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Content-Based Color Image Retrieval Using Adaptive Lifting

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ABSTRACT

An image retrieval system is a computer system for browsing, searching and retrieving images from a large database of digital images. CBIR aims at avoiding the use of textual descriptions and instead retrieves images based on their visual similarity to a user-supplied query image or user-specified image features. Although classical wavelet transform is effective in representing image feature and thus is suitable in CBIR, it still encounters problems especially in implementation, e.g. floating-point operation and decomposition speed, which may nicely be solved by lifting scheme, a novel spatial approach for constructing biorthogonal wavelet filters. Lifting scheme has such intriguing properties as convenient construction, simple structure, integer-to-integer transform, low computational complexity as well as flexible adaptivity, revealing its potentialsin CBIR. In this paper, by using general lifting and its adaptive version, we decompose HSI color images into multi-level scale and wavelet coefficients, with which, we can perform image feature extraction.

Keywords: Content based image retrieval, Lifting Scheme , Adaptive Lifting.

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1. INTRODUCTION:

Content-based image retrieval (CBIR)[1]–[2] ,allows to automatically extract targets according to objective visual contents of image itself (e.g. color, texture and shape), has become increasingly attractive in multimedia information service system (MISS). With appealing time-frequency localization and multi-scale properties, wavelet transform proved to be effective in feature extraction and representation, and thus has been successfully applied especially in image coding and denoising. In CBIR, wavelet approaches mainly include direct wavelet coefficients, wavelet histogram and wavelet moment of image, etc. However, classical wavelet encounters some inherent limitations in image processing. First, classical construction relying heavily on frequency domain is basically unfit for spatial realization, inevitably losing desirable properties exclusively owned in spatial domain. Second, its floating-point operation makes it not only inefficient but also inaccurate when processing integer image coefficients[6]. Third, finding an ideal preprocessing method from classical viewpoint is somewhat difficult, e.g. hard to seek a boundary extension method ensuring perfect reconstruction, while simultaneously maintaining boundary continuity. Hence, traditional wavelet approaches, though effective in general case, may still result in reduced performance in CBIR.

Lifting scheme [3]-[6] ,a novel approach for constructing the so-called second-generation wavelet, provides feasible alternative for problems facing the classical first-generation wavelet in image applications. Constructed entirely in spatial domain and based on the theory of biorthogonal wavelet filter banks with perfect reconstruction, lifting scheme can easily build up a gradually improved multi-resolution analysis through iterative primal lifting and dual lifting. It turns out that lifting scheme outperforms the classical especially in effective implementation, such as convenient construction, in-place calculation, lower computational complexity and simple inverse transform, etc. With lifting, we can also build wavelets with more vanishing moments and/or more smoothness, contributing to its flexible adaptivity and non-linearity.

In this paper, based on direct wavelet decomposition of image, we present a progressive CBIR strategy. With lifting wavelet filter obtained by factoring its classical counterpart, we decompose color images into multi-level scale and wavelet coefficients, which are then employed to perform image feature extraction and similarity match by virtue of F-norm theory. During lifting, considering the

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diversity of prediction and update operators as linear, non-linear or spatially variable, we thus design corresponding adaptive filters via lifting to make them data-dependent, as a result, optimal image representation and accordingly, improved retrieval performance may be achieved. The rest of this paper is organized as follows. In Section 2, we introduce image decomposition approaches via general lifting and its adaptive version as well as classical wavelets. Section 3 provides image feature extraction and similarity criteria based on F-norm theory. Section 4 describes a progressive CBIR strategy. Section 5 presents the implementation and experimental results of above wavelet approaches applied in CBIR. Finally, conclusions and future research are provided
in chapter 6.

2. Image decomposition with wavelet approaches

We intend to use three wavelet approaches for image decomposition, namely classical wavelet, general lifting and its adaptive version. With resulting decomposition coefficients, we can take measures to extract image feature and perform similarity match.

2.1 CLASSICAL WAVELET TRANSFORM

A main goal of wavelet research is to create a set of expansion functions and transforms that give informative, efficient, and useful description of a function or signal. In applications working on discrete signals, one never has to directly deal with expansion functions. Discrete wavelet transform (DWT) is obtained simply by passing a discrete signal through a filter bank. Wavelet theory can be understood and developed only by using such digital filters. This is the meeting point between wavelets and sub band coding and the origin of two different nomenclatures for the same concepts. In fact, wavelet transform and sub band coding are so closely connected that both terms are often used interchangeably. Filter banks are structures that allow a signal to be decomposed into sub signals through digital filters, typically at a lower sampling rate. Figure 1 shows a two-band filter bank.

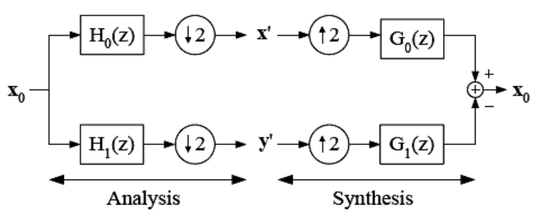

Figure 1.one level 2 band perfect reconstructions**.**

It is formed by the analysis filters ($H_i(z)$, i = 0, 1) and the synthesis filters ($G_i(z)$, for i = 0, 1).Filters $H_0(z)$ and $G_0(z)$ are low-pass filters. In an M-band filter bank, $H_i(z)$ and $G_i(z)$ for $0 < i < M - 1$ are band-pass filters, and $H_{M-1}(z)$ and $G_{M-1}(z)$ are high-pass filters. For a two-band filter bank, M = 2 and $H_1(z)$ and $G_1(z)$ are high-pass filters. If the input signal can be recovered without errors from the sub signals, the filter bank is said to be a perfect reconstruction (PR) or a reversible filter bank. To enable PR, the analysis and synthesis filters have to satisfy a set of bilinear constraints.

Every finite impulse response (FIR) filter bank with an additional linear constraint on the low-pass filter is associated with a wavelet basis. The low-pass synthesis filter $G_0(z)$ is associated with the scaling function, and the remaining band-pass synthesis filters ($G_1(z)$ in the 2-band case) are each associated with the wavelet functions. Analysis low-pass filter $H_0(z)$ is associated with the so-called dual scaling function and analysis band-pass filters with the dual wavelet functions.

The notion of channel refers to each of the filter bank branches. A channel is the branch of the 1-D scaling coefficients (or approximation signal) and also each branch of the wavelet coefficients (or detail signals). The concept of band involves the concept of frequency representation, but it is commonly used in image processing to refer to each set of samples which are the output of the same 2-D filter. In 1-D linear processing both concepts are interchangeable.

2.2 LIFTING SCHEME

The discrete wavelet transform applies several filters separately to the same signal. In contrast to that, for the lifting scheme the signal is divided like a zipper. Then a series of prediction-update operations across the divided signals is applied. It starts with a set of well known filters, thereafter lifting steps are used in an attempt to improve (lift) the properties of corresponding wavelet decomposition. A number of such lifting steps can be used in order to obtain desired properties of a wavelet transform.

The basic lifting scheme for DWT consists of three steps: Split, Predict and Update. The lifting analysis stage is as shown in Figure 2.

A. Split:

The signal s is split into even and odd sub arrays s_o and s_1.

$$s_0 = \{S[l_0]\, l_0 \in \Pi_0 = \Pi_{00} \cup \Pi_{01}\} \qquad (1)$$

$$s_1 = \{S[l_1]\, l_1 \in \Pi_1 = \Pi_{10} \cup \Pi_{11}\} \qquad (2)$$

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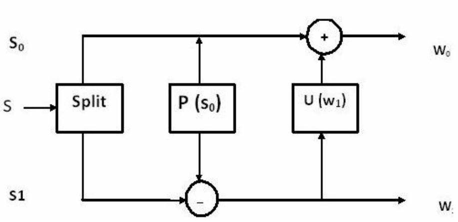

Figure 2.Lifting Scheme

B. Predict:

The filtered even array is used to predict the odd array. Then the odd array is redefined as the difference between the existing array and the predicted one. This gives detail coefficients w_1.

$$w_1[l_1] = g_H(S[l_1] - P_{l1}(s_0)), \forall l_1 \in \Pi_1 \qquad (3)$$

*C. Update***:**

To eliminate aliasing, which appears while down sampling the original signal and to obtain the low-frequency component of the signal, the even array is updated using the filtered new odd array to get coarser coefficients w_0.

$$w_0[l_0] = g_L(S[l_0] + g_H^{-1} \cdot U_{l_0}(w_1)), \forall l_0 \in \Pi_0 \qquad (4)$$

2.3ADAPTIVE LIFTING USED IN CBIR

In CBIR, since feature extraction requires accurate expression of image contents, thus more precise image decomposition, the basis of effective feature extraction, may be obtained by introducing adaptive lifting. In this work, adaptivity is acquired by using a suite of predictors for smooth and unsmooth parts of the image. In this adaptive lifting scheme Cohen-Daubechies-Feauveau (CDF) wavelet family is employed.

For fast decomposition, we perform a N_1=1 point update and then for each N, chooses the N ∈ {1, 3, 5} point prediction below.

P_1 = [0, 0, 1, 0, 0]

P_2 = [0, -1, 8, 1, 0]/8

P_3 = [-3, 22, 128, -22, 3]/128

U = [1, 1]/2

The RLV yields a decision map indicating which prediction filters should be used at which positions. The moderate order predictor is applied first, namely P_2 for high-pass filtering, RLV for all subsequent pixels (i, j) to be predicted is computed,

Higher order predictors are used where the image is locally smooth, resulting in many negligible detail coefficients for better image representation. Whether an image I is locally smooth, namely, the smoothness is determined by measuring the relative local variance (RLV) .

2.3.1 RELATIVE LOCAL VARIANCE (RLV)

A measure is proposed, on which the decision operator in the 2D adaptive lifting scheme can be based on, namely the relative local variance (RLV) of an image. This RLV of an image ‘I’ is given by

$$\mathrm{rlv}[I](i,j) = \sum_{k=i-T}^{i+T} \sum_{l=j-T}^{j+T} (I(k,l) - \overline{\mu_{i,j}})^2 \Big/ \mathrm{var}(I) \qquad (5)$$

with

$$\overline{\mu_{i,j}} = \sum_{k=i-T}^{i+T} \sum_{l=j-T}^{j+T} I(k,l) \Big/ (2T+1)^2 \qquad (6)$$

Where, T is the size of sliding window, σ (I) is the standard variance of the image I.

For all pixels (i, j) to be predicted, we first compute rlv[I] (i, j). Then thresholding the values of the RLV yields a decision map indicating which prediction filters should be used at which positions. The moderate order predictor is applied first, namely P_2 for high-pass filtering, RLV for all subsequent pixels (i, j) to be predicted is computed, and suitable predictors are chosen. Two thresholds are chosen preliminarily according to practical situations . Threshold values can be taken as multiples of the mean of the RLV. Test results have shown that [μ(rlv) 1.5μ(rlv) 2μ(rlv)] are the threshold levels that yield a good performance. RLV value above the bigger threshold indicates that a lower order predictor namely P_1 should be selected. When RLV value is below the smaller threshold suggests that a higher order predictor, namely P_3 should be activated. Otherwise P_2 remains unchanged.

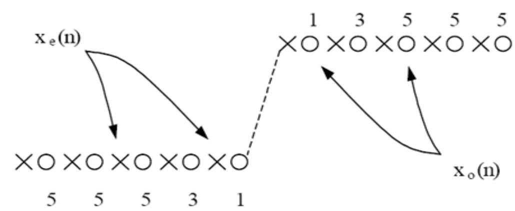

Figure 3. Adaptive prediction using CDF wavelets

2.3.2 TWO LEVEL LIFTING FRAME WITH UPDATE-FIRST

In non-linear wavelet transform for image coding via lifting, under the “predict-first” frame, adaptive multi-predictors strategy aims at better image decomposition which in turn, introduce stability and synchronization

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problems to reconstruction part and results in serious reconstruction errors.So, an update-first structure is proposed to make the prediction outside of the lifting loop.Therefore, the resulting coarse coefficients can be directly iterated to the lowest scale [8] .

In CBIR, dealing with no reconstruction, we just borrow this idea in the proposed adaptive scheme. With update first, coarse coefficients representing the main part of image can be calculated fast, which are used to perform fast retrieval, simultaneously, to compensate the retrieval precision. Because of update first scheme, the order of the high pass filters can be increased to obtain more accurate detail coefficients without any affecting the calculation of coarse coefficient

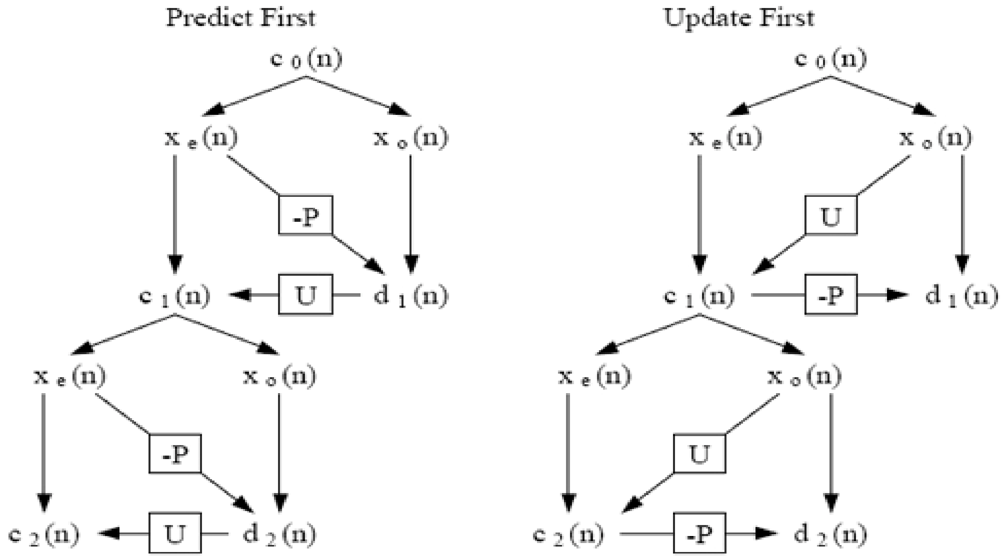

Figure 4 Two-level lifting frames with predict-First (Left) and Update-First (right)

3. F-NORM THEORY

Our CBIR algorithm is based on direct wavelet decomposition of image in HSI colour space and utilizes the “query by example” method. With approaches mentioned in previous chapters, database images are decomposed offline into multi-level coefficients from -1 to -J levels, with which, we can generate colour feature database and perform similarity match between images. After decomposition, each resulting sub image is in fact a coefficient matrix, where, by special processing, large coefficients with more energy can be distributed in the up-left area, therefore, with F-norm theory , we can well decrease the dimension of image feature and perform highly efficient image matching.

3.1 QUERY BY EXAMPLE METHOD

‘Query by Example method’ is a query technique that involves providing the CBIR system with an example image that it will then base its search upon. The underlying search algorithms may vary depending on the application, but result images should all share common elements with the provided example.

Options for providing example images to the system include:

- A preexisting image may be supplied by the user or chosen from a random set.
- The user draws a rough approximation of the image they are looking for, for example with blobs of color or general shapes.

This query technique removes the difficulties that can arise when trying to describe images with words.

3.2 FEATURE VECTOR EXTRACTION USING F-NORM THEORY

Feature vectors for all the images in the database are found using F-norm theory . Every image is considered as a square matrix and feature vector is found as follows:

Suppose *A* is a square matrix and A_i is its i^{th} order sub matrix:

$$A = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \dots & \dots & \dots \\ a_{n1} & \dots & a_{nn} \end{bmatrix}, \quad A_i = \begin{bmatrix} a_{11} & \dots & a_{1i} \\ \dots & \dots & \dots \\ a_{i1} & \dots & a_{ii} \end{bmatrix} \quad (i=1\sim n)$$

The F-norm of A_i is given as:

$$\|A_i\|_F = \left(\sum_{k=1}^{i} \sum_{l=1}^{i} |a_{kl}|^2 \right)^{1/2} \tag{7}$$

Let

$$\Delta A_i = \|A_i\|_F - \|A_{i-1}\|_F \text{ and } \|A_0\|_F = 0,$$

We can define the feature vector of A as:

$$V_{AF} = \{\Delta A_1, \Delta A_2, \dots\dots\dots, \Delta A_n\} \tag{8}$$

3.3 SIMILARITY CRITERIA

Consider two images A and B. Let the feature vectors of the two images be V_{AF} and V_{BF}. Vector elements in the feature vector are represented by ΔA_i and ΔB_i. The similarity between the two images is given by the following similarity criteria . Let α_i be the similarity of ΔA_i and ΔB_i.

$$\alpha_i = \begin{cases} \min(\Delta A_i, \Delta B_i) / \max(\Delta A_i, \Delta B_i) & , \Delta A_i \neq 0 \ \text{or} \Delta B_i \neq 0 \\ 1 & , \Delta A_i = \Delta B_i = 0 \end{cases} \tag{9}$$

And we can give the similarity α of the two images A and B as:

$$\alpha = \sum_{i=1}^{n} c_i \alpha_i \tag{10}$$

Where,

$$c_i = \frac{2i-1}{n^2} (i = 1, 2, \dots, n)$$

and $\sum_{i=1}^{n} c_i = 1$

Similarity between the two images lies in between $0 \le \alpha \le 1$.

4. PROGRESSIVE RETRIEVAL STRATEGY

When a user submits a query, we must compute the feature vector for the querying image and match it to the pre-computed feature vectors of the images in the database. This is done in two phases. In the first phase, we compare the standard deviations stored for the querying image with the standard deviations stored for each image in the database. The following criteria is used for rough filtering of the database. Denote the standard deviation information computed for the querying image as σ_H^e, σ_S^e and σ_I^e. Denote the standard deviation of target image as σ_H^t, σ_S^t and σ_I^t. If this acceptance criterion is satisfied the target image is kept for further retrieval or else it is discarded.

$$F = (\beta\sigma_H^e < \sigma_H^t < \sigma_H^e/\beta) \,\|((\beta\sigma_S^e < \sigma_S^t < \sigma_s^e/\beta) \\ \&\&(\beta\sigma_I^e < \sigma_I^t < \sigma_I^e/\beta)) \tag{11}$$

Where, β is a filtering constant. The value of β = 1-percent\100 and percent is a threshold variable set to control the number of images passing the first matching phase. It is usually set to 50.In second phase, with the obtained LL coefficients, which best reflect the general feature of image; we use the similarity criteria to determine more precise targets. We use all the three colour components(HSI) for feature extraction to get better retrieval accuracy If α exceeds a given threshold, it means that mismatch occurs and I_t should be discarded; else, I_t be kept for further match.

5.EXPERIMENTAL RESULTS

A database of various images each image containing similar group of images is selected. All the images in database are pre-processed to 256x256 size for convenience. All the images are decomposed using Classical wavelet transform, general lifting scheme using 9/7 wavelet and adaptive lifting scheme using CDF wavelets offline. The maximal decomposition level is 4. Query image is also decomposed using the above wavelet transform methods. Using F-norm theory, features vectors are extracted. Feature vectors are extracted for all the images in the database and are stored in one more database called feature vector database. Using similarity measure, we find the target images for the given query image and the target images are ranked in terms of similarity measure. Then the three methods are compared in terms of accuracy and speed.

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Figure 5.CBIR Results Using Classical Wavelet Transform

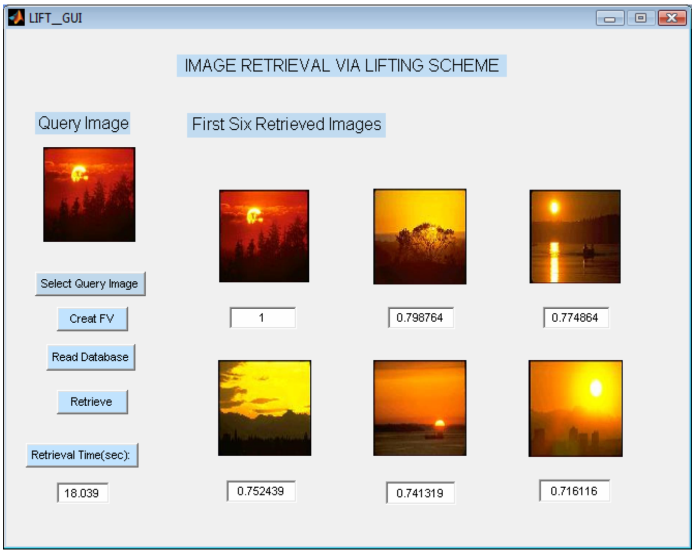

Figure 6.CBIR Results Via Lifting Scheme Using 9/7 Wavelet

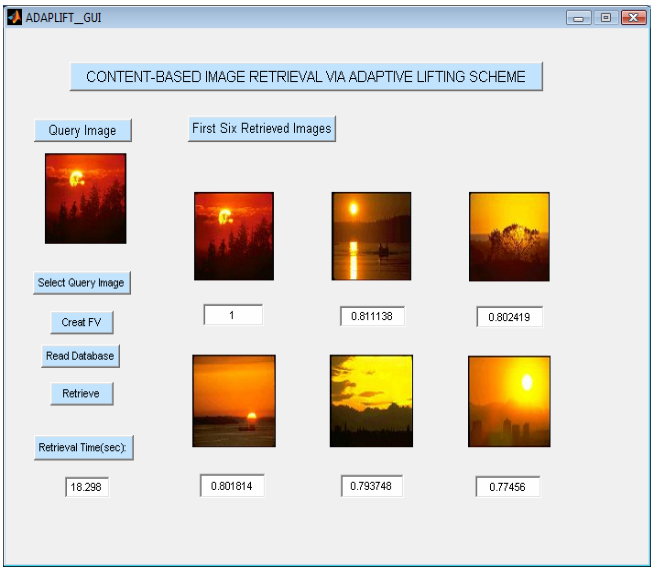

Figure 7.CBIR Results Via Adaptive Lifting Scheme Using CDF Wavelets

5.1RETRIEVALCOMPARISON PAPAMETERS

The two important retrieval comparison parameters are

- Retrieval accuracy
- Retrieval time

5.1.2 Retrieval accuracy

The retrieval accuracy is defined as the ratio between the number of relevant (belongs to the same category) retrieved images and the total number of retrieved images (known as a single precision).

$$\text{Retrieval Accuracy} = \frac{\text{No. Revelent Retrieved Images}}{\text{Total No. of Retrieved Images}}$$

Six different groups of images are selected in advance as the desired retrieval results for a query image in each group. Each group contains 6 images of the same kind. Retrieval rates are given by the mean number of retrieved images in the class of the query image versus the number of considered top results (smallest distances). Ideally both numbers are equal to each other until the number of top results equals the number of remaining images in one class. The average retrieval results of the six groups are shown in the table 1.

Wavelet Transform Method	Six Retrievals	Five Retrievals	Four Retrievals	Three Retrievals	Two Retrievals	One Retrievals
Classical Wavelet Transform	5.3333	4.6945	3.9722	3	2	1
General Lifting Scheme	5.6111	4.8888	4	3	2	1
Adaptive Lifting Scheme	5.8611	5	4	3	2	1

TABLE-1: **COMPARISON OF RETRIEVAL ACCURACY**

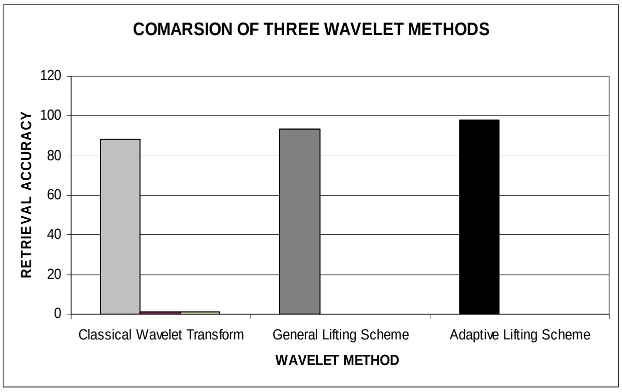

Figure-8**:** Comparison of retrieval accuracy

From Figure-8 it is obvious that retrieval rates were improved by using adaptive lifting filters instead of general non-adaptive wavelet filters

5.1.3 Retrieval time

It is the average time taken for the retrieval of target images after query image has been given.

Wavelet Method	Classical Wavelet Transform	General Lifting Scheme	Adaptive Lifting Scheme
Retrieval time(sec)	22.809	18.415	19.922

TABLE 2. COMPARISON OF RETRIEVAL TIMES FOR THE THREE WAVELET METHOD

From the table.2 it is obvious that classical wavelet method takes much time than lifting scheme. Adaptive lifting scheme takes a little more time. It is because the time taken for deciding proper predictor filter according to the image content. But adaptive lifting scheme takes less time than classical wavelet transform and it has high retrieval accuracy. Hence, with adaptive version of lifting scheme we can build a precise image retrieval system.

6. CONCLUSION AND FUTURE ENHANCEMENT

In this paper, a novel approach to CBIR via adaptive lifting scheme is introduced. A database of images is formed, and then all the images are decomposed by three wavelet transform methods. It is followed by feature extraction and similarity match under F-norm theory. Retrieval performance of adaptive lifting scheme, general lifting scheme and classical wavelet transform are compared in terms of accuracy and time.

In CBIR, factoring classical wavelet filters into lifting steps can greatly accelerate the retrieval. Meanwhile, still maintain enough retrieval accuracy comparable with that of classical ones. This is alsothe most apparent advantage of the lifting in real-time image applications. It turns out that lifting has great speed retrieval as well as ensure enough retrieval accuracy comparable with its classical counterpart. Adaptive lifting may further enhance the retrieval accuracy. Despite the time-consuming decision of whether a higher or lower order lifting filter should be chosen, it is still faster than its classical counterpart; Moreover, the flexible adaptive lifting with multi-predictors and "update first" methods may further enhance retrieval performance. In addition, the progressive retrieval strategy helps to achieve flexible compromise among retrieval indices.

Since the applications of lifting scheme in CBIR are just germinating, further researches, including involving more predictors as well as U operators and their coordination, non-separable cases including directional filters, and construction of more effective lifting filters, e.g. the so-called second-generation wavelet not relying on existing classical filters, have to be carried out for better modelling of image decomposition and thereby, better retrieval performance.

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