2009 International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS 2009) December 7-9, 2009

TA2-B-6

Texture Image Retrieval Using Adaptive Directional Wavelet Transform

Yuichi Tanaka, Madoka Hasegawa, and Shigeo Kato
Graduate School of Utsunomiya University
7-1-2, Yoto, Utsunomiya, Tochigi, 321-8585 Japan
E-mail: {tanaka, madoka, kato}@is.utsunomiya-u.ac.jp Tel: +81-28-689-6267

***Abstract*—In this paper, we present an application of adaptive directional wavelet transform (WT) for content-based texture image retrieval. The adaptive directional WT is an alternative of the traditional separable WT for image coding since it is able to transform along diagonal orientations as well as horizontal/vertical orientations and keeps perfect reconstruction property by lifitng factorization. We use its transform direction data to increase the image retrieval ratio. The proposed approach obtains higher retrieval ratio than the separable WT and the contourlet transform.**

I. Introduction

In image and video processing using wavelet transform (WT), multiresolution decomposition is one of the most important features [1], [2]. It represents an image by several multiresolution subbands. Since most images have higher energy in low-frequency subbands than high-frequency ones, the decomposition is very effective for compression, denoising, etc.

Traditionally, 2-D WT is based on 1-D filterings along horizontal and vertical directions. However, edges usually exist along various directions. Those limited transform directions cause poor directional selectivity in the traditional 2-D WT, especially in compression where the high-frequency subbands are often quantized coarsely. Consequently, the reconstructed image has significant blurry artifacts.

To overcome the problem, several transforms have been presented. As the critically-sampled transforms, the quincunx directional filter bank [3] and HWD (hybrid wavelets and directional filter banks) transform [4] are efficient. As the overcomplete transforms, the contourlet transform [5]–[7], which is strongly related to curvelets [8], is well known as an effective filter bank structure. It is an overcomplete transform due to Laplacian pyramid and has good performance in image denoising and enhancement [6], [7].

Adaptive directional WT with lifting implementation [9], [10] is one of the most efficient transforms against the directional selectivity problem, and it yields a multiresolution image fully compatible with that of the traditional WT. They apply *directional* lifting in each lifting step. Prediction and updating steps for directional lifting can be in several diagonal orientations as well as traditional horizontal/vertical ones. Lifting factorization always guarantees perfect reconstruction even in directional lifting steps. As a result, it is regarded as a good alternative for the 2-D WT.

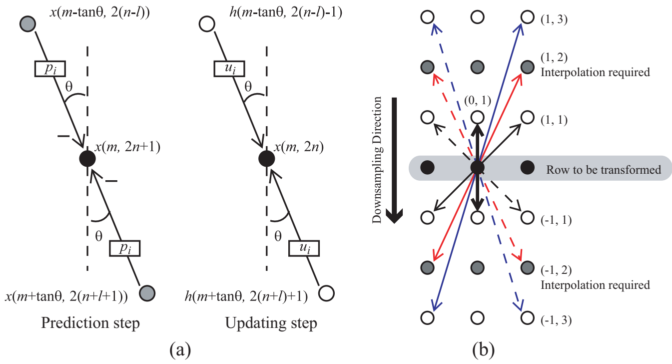

Fig. 1. Directional lifting for the directional WT. (a) prediction and updating steps. (b) typical transform directions.

The authors have proposed an efficient realization of the adaptive directional WT based on prefilterings of an original image [11], [12]. The obtained subbands by the prefilterings are used as “reference frames” to calculate transform directions. The method succeeds to reduce computation complexity significantly compared with the previously proposed ones in spite of comparable image coding performance and simple framework.

In this paper, we consider one possible application of our adaptive directional WT to content-based texture image retrieval (CBIR). CBIR is a good measure to estimate directional selectivity of frequency plane partitions [13]–[18]. It can be also straightforwardly applied to general images, such as face recognition. Our WT will keep local texture information as the transform direction data as well as transformed coefficients in subbands. In other words, traditional CBIR approaches can use only subbands' statistics, whereas the proposed method exploits additional directional data.

Generally critically-sampled transforms do not perform as well comparing to the oversampled ones in CBIR. However, in the scenario that transformed coefficients are used for both coding and image retrieval, critically-sampled ones are desired for its good image coding performance. We show the direction data can *boost* the performance of image retrieval ratio and our prefiltering-based method outperforms the separable WT and the contourlet transform.

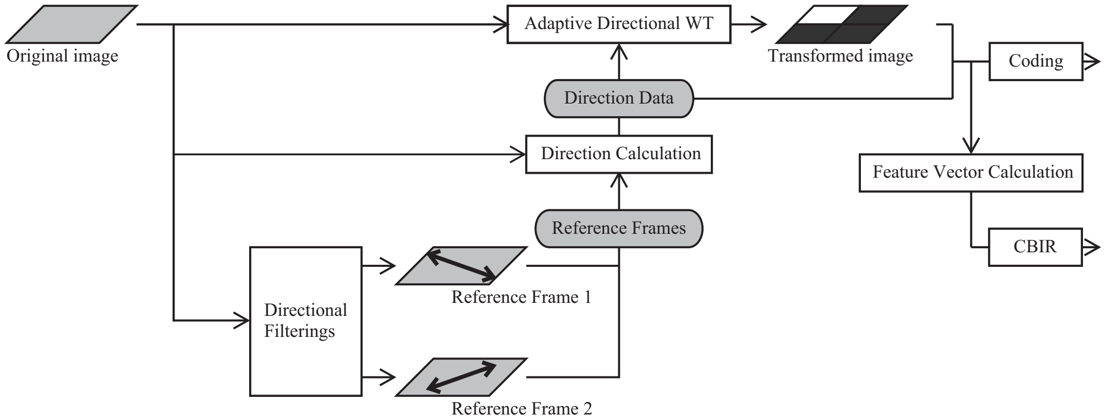

Fig. 2. Framework of D1F-WT. The arrowheads in the high-frequency subbands represent the main directions of the diagonal lines in them.

II. Directional Lifting

Adaptive directional WTs partition an image into a set of small blocks. Each block is assumed to have one transform direction and it is transformed by the directional lifting. The directional lifting steps are illustrated in Fig. 1(a). Let $x(m, n)$ denote the pixel value at (m, n). A prediction step for a direction θ with the vertical downsampling is represented as

$$h(m, 2n+1) = x(m, 2n+1) - P(m, 2n) \tag{1}$$

where $h(m, 2n+1)$ represents a highpass branch of the directional lifting step and

$$P(m, 2n) = \\ p_i(x(m - \tan\theta, 2(n-l)) + x(m + \tan\theta, 2(n+l+1))) \tag{2}$$

in which p_i is a coefficient for this prediction step and l is a nonnegative integer. An updating step is given by

$$l(m, 2n) = x(m, 2n) + U(m, 2n+1) \tag{3}$$

where $l(m, 2n)$ represents a lowpass branch and

$$U(m, 2n+1) = u_i(h(m - \tan\theta, 2(n-l) - 1) \\ + h(m + \tan\theta, 2(n-l) + 1)), \tag{4}$$

in which u_i is an updating coefficient. In practical, pixels used for directional lifting are interpolated to represent fractional-pel transform [10] or carefully chosen from integer pixels which represent diagonal directions well [9]. Clearly these lifting steps are perfect reconstruction and can be cascaded with other lifting steps similar to the separable WTs. Moreover, the resulting subbands are compatible with those using the separable WTs.

Hereafter, we define the notations of the transform directions of directional lifting as the relative pixel position from the pixel to be transformed. Some typical directions are illustrated in Fig. 1(b) where the direction for the separable WT are defined as (0, 1).

III. Adaptive Directional WT Using Prefiltering

We have recently proposed an efficient realization of the adaptive directional WT [11], [12]. Its analysis side framework is shown in Fig. 2. Despite of the other frameworks [9], [10], our scheme has “directional filtering” stage, which transforms an input image before calculating transform directions. These directional filters extract directional information from the image and resulting subbands are used as reference frames to calculate transform directions of the adaptive directional WT since these reference frames indicate the place of diagonal lines in the image. Finally, both of the multiresolution image and the direction data are used for coding and/or CBIR.

The reference frames are only used on the analysis side to calculate the transform directions. Hence, the synthesis side of this framework is exactly the same as that of the previously proposed ones [9], [10]. In this paper, the directional filtering stage simply uses directional WT highpass filters along two fixed directions $(1, 1)$ and $(-1, 1)$. Their frequency plane partitions are shown in Fig. 3. We call this adaptive directional WT as D1F-WT, which is the acronym of Directional 1-D Filtering. The enlarged *Barbara* image with transform directions (overwritten on the image) is also illustrated in Fig. 3. Clearly the regions with different diagonal lines are well classified and have accurate transform directions.

IV. Texture Image Retrieval

In the transform-based CBIR method, various transforms yield good retrieval ratio; Gabor wavelet, dual-tree complex wavelet, directional filter bank, and contourlet transform [13]–[18]. Most of these transforms are overcomplete and nonseparable since textures in different directions should be extracted into different subbands for CBIR. Therefore, the method using critically-sampled transforms is considered to have less performance. However, they are required in the scenario that multiresolution images obtained from a critically-sampled and separable transform are used for various applications, including compression and retrieval [19]. In this paper, we present a method to improve the retrieval performance by using the D1F-WT.

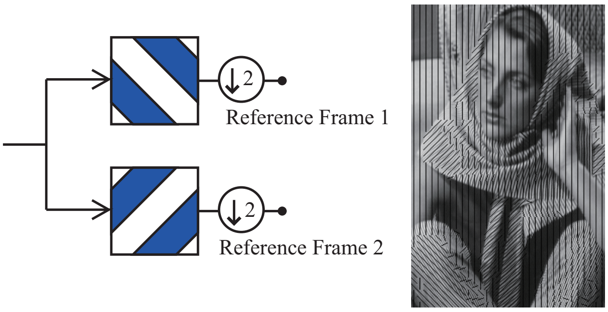

Fig. 3. Directional filterings and transform directions of D1F-WT. (Left) Directional filterings of D1F-WTs. Each square represents a frequency plane from $(-\pi, -\pi)$ to (π, π), and colored regions show the passband of the filter. (Right) transform directions for *Barbara* image.

A. Distance of Feature Vectors and Image Database

In transform-based retrieval, the distance of feature vectors between a query and database is calculated and compared. Indeed there are many methods to calculate a distance between two vectors x and y for CBIR [15], [19]. However, the scope in this section is to present the potential of D1F-WT, hence we use the normalized Euclidian distance $\delta(x, y)$ for simplicity:

$$\delta(x, y) = \sum_m \delta_m(x, y) \tag{5}$$

where

$$\delta_m(x, y) = \left| \frac{\mu_m(x) - \mu_m(y)}{\sigma(\mu_m)} \right| + \left| \frac{\sigma_m(x) - \sigma_m(y)}{\sigma(\sigma_m)} \right|, \tag{6}$$

in which $\mu_m(\cdot)$ and $\sigma_m(\cdot)$ are mean and standard deviation of m-th subband, respectively, and $\sigma(\mu_m)$ and $\sigma(\sigma_m)$ are standard deviations of the respective features over the entire database. Moreover, for the adaptive directional WTs, a feature vector is also appended.

$$\tau(x, y) = \sum_k \tau_k(x, y) \tag{7}$$

where

$$\tau_k(x, y) = \left| \frac{\gamma_k(x) - \gamma_k(y)}{\sigma(\gamma_k)} \right| \tag{8}$$

where $\gamma_k(\cdot)$ is the number of blocks for a transform direction index k (typically, $k = 0, \ldots, 8$ for nine direction candidates), and $\sigma(\gamma_k)$ is the standard deviation of $\gamma_k(\cdot)$ over the entire database. Consequently, a distance between x and y using the adaptive directional WTs is formalized as follows:

$$d(x, y) = \alpha\delta(x, y) + (1 - \alpha)\tau(x, y) \tag{9}$$

where α is a positive constant and can be empirically set. In our experimental result, $\alpha = 0.65$ obtains good retrieval ratio for the D1F-WT.

The database used is Brodatz album [20], which has 111 images from D1 to D112 (D14 is missing). Each 512×512 image is divided into sixteen 128×128 nonoverlapping subsets. The entire database has 1776 texture images in total. To eliminate the effects of gray level correlation in images, every image is normalized to have zero-mean and unit variance.

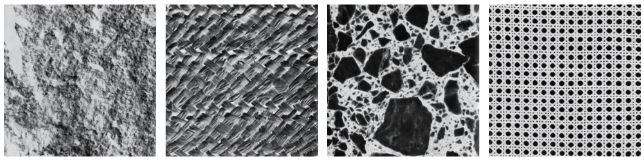

Fig. 4. Texture image examples in Brodatz album [20]. From left to right: D2, D18, D64, and D101.

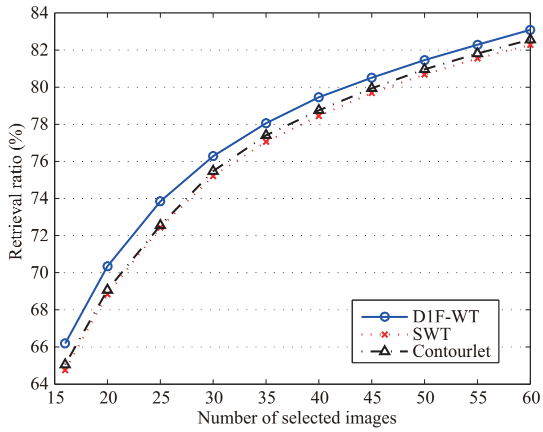

Fig. 5. Image retrieval ratio according to the number of selected images K.

Some examples of the original 512×512 images are shown in Fig. 4.

For each image in the database, a feature vector is calculated and stored. The separable WT is compared with the D1F-WT. Moreover, the contourlet transform [5] is used as an overcomplete transform (with low redundancy ratio) since it uses the separable WT and the directional filter bank [21]. For each transform, a 3-level decomposition is applied. The D1F-WT transforms adaptively in the first two levels and transform directions are determined for each 8×8 block. The contourlet transform is chosen to have eight-channel decomposition in each scale using directional filter bank. Consequently, the D1F-WT, the separable WT and the contourlet transform have 42 (24 for subbands, 18 for transform directions), 24 and 54 features, respectively. The normalized Euclidian distance is calculated between the query image and ones in the database and K nearest neighbors are selected as similar images. The number of correct subsets is counted and it is divided by 15 to obtain the retrieval ratio.

B. Experimental Results

Table I shows the retrieval ratio of various transforms in the case of $K = 15$. In the table, D1F, SWT, CT refered to as the D1F-WT, the separable WT, and the contourlet transform, respectively. Clearly the D1F-WT has the best retrieval ratio among the transforms including the contourlet transform. Fig. 5 also shows retrieval ratio according to the number of selected images K. Similar to Table I, the D1F-WT presents uniformly better results than the other two transforms. They validate that the D1F-WT can accomplish the localized transform directions which are regarded as local texture information. Consequently,

TABLE I
IMAGE RETRIEVAL PERFORMANCE (%)

Index	D1F	SWT	CT	Index	D1F	SWT	CT	Index	D1F	SWT	CT
D1	74.17	67.08	71.67	D39	57.08	57.50	58.75	D76	95.83	100.00	99.17
D2	57.08	41.25	47.50	D40	55.00	53.75	57.50	D77	100.00	100.00	100.00
D3	76.25	85.42	53.33	D41	84.58	87.50	79.58	D78	98.33	97.92	99.58
D4	88.75	73.75	92.92	D42	26.25	23.33	25.83	D79	90.42	99.17	92.50
D5	67.50	65.83	65.42	D43	7.92	5.42	5.83	D80	85.83	85.83	94.58
D6	100.00	100.00	100.00	D44	10.00	15.42	11.67	D81	90.42	88.33	98.33
D7	22.08	15.00	25.42	D45	23.33	22.92	21.67	D82	100.00	98.33	100.00
D8	82.50	89.58	93.75	D46	51.67	56.25	59.58	D83	99.17	97.92	100.00
D9	70.00	67.50	66.67	D47	100.00	100.00	100.00	D84	100.00	100.00	99.58
D10	91.25	90.00	91.25	D48	100.00	100.00	100.00	D85	95.83	75.42	100.00
D11	100.00	100.00	100.00	D49	100.00	100.00	100.00	D86	40.42	35.00	36.67
D12	64.58	61.67	75.42	D50	52.92	49.58	52.50	D87	96.67	93.33	90.83
D13	36.25	33.33	35.42	D51	78.33	78.33	80.00	D88	36.25	37.50	35.83
D15	55.00	64.17	55.00	D52	97.08	97.92	100.00	D89	18.33	17.92	14.17
D16	100.00	100.00	100.00	D53	100.00	100.00	100.00	D90	16.67	14.58	17.92
D17	100.00	100.00	100.00	D54	40.83	38.75	39.17	D91	34.58	29.58	35.83
D18	75.83	61.25	80.42	D55	95.42	93.75	100.00	D92	96.67	93.75	91.25
D19	84.58	82.92	90.00	D56	100.00	100.00	100.00	D93	73.75	57.50	72.08
D20	100.00	100.00	100.00	D57	100.00	100.00	100.00	D94	62.50	60.42	73.33
D21	100.00	100.00	100.00	D58	8.33	6.67	7.92	D95	97.92	98.33	97.50
D22	80.83	99.58	75.83	D59	30.83	28.33	24.58	D96	69.58	60.83	65.42
D23	42.92	37.50	39.17	D60	23.33	20.42	24.58	D97	21.67	21.25	19.58
D24	88.33	95.42	96.67	D61	28.33	28.75	30.83	D98	53.33	51.67	47.08
D25	42.92	41.67	40.83	D62	51.67	48.33	51.25	D99	32.08	31.67	32.08
D26	75.83	77.50	79.58	D63	20.83	15.83	13.75	D100	43.33	37.92	38.75
D27	40.83	36.67	42.92	D64	90.00	89.58	90.83	D101	53.75	52.92	54.17
D28	62.50	59.17	60.00	D65	98.33	96.25	97.08	D102	62.08	65.42	63.75
D29	100.00	99.58	100.00	D66	97.50	92.92	88.75	D103	54.17	55.42	50.00
D30	25.00	25.42	36.25	D67	33.75	32.08	31.67	D104	62.08	62.08	52.08
D31	31.25	29.58	36.25	D68	98.33	99.58	93.33	D105	57.92	52.92	57.50
D32	83.33	70.42	69.58	D69	26.67	17.92	15.83	D106	50.42	52.08	62.08
D33	98.75	98.33	95.83	D70	47.92	45.00	44.58	D107	38.75	38.33	29.58
D34	100.00	100.00	100.00	D71	64.58	62.50	59.17	D108	36.67	30.83	23.75
D35	73.75	70.00	70.83	D72	36.67	48.75	40.83	D109	73.75	68.75	63.33
D36	63.75	68.33	46.25	D73	35.83	32.50	40.00	D110	74.17	78.33	62.92
D37	77.92	75.83	77.50	D74	73.33	71.67	60.83	D111	74.17	74.58	63.75
D38	75.00	72.08	69.17	D75	58.33	57.92	54.17	D112	46.25	40.42	42.92
								Ave.	**66.19**	64.75	65.05

the D1F-WT could boost the image retrieval performance by using the transform directions.

V. CONCLUSIONS

In this paper, an application of the adaptive directional WT for CBIR is shown. It uses transform direction data as well as tranformed coefficients to increase the retrieval ratio. It is a critically-sampled transform and special side information for image retrieval is no longer required since transform directions are necessary data to decode/reconstruct the transformed image. In the experimental result, the proposed transform outperforms the separable WT and the contourlet transform.

REFERENCES

[1] P. P. Vaidyanathan, *Multirate Systems and Filter Banks*, Prentice-Hall, NJ, 1993.

[2] G. Strang and T. Q. Nguyen, *Wavelets and Filter Banks*, Wellesley-Cambridge, MA, 1996.

[3] T. T. Nguyen and S. Oraintara, "A class of multiresolution directional filter bank," *IEEE Trans. Signal Process.*, vol. 55, no. 3, pp. 949–961, 2007.

[4] R. Eslami and H. Radha, "A new family of nonredundant transforms using hybrid wavelets and directional filter banks," *IEEE Trans. Image Process.*, vol. 16, no. 4, pp. 1152–1167, 2007.

[5] M. N. Do and M. Vetterli, "The contourlet transform: an efficient directional multiresolution image representation," *IEEE Trans. Image Process.*, vol. 14, no. 12, pp. 2091–2106, 2005.

[6] Y. Lu and M. N. Do, "A new contourlet transform with sharp frequency localization," in *Proc. ICIP'06*, 2006, pp. 1629–1632.

[7] A. L. Da Cunha, J. Zhou, and M. N. Do, "The nonsubsampled contourlet transform: Theory, design, and applications," *IEEE Trans. Image Process.*, vol. 15, no. 10, pp. 3089–3101, 2006.

[8] E. Candès and D. L. Donoho, "Curvelets — a surprisingly effective nonadaptive representation for objects with edges," in *Curves and Surfaces Fitting*, A. Cohen, C. Rabut, and L. L. Schumaker, Eds. Vanderbilt University Press, Saint-Malo, 1999.

[9] C.-L. Chang and B. Girod, "Direction-adaptive discrete wavelet transform for image compression," *IEEE Trans. Image Process.*, vol. 16, no. 5, pp. 1289–1302, 2007.

[10] W. Ding, F. Wu, X. Wu, S. Li, and H. Li, "Adaptive directional lifting-based wavelet transform for image coding," *IEEE Trans. Image Process.*, vol. 16, no. 2, pp. 416–427, 2007.

[11] Y. Tanaka, M. Hasegawa, and S. Kato, "Highpass-filtering based adaptive directional wavelet transform," in *Proc. 27th Picture Coding Symposium*, 2009.

[12] Y. Tanaka, M. Hasegawa, S. Kato, M. Ikehara, and T. Q. Nguyen, "Adaptive directional wavelet transform using pre-directional filtering," in *Proc. ICIP'09, accepted*, 2009.

[13] B. S. Manjunath and W. Y. Ma, "Texture features for browsing and retrieval of image data," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 18, no. 8, pp. 837–842, 1996.

[14] S. Hatipoglu, S. K. Mitra, and N. Kingsbury, "Image texture description using complex wavelet transform," in *Proc. ICIP'00*, 2000, pp. 530–533.

[15] M. Kokare, P. K. Biswas, and B. N. Chatterji, "Texture image retrieval using new rotated complex wavelet filters," *IEEE Trans. Syst., Man, Cybern. B*, vol. 35, no. 6, pp. 1168–1178, 2005.

[16] A. P. N. Vo, T. T. Nguyen, and S. Oraintara, "Texture image retrieval using complex directional filter banks," in *Proc. ISCAS'06*, 2006, pp. 5495–5498.

[17] T. T. Nguyen and S. Oraintara, "The shiftable complex directional pyramid–part ii: Implementation and applications," *IEEE Trans. Signal Process.*, vol. 56, no. 10, pp. 4661–4672, 2008.

[18] D. D.-Y. Po and M. N. Do, "Directional multiscale modeling of images using the contourlet transform," *IEEE Trans. Image Process.*, vol. 15, no. 6, pp. 1610–1620, 2006.

[19] M. N. Do and M. Vetterli, "Wavelet-based texture retrieval using generalized Gaussian density and Kullback-Leibler distance," *IEEE Trans. Image Process.*, vol. 11, no. 2, pp. 146–158, 2002.

[20] P. Brodatz, *A Photographic Album for Artists and Designers*, New York: Dover, 1966.

[21] R. H. Bamberger and M. J. T. Smith, "A filter bank for the directional decomposition of images: theory and design," *IEEE Trans. Signal Process.*, vol. 40, no. 4, pp. 882–893, 1992.