibility than JPEG, no blocking effect, can support both lossless and lossy compression etc[1]. Although the wavelet transform is a great success, it has shown some limitations in dealing with two-dimensional images[2]. In wavelet image coding system, coding the wavelet coefficients usually start from the largest one. Therefore, after wavelet transform, the sparser coefficients are, the more concentrated energy is, the more efficient image coding will be. The two-dimensional wavelet used at common situation is just the tensor product of one-dimensional wavelet[3] and has only horizontal and vertical two directions of filtering operation. That means more vertical and horizontal information image contains will lead to sparser of the coefficients in transform domain. However, natural images have a lot of directional information besides these two directions, and therefore, the performance of two-dimensional wavelet in this area is usually not satisfactory[4].

As means to offset this deficiency of wavelet, multi-scale geometrical analysis theory has been rapidly developed, such as bandelet[5], ridgelet[6], curvelet[7], directionlets[8] etc. Contourlet[9] is also a well-known multi-scale analysis algorithm proposed by Do and Vetterli. Contourlet transform can optimally represent images by using Laplacian pyramid(LP)[10] decomposition and directional filter banks(DFB)[11]. However, it is not the optimum choice for image compression because of its 4/3 redundancy introduced by LP decomposition.

By employing wavelet instead of LP decomposition, Eslami and Radha proposed wavelet-based contourlet transform(WBCT)[12][13], which is a non-redundant transform and is more superior for image coding.

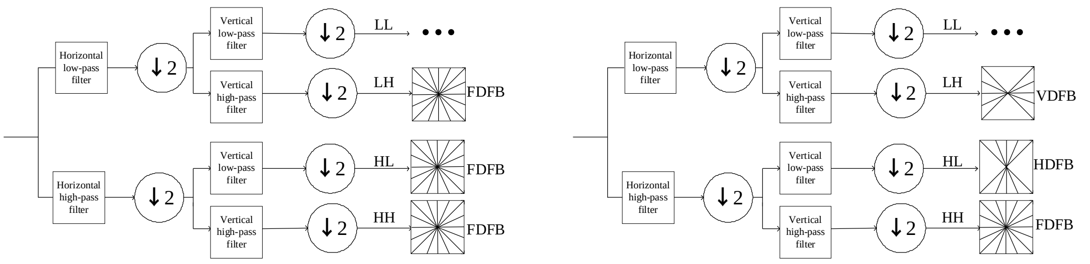
Hybrid wavelet and directional filter banks(HWD)[1] is an extension of WBCT, and it is on the highest level among those multi-scale geometrical analysis methods based on DFB. Three types of DFBs are defined in HWD, which make the combining of wavelet and DFBs more flexible.

Many scholars were interested in WBCT and HWD. Some image compression algorithms based on WBCT transform have been proposed. Yang et al. introduced WBCT transform into SPIHT[15], Tian et al. introduced WBCT into SPECK[16], Song et al. introduced WBCT into JPEG2000 by calculating the decomposition vector according to the size of EBCOT block[17]，and Gu et al. also did JPEG2000 coding in WBCT domain by using complex weighting algorithm[18]. Although these compression algorithms have made some improvements, they did not mention how to solve the problem of ringing artifact caused by using directional decomposition. Ringing artifact which occurs at the time of quantizing transform coefficients is a major drawback of HWD and WBCT for image compression.

In this paper, the relationship between ringing artifact and directional decomposition is first discussed. Then, an improved decomposition approach of HWD(IHWD) and directional weighting model are proposed to reduce the ringing artifact. Moreover, by applying the IHWD algorithm and directional weighting model into JPEG2000 framework, a new still image compression algorithm IJPEG2000 is proposed. The experimental results show that IJPEG2000 can better reflect contours

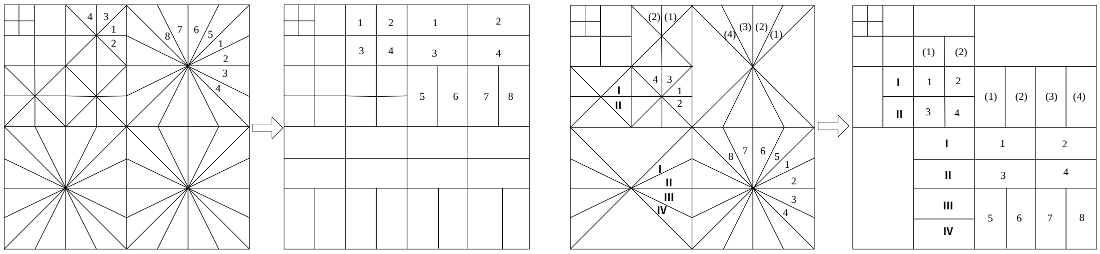
This work is supported by National Natural Science Foundation (No.60972135) and the Fundamental Research Funds for the Central Universities, SCUT (No. 2009ZM0231).

The authors are all with the School of Electronic and Information Engineering, South China University of Technology, Guangzhou, China.



(a) HWD-F (b) HWD-H

Figure 1. Two decomposition types of conventional HWD



(a) HWD-F (b) HWD-H

Figure 2. Location of directional subbands in HWD domain

and texture information of images, as compared to JPEG2000 coding at same rate conditions.

II. Hybrid Wavelet and Directional Filter Banks

In Reference[1], Eslami and Radha proposed HWD transform. The main idea is to apply wavelet transform to original image first, and then apply DFB decomposition to those high frequency bands. DFB can be classified as FDFB, HDFB and VDFB. FDFB is the full-tree DFB. VDFB and HDFB are the half-tree DFBs. An L-level FDFB produces 2^L subbands, including 2^{L-1} horizontal subbands and 2^{L-1} vertical subbands. While an L-level VDFB(HDFB) produces 2^{L-1} horizontal(vertical) subbands and one vertical(horizontal) subband.

By choosing different DFBs, conventional HWD can be classified as two types: HWD-F(HWD using full-tree DFBs) and HWD-H(HWD using half-tree DFBs). Fig.1 shows the diagram of HWD-F and HWD-H decomposition.

In this paper, the high frequency bands in wavelet domain are divided into k frequency bands in accordance with the frequency from high to low. In HWD decomposition, we use L_1, L_2, $\cdots$, L_k to mark the directional decomposition level from the highest frequency band(HL_1, LH_1, HH_1) to the lowest frequency band(HL_k, LH_k, HH_k). We define vector $\boldsymbol{V}=[L_1, L_2, \cdots, L_k]$ as the decomposition vector of HWD transform. Placed all the directional subbands and LL frequency band together in a certain order, we can get a data matrix with the same size as original image. Fig.2 shows the decomposition diagram and the location of directional subbands of HWD-F and HWD-H. Here, the decomposition vector is [3 2 0 0].

III. An Improved Decomposition Approach of HWD—IHWD

A. Theoretical Basis of IHWD Algorithm

Eslami and Radha proposed two decomposition approaches of HWD(HWD-F and HWD-H), but they are not the optimal approach for image coding. The IHWD algorithm is mainly based on the following three points.

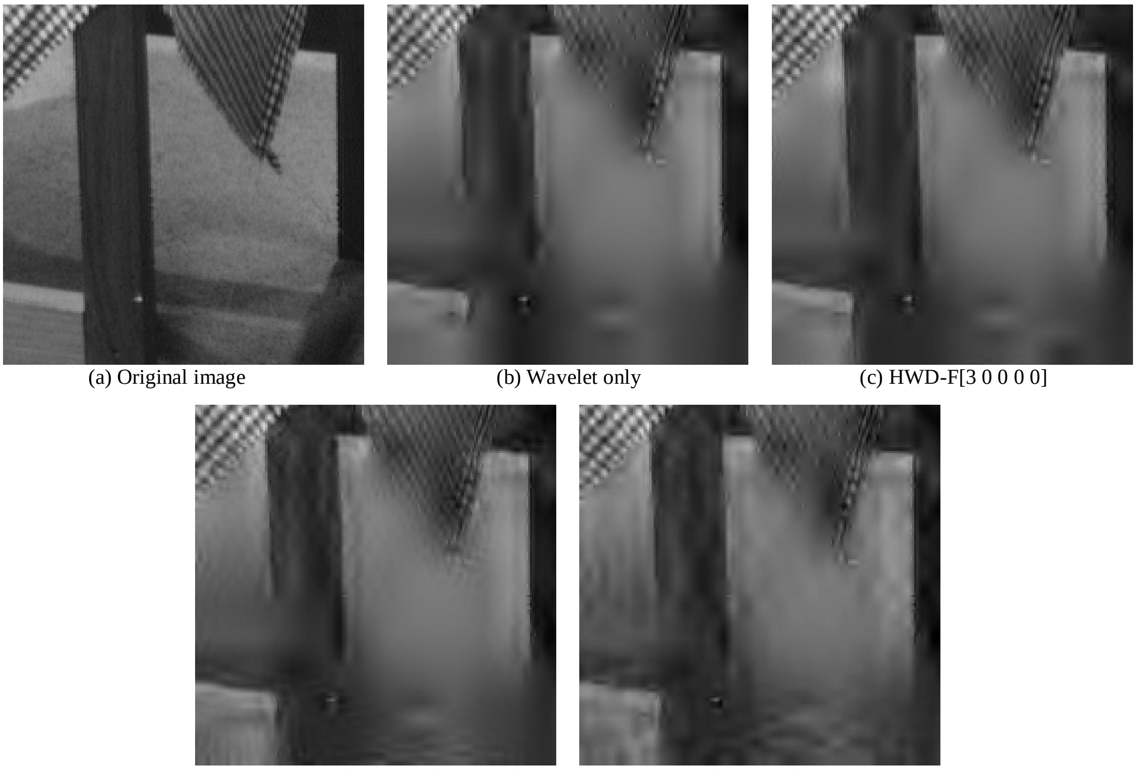
1. Ringing artifact is mainly introduced in those low frequency bands.

It is known that directional filtering for low frequency bands may introduce severe ringing artifact[1]. We try to perform NLA[19] experiments to prove this conclusion. We apply 3-level FDFB decomposition to each frequency bands of image after 5-level wavelet transform, reserve 1/16 largest coefficients in HWD domain and reconstruct the image in pixel domain. Fig.3 shows the reconstructed images of the experiment.

From Fig.3, we can find that the ringing artifact in decoded image is slight when only applying DFB to the highest frequency band. Compared to Fig.3(b), the improvement of visual feelings is obvious in Fig.3(c). However, the decoded image has a bad visual quality when applying DFB to the second-high frequency band or lower.

2. The improvement of PSNR is mainly from the decomposition of the highest frequency band.

Repeat the experiment above, the four curves in Fig.4 represent the different PSNR values of the decoded images by different decomposition vector. Horizontal coordinate $\log_2 M$ is the number of reserved coefficients. Compared to wavelet, the improvement of PSNR is mainly from the decomposition of the highest frequency band and the improvement of the decomposing second-



(a) Original image (b) Wavelet only (c) HWD-F[3 0 0 0 0]

(d) HWD-F[0 3 0 0 0] (e) HWD-F[0 0 3 0 0]

Figure 3. Decoded images of NLA experiment

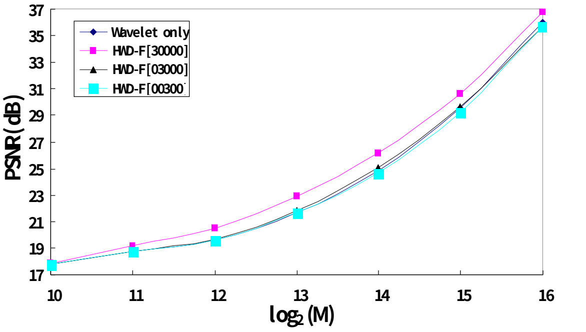


Figure 4. PSNR of decoded images in NLA experiment

high frequency band is tiny and negligible. The reason is that the ringing artifact introduced in second-high frequency band seriously impact on the encoding performance. To the third-high or even lower frequency band, applying any forms of DFB is inappropriate.

3. Full-tree DFB and half-tree DFB have their own advantages and disadvantages.

Compared to half-tree DFB(HDFB and VDFB), full-tree DFB(FDFB) can work well on capturing the directional information of image. However, full-tree DFB decompose the low frequency information in HL and LH bands, which introduces severer ringing artifact in decoded image. In HWD-H scheme, half-tree DFB is applied to decompose HL and LH bands for the sake of avoid decomposing low frequency information and so as to suppress ringing artifacts. Unfortunately, its PSNR is accordingly reduced. Generally speaking, full-tree DFB and half-tree DFB have their own advantages and disadvantages.

B. IHWD Algorithm

According to the experiments and analysis above, if we apply full-tree DFB to the highest frequency band, the directional information will be encoded well and the ringing artifact will be slight, for ringing artifact is not sensitive to high frequency. As for the second-high frequency band, we may apply half-tree DFBs. Thus, from the global perspective, this approach can not only maintain high encoding quality, but also control the ringing artifact. This is the IHWD decomposition scheme we proposed. It can be described by the following 3 steps.

1. Apply wavelet transform to original image.

2. Apply HWD-F transform to the highest frequency band.

3. Apply HWD-H transform to the second highest frequency band.

IV. Directional Weighting Model

A. Motivation of Directional Weighting

Take HDFB decomposition in HL band for example, HL band contains high frequency information in horizontal direction and low frequency information in vertical direction. In wavelet domain, the vertical direction is the main direction of the texture in HL band. Since DFB is not suitable to decompose low frequency information, HDFB is chosen to decompose the HL band so that the low frequency information would not be decomposed. According to this viewpoint, when applying

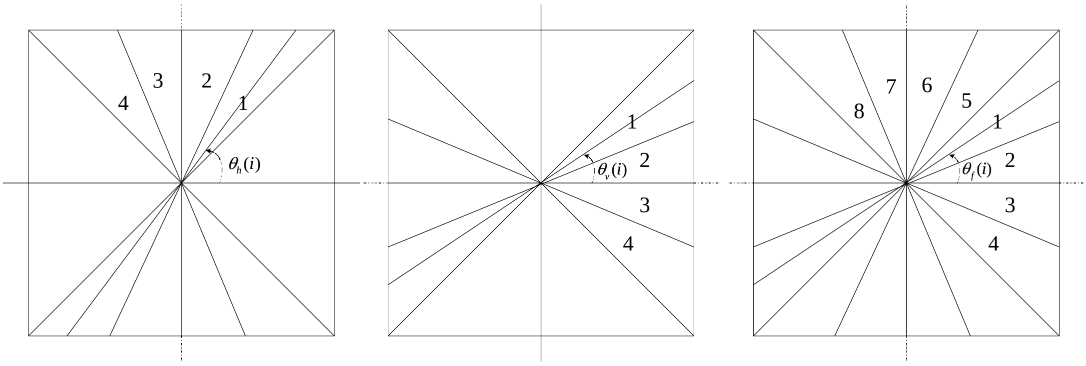


Figure 5. Directional angle in DFB decomposition

HDFB decomposition to HL band, the directional subbands that are closer to vertical axis contain less low frequency information and will introduce less ringing artifact. In contrast, the directional subbands that are closer to horizontal axis contain more low frequency information and will introduce severer ringing artifact. Thus, in DFB(either HDFB or FDFB) decomposition domain of HL band, the directional subbands that are closer to vertical direction are more important. For the same reason, in DFB(either VDFB or FDFB) decomposition domain of LH band, the directional subbands that are closer to horizontal direction are more important.

Thus, weighting the HWD coefficients according to the directions of subbands may enhance the importance of the high frequency information, which can also control the ringing artifact to some extent.

B. The Directional Angle of Subband

Fig.5 shows the directions of subbands in DFB decomposition. Use i =1, 2, $\cdots$ to mark these subbands. Define the angle of ith directional subband $\theta(i)$ as follows: the horizontal axis for the start edge and the central axis of the subband for the final edge, as is shown Fig.5.

According to Fig.5(a), the angle of ith directional subband in HL band $\theta_h(i)$ can be calculated by (1). Here, the subscript h means HDFB decomposition domain.

$$\theta_h(i) = (\frac{1}{4} - \frac{1}{2^{L+1}} + \frac{i}{2^L})\pi, \quad 1 \le i \le 2^{L-1} \qquad (1)$$

For the same reason, the direction angle in LH and HH band can be calculated by (2) and (3).

$$\theta_v(i) = (\frac{1}{4} + \frac{1}{2^{L+1}} - \frac{i}{2^L})\pi, \quad 1 \le i \le 2^{L-1} \qquad (2)$$

$$\theta_f(i) = \begin{cases} (\frac{1}{4} + \frac{1}{2^{L+1}} - \frac{i}{2^L})\pi, & 1 \le i \le 2^{L-1} \\ (\frac{i}{2^L} - \frac{1}{2^{L+1}} - \frac{1}{4})\pi, & 2^{L-1}+1 \le i \le 2^L \end{cases} \qquad (3)$$

Thus, the directional angle $\theta(i)$ of directional subbands can be obtained by (4).

$$\theta(i) = \begin{cases} \theta_h(i), & \text{HDFB domain} \\ \theta_v(i), & \text{VDFB domain} \\ \theta_f(i), & \text{FDFB domain} \end{cases} \qquad (4)$$

C. Weighing Value

Because $\theta(i)$ represents for the direction of the ith subband, the value of $\cos\theta(i)$ can represent how close the subband is to the horizontal axis. For the same reason, the value of $\sin\theta(i)$ can represent how close the subband is to the vertical axis. For HL band, in order to enhance the importance of vertical texture information, the coefficients can be weighted by

$$w_{hl}(i) = 1 + \lambda(|\sin\theta| - 0.5) \qquad (5)$$

For the same reason, in order to enhance the importance of horizontal texture information, the coefficients can be weighted by

$$w_{lh}(i) = 1 + \lambda(|\cos\theta(i)| - 0.5) \qquad (6)$$

Here, λ is a constant using for adjust the range of the weight.

D. Weighting Formula

Suppose $s(x,y)$ is an original coefficient of transform domain, and $s'(x,y)$ is the corresponding coefficient that is weighted. The weighting algorithm can be expressed by (7).

$$s'(x,y) = \begin{cases} s(x,y) \times w_{hl}(i), & (x,y) \in HL \\ s(x,y) \times w_{lh}(i), & (x,y) \in LH \\ s(x,y), & (x,y) \in HH \end{cases} \qquad (7)$$

It is worth mentioning that the directional weighting model can be used whether the transform is HWD-F, HWD-H or IHWD.

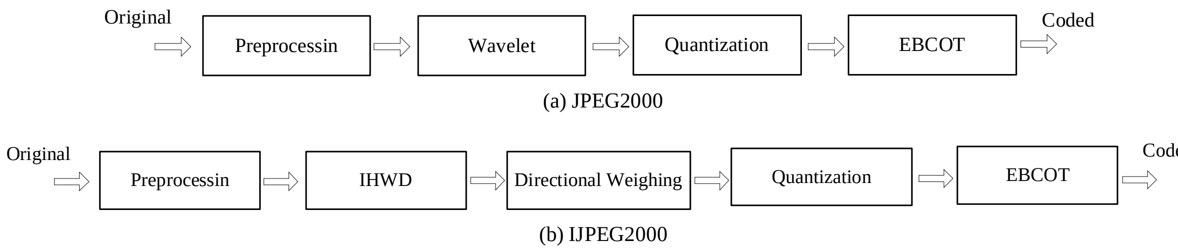


Figure 6. JPEG2000 and IJPEG2000 encoder

TABLE I.
COMPARATIVE EXPERIMENT IN DIFFERENT DOMAINS (dB)

Rate/bpp	0.05	0.1	0.2	0.3	0.4	0.5	0.6
HWD-F	22.99	25.14	27.56	29.42	30.75	32.08	33.17
HWD-H	22.81	24.99	27.48	29.42	30.83	32.19	33.28
IHWD	22.99	25.15	27.60	29.50	30.84	32.19	33.27

V. IJPEG2000 ALGORITHM

Because HWD has the same size of coefficients matrix as wavelet, it can be used to take place of wavelet in JPEG2000 coding. Here, IHWD is applied as for the HWD decomposition scheme. The directional weighting model illustrated in Section IV is also introduced. JPEG2000 and IJPEG2000 encoder is shown in Fig.6. In the decoder side, there is the corresponding weighting algorithm and inverse transform.

VI. EXPERIMENT AND ANALYSIS

In this section, we will do various forms of JPEG2000 experiments in HWD domain, including IJPEG2000. In these experiments, 5-level Daubechies 9-7 wavelet is used in HWD transform. The decomposition vector of HWD is [3 2 0 0 0]. The directional filter bank is based on triplet[20]. The block size of EBCOT is 32×32. The constant λ =2.

A. Advantage of IHWD

We separately do JPEG2000 experiment in HWD-F, HWD-H and IHWD domain. We don’t apply directional weighting model in this experiment. Table I shows the PSNR of the decoded images in this set of comparative experiments.

Comparing the JPEG2000 results of HWD-F and HWD-H, we find that HWD-F has better performance in low bit rate while HWD-H has better performance in high bit rate. The main reason is that ringing artifact is not the key factor in decision of good or bad performance of coding algorithm in low bit rate. The key factor is whether the directional information of the image is well captured. So in low bit rate, HWD-F shows its advantage of full directions. While in high bit rate, most information has been coded well, especially in the bit rate above 0.5bpp, the decoded image has been very close to the original image under human visual system. At this time, ringing artifact becomes the key factor of coding performance and HWD-F shows its advantage of good control of ringing artifact.

As for the IHWD algorithm, it has similar performance as HWD-F in low bit rate and as HWD-H in high bit rate. IHWD shows the advantage of both HWD-F and HWD-H, as is mentioned in section III.

B. Meaning of Directional Weighting

Another set of comparative experiments about directional weighting is done in this paragraph. We do two JPEG2000 experiments in IHWD domain. One is with directional weighting model and the other is not.

In this set of experiments, we find the PSNR values of the decoded images are very close to each other. The maximum error of them does not exceed 0.05bpp. Clearly, weighting algorithm has not brought improvement of PSNR. Of course, this is not the meaning of directional weighting algorithm. In human visual feeling, directional information like contours and textures in image is usually more important. However, in PSNR image quality evaluation system, each pixel of the image is equal. Enhancing the weight of directional information is clearly not able to improve the PSNR value. But it may bring better human visual feeling.

Fig.7 and Fig.8 show a decoded image of the experiment contrast in some details. The edge of the table in Fig.7(c) is much clearer than in Fig.7(b). The contours of the arm in Fig.8(c) is also clearer than in Fig.8(b). The improvement of human visual feeling is the meaning of directional weighting.

C. Comparison of JPEG2000 and IJPEG2000

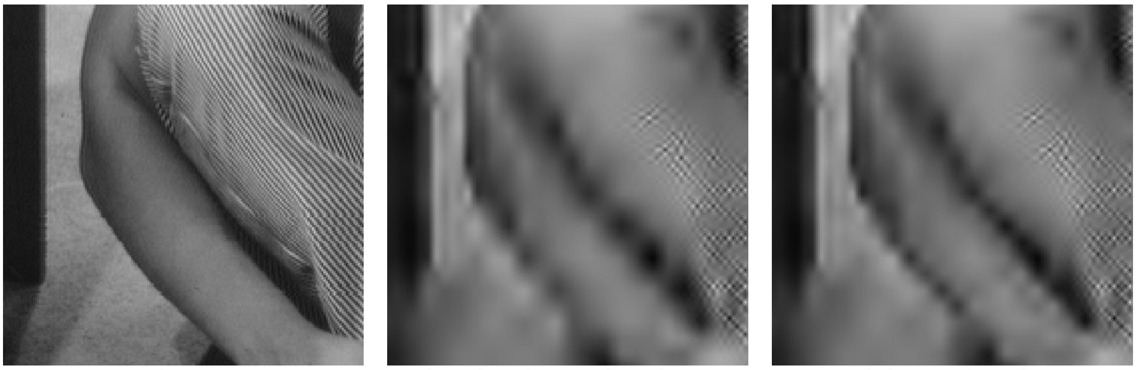
Fig.9 shows the comparative experiments results of barbara image in JPEG2000 and IJPEG2000 experiment. From Fig.9, it can be seen that the PSNR curve of decoded images of IJPEG2000 is higher than the one of JPEG2000. Especially in low bit rate, the improvement is more evident. This shows that IJPEG2000 can better capture the directional information of image than JPEG2000, for it is based on IHWD transform.

Fig.10 shows the decoded images of JPEG2000 and IJPEG2000 at 0.05bpp. In this set of comparative figures, we can see the texture information of the pants is lost in JPEG2000 coding. However it can be clearly seen in the decoded image of IJPEG2000. Compared to original image, the decoded image of IJPEG2000 has better visual feeling.

Fig.11 shows the corresponding experiment results of buildings image in 0.3bpp. From the comparison of the

(a) original image (b) without directional weighting (c) with directional weighting

Figure 7. Comparative experiment of directional weighting—detail 1



(a) original image (b) without directional weighting (c) with directional weighting

Figure 8. Comparative experiment of directional weighting—detail 2

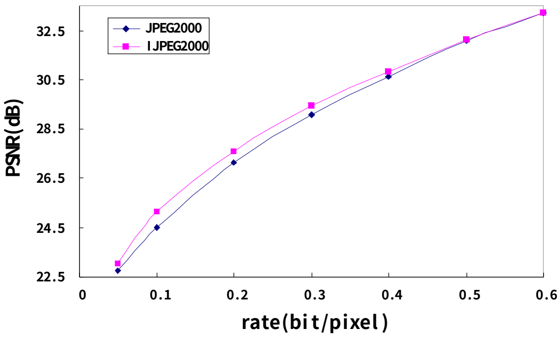


Figure 9. PSNR of decoded images in JPEG2000 and IJPEG2000 comparative experiment

decoded images, it is clear that texture information of the windows in original image is lost in Fig.11(b), while it appears in Fig.11(d).

Table II shows the results of 5 typical images in JPEG2000 and IJPEG2000 comparative experiment coding at 0.05bpp and 0.1bpp. From the table, we can see that the PSNR values of IJPEG2000 are higher than those of JPEG2000. The conclusion is similar as what the above experiments shows.

VII. Conclusion

Because the wavelet transform in JPEG2000 has only limited directions, JPEG2000 can not well represent the directional information like contours and textures in image. In this paper, a multi-scale geometrical analysis method—HWD is introduced into JPEG2000 framework. Since the conventional decomposition models of HWD have their own advantages and disadvantages, we proposed an improved decompression model of HWD—IHWD. The IHWD algorithm can maintain the advantages of both the two conventional models. In order to better control the ringing artifact, we proposed directional weighting model according to the frequency characteristics of the directional subbands and get better human visual feelings in decoded images. IJPEG2000 still image compression algorithm includes both the IHWD algorithm and directional weighting model. It can better represent the directional information than JPEG2000. The experimental results show that IJPEG2000 has better performance than JPEG2000 whether on objective evaluation method or on subjective visual feeling. Although we have get some results on improving coding the directional information of images, there are still some places needing further research. For example, we may get a marked improvement in the results when the image is full of texture and contours. But when the image is smooth, the improvement will be small. What's more, how to select the parameter λ in the directional weighting model is also questionable.

Acknowledgment

The authors wish to thank the reviewers for their careful reading and helpful comments.

(a) original image (b) JPEG2000 (c) IJPEG2000

Figure 10. Barbara image coded at bit-rate of 0.05bpp

(a) original image (b) JPEG2000 (c) IJPEG2000

Figure 11. Buildings image coded at bit-rate of 0.3bpp

TABLE II.
JPEG2000 AND IJPEG2000 EXPERIMENT OF 5 TYPICAL IMAGES (dB)

images	0.05bpp		0.1bpp	
	JPEG2000	IJPEG2000	JPEG2000	IJPEG2000
cfield	22.198	22.207	24.222	24.285
girldisk	33.750	33.883	37.344	37.557
yacht	24.360	24.447	27.097	27.247
buildings	18.706	18.755	20.393	20.484
lighthouse	24.485	24.601	26.538	26.553

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Chunling Yang (He'nan province, China, 1970) received the B.S. degree from Department of Electronic Engineering, Zhengzhou University, Zhengzhou, China, in 1991, the M.S. degree in 1996 and the Ph.D. degree in 1999, both from department of electronic engineering, Nanjing University of Science and Technology, Nanjing, China.

She is a professor at School of Electronic and Information Engineering, South China University of Technology (SCUT). Her research interests include image quality assessment and image/video compression. She has more than 40 publications in these fields.

Dr. Yang is an IEEE member.

Duanwu Cao (Zhejiang Province, China, 1986) received the B.S. degree in Department of Information and Electronic Engineering, Zhejiang Gongshang University, Hangzhou, China, in 2008. He is now a post-graduate student in School of Electronic and Information Engineering, SCUT, Guangzhou, China.

Li Ma (Zhejiang Province, China, 1987) received the B.S. degree in School of Electronic and Information Engineering, SCUT, Guangzhou, China, in 2009. He is now a post-graduate student in School of Electronic and Information Engineering, SCUT, Guangzhou, China.