Grading Image Retrieval Based on DCT and DWT Compressed Domains Using Low-Level Features

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Abstract —Nowadays, the majority of images are in JPEG and MPEG compressed formats, and JPEG2000 is considered to be the next generation of compression standard due to the high-performance of discrete wavelet transform (DWT). It is time-consuming and occupies too much memory in conventional image retrieval ways. In order to solve these problems, we use grading retrieval techniques to implement image retrieval based on discrete cosine transform (DCT) compressed domain and DWT compressed domain. For image retrieval based on DCT domain, we use color features: color moment and color histogram, to describe content of images and propose a new dynamic color space quantization based on color distribution; For image retrieval based on DWT domain, we use texture features as two level feature vectors. The mean and standard deviation of low frequency sub-band coefficients are used as the first level retrieval. The means and standard deviations of selected high frequency sub-band coefficients are used as the second level retrieval. Furthermore, the third level retrieval is achieved by the fast wavelet histogram. Our experiment results clearly show that the two grading image retrieval algorithms work better than other algorithms: store memory is reduced and retrieval accuracy is improved.

Index Terms—Content based image retrieval (CBIR), compressed domain, discrete cosine transform (DCT), discrete wavelet transform (DWT), color features, texture features

I. Introduction

The query conditions of content based image retrieval (CBIR) [1] are images or the descriptions of images. We can extract image features and find the approximate images by similarity measure algorithms. However, with appearance of compression standards, the application of compressed images has become common. Fig. 1 shows the coding and decoding processes of images. Image retrieval technique based on pixel domain extracted the image features at point 3, but image retrieval techniques based on compressed domain [2] extracted the image features at point 0, point 1 or point 2. It can be seen that image retrieval techniques based on compressed domain omit fully decoding and save the spending on equipments and reduce the quantity of calculation. In this paper we extracted image features at point 2.

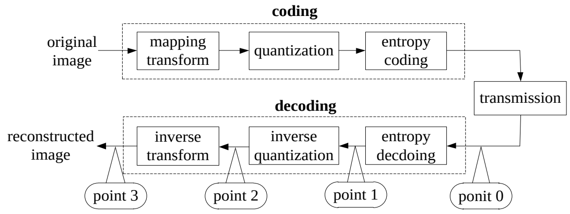

Fig. 1. Image coding and decoding.

Recently, the research on image retrieval based on compressed domain has focused on transform domain mainly, such as discrete Fourier transform (DFT) domain, discrete cosine transform (DCT) domain and discrete wavelet transform (DWT) domain. Stone and Li proposed extracting image features by DFT coefficients and controlling similarity measure of luminance and texture by two thresholds [3]. Lu et al. in [4] proposed an image retrieval scheme in the DCT domain that is suitable for retrieval of color JPEG images of different sizes. Smith and Chang proposed extracting image features by the mean and standard deviation of DCT coefficients [5] and reducing the dimensions of characteristic vector by Fisher discriminate analysis (FDA) [6]. Baharudinl proposed extracting texture features by histograms which are constructed by direct current (DC) coefficients and partial alternating current (AC) coefficients [7]. Lay proposed energy histogram based on DFT coefficients [8]. Eom proposed DCT based edge histogram [9]. In [10] a novel evolutionary method called evolutionary group algorithm (EGA) was proposed for complicated time-consuming optimization problems based on content-based image indexing algorithms. Zhang proposed extracting the contour of binary images at point 1 and describing image features by invariant moments [11]. Smith proposed using wavelet histogram techniques to extract texture features [12]. Albanesi proposed extracting texture features by using correlation in wavelet sub-bands [13]. The retrieval method based on Hadamard matrix and DWT (HDWT) proposed by Farsi and Mohamadzadeh in [14] has been discussed.

In this paper, we study image retrieval based on DCT compressed domain and DWT compressed domain. We realize image retrieval based on DCT compressed domain by grading retrieval and propose dynamic color space quantization algorithm based on color distribution to

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reduce dimensions of color histograms; we realize image retrieval based on DWT compressed domain by grading retrieval and propose a new retrieval method which uses the mean and standard deviation of low frequency wavelet sub-band coefficients and selects high frequency wavelet sub-band coefficients as two level feature vectors.

The organization of the paper is as follows. The techniques we used are provided in Section II. The specific details to realize image retrieval based on DCT compressed domain and DWT compressed domain are presented in Section III and Section IV, respectively. Experimental results of algorithms we proposed and analysis are presented in Section V. Conclusion of this paper is presented in Section VI.

II. Feature Vectors Based on DCT Domian and DWT Domain

This section introduces feature vectors based on DCT domain and DWT domain which we use to describe the content of images.

A. *Feature Vectors Based on DCT Domain*

1) *Color moment*

We choose color moment [15] as the first level feature vector. If the color value at point (x, y) is $p(x, y)$, the first two moments, namely, the mean and the standard deviation of color are:

$$E = \frac{1}{N \times M}\sum_{x=1}^{N}\sum_{y=1}^{M} p(x, y),\ \sigma = \left(\frac{1}{N \times M}\sum_{x=1}^{N}\sum_{y=1}^{M}\left(p(x, y) - E\right)^2\right)^{\frac{1}{2}} \quad (1)$$

2) *Color histogram*

We use color histogram [16] to describe the content of images to improve retrieval accuracy. The definition of the color histogram is:

$$h(i) = \frac{n_i}{n} \quad (2)$$

where n_i represents the number of pixels of the *i*-th color, n represents the number of pixels of images.

B. *Feature Vectors Based on DWT Domain*

1) *Wavelet sub-band mean and standard deviation*

The low-frequency wavelet sub-band and high-frequency wavelet sub-band describe the outline and details of images, respectively. We can calculate the mean E and standard deviation σ of wavelet sub-band as texture feature. If the wavelet sub-band coefficient value at point (x, y) is $W(x, y)$, they can be defined as:

$$E = \frac{1}{N \times M}\sum_{x=1}^{N}\sum_{y=1}^{M} W(x, y), \sigma = \left(\frac{1}{N \times M}\sum_{x=1}^{N}\sum_{y=1}^{M}\left(W(x, y) - E\right)^2\right)^{\frac{1}{2}} \quad (3)$$

2) *Wavelet histogram*

We use fast wavelet histogram techniques [17] to construct wavelet histogram to describe the texture feature of images. We assume that images are decomposed by 3-level wavelet transform during image coding. Firstly, calculate energy of each wavelet sub-band in every point:

$$ENE_{x,y} = \left|W(x, y)\right| \quad (4)$$

where $ENE_{x,y}$ denotes the energy at point (*x*, *y*).

Secondly, In order to minimize the computational complexity, take level 3 for example, each wavelet sub-band is down-sampled into 3-level wavelet sub-band size to obtain texture channel. Every texture point is changed into 9-dimensional vector by considering texture channels are generated from other 8 sub-bands. Thirdly, each component of 9-dimensional vector is threshold to two levels – high (1) or low (0). It can be defined as:

$$B_i^{ENE} = \begin{cases} 0, \ \boldsymbol{T}(i) < \tau \\ 1, \ \boldsymbol{T}(i) \ge \tau \end{cases}, \ (i = 1, 2, 3, \cdots, 9) \quad (5)$$

where $\boldsymbol{T}$ is the 9-dimensional vector at point (*x*, *y*) in level 3, τ is the median of every texture channel, B_i^{ENE} is the result of vector binaryzation.

Fourthly, represent each 9-dimensional vector $\boldsymbol{L}$ by eigenvalue V:

$$V = 2^8 \times L(9) + 2^7 \times L(8) + \cdots + 2^0 \times L(1) \quad (6)$$

Count the occurrence frequency of each eigenvalue V to construct histogram.

III. Image Retrieval Based on DCT Compressed Domain

We proposed 2-level grading image retrieval algorithm to realize image retrieval based on DCT compressed domain. We used color features: color moments and color histogram, to describe content of images, in addition, we proposed dynamic color space quantization algorithm based on color distribution to improve retrieval accuracy. Fig. 2 shows the diagram of retrieval based on DCT compressed domain.

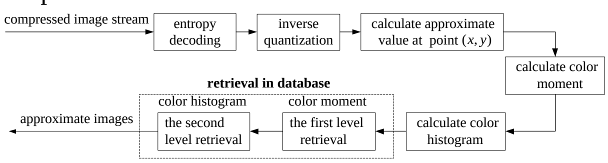


Fig. 2. Retrieval based on DCT compressed domain.

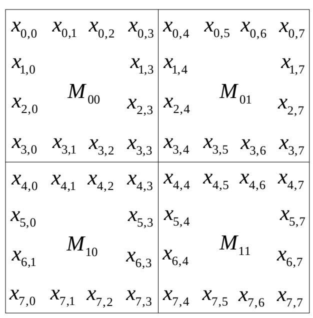


Fig. 3. Partition sketch.

Feng [18] divided each 8×8 image block into four 4×4 image blocks and held that the color values in each

4×4 block are consistent. He used the average color value of each 4×4 block M_{00}, M_{01}, M_{10}, M_{11} to represent the color values of the entire 4×4 image blocks, as shown in Fig. 3.

He used the top left 4 DCT coefficients $F(0,0)$, $F(0,1)$, $F(1,0)$, $F(1,1)$ of each 8×8 DCT block to calculate M_{00}, M_{01}, M_{10}, M_{11}:

$$\begin{aligned} M_{00} &= \frac{2F(0,0)+2F(1,0)+2F(0,1)+\sqrt{2}F(1,1)}{16} \\ M_{01} &= \frac{2F(0,0)+2F(1,0)-2F(0,1)-\sqrt{2}F(1,1)}{16} \\ M_{10} &= \frac{2F(0,0)-2F(1,0)+2F(0,1)-\sqrt{2}F(1,1)}{16} \\ M_{11} &= \frac{2F(0,0)-2F(1,0)-2F(0,1)+\sqrt{2}F(1,1)}{16} \end{aligned} \tag{7}$$

A. The First Level Retrieval

1) The first level feature vector

We use the algorithm above-mentioned to calculate the approximate color value of images and extract color moments as the first level feature vector. The function of color moments is to discard images which are not consistent with the query image in color extremely. We use low dimensional color moments as the first level feature vector given that the function of the first level feature vector is preliminary screening. In order to reduce retrieval time, we use the first two color moment, formula (1) shows their definitions, as the first level feature vector to reduce retrieval time further. In this way, for color images which have three color channels, the first level feature vector is:

$$[E_1,\sigma_1,E_2,\sigma_2,E_3,\sigma_3] \tag{8}$$

where E_1, E_2, E_3 represent mean values of three color channels, respectively; σ_1, σ_2, σ_3 represent standard deviation of three color channels, respectively.

2) Similarity measure

For the first level feature vector, we use block distance [19] to measure the similarity between feature vector $\boldsymbol{I}$, $\boldsymbol{M}$:

$$D(\boldsymbol{I},\boldsymbol{M})=\sum_{j=1}^{N}\left|I_j-M_j\right| \tag{9}$$

The JPEG images use YCbCr color space, and we assign different weights to each color channel given that we are more sensitive to Y channel than Cb channel and Cr channel. The weights ω_1, ω_2, ω_3 are 0.6, 0.2 and 0.2, respectively.

B. The Second Level Retrieval

1) The second level feature vector

In order to improve retrieval accuracy, we use color histogram as the second level feature vector. The dimensions of color space decides the dimensions of color histograms.

If the dimensions of histograms is too high, we need more memory to storage feature vectors and longer retrieval time due to the huge calculation; on the contrary, if the dimensions of histograms is too low, the color histogram can't be used as an effective feature vector and the retrieval accuracy decreases.

We propose a dynamic color space quantization algorithm based on the image color distribution. We use Elephant image as an example and count frequency of each color occurring in the image, as shown in Fig. 4(a) and Fig. 4(b), respectively. It can be seen from Fig. 4 that the occurrence frequency of colors in area L_2 is higher than colors in area L_1, L_3. The colors in area L_2 have a greater effect on retrieval result due to the higher occurrence frequency. We define area L_2 as main color interval and define area L_1, L_3 as minor color intervals. The central idea of algorithm is that we choose smaller quantization intervals for main color intervals and bigger quantization intervals for minor color intervals to realize non-uniform quantization. For different images which have different color distributions, we can partition different quantization intervals to achieve the goal of dynamic quantization.

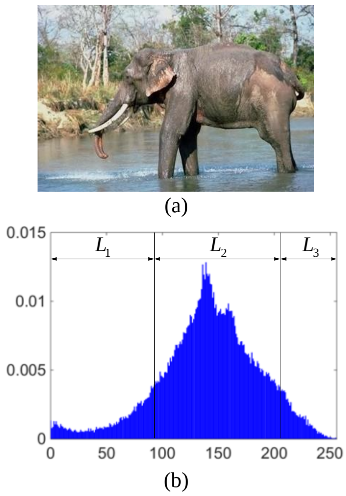


Fig. 4. Elephant image: (a) Original image, (b) Color distribution.

The concrete steps of quantization algorithm are as follows:

Step 1. Count the occurrence frequency of each color and save in vector $\boldsymbol{h}$. The calculation formula is:

$$\boldsymbol{h}(i)=\frac{n_i}{N},\ i=1,2,3,\cdots,256\,, \tag{10}$$

where n_i is the number that the *i*-th color occurs in image and N is the number of pixels.

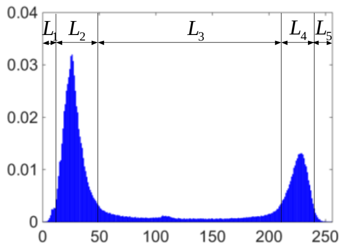
Step 2. Color classification. We divide colors into two types: main color and minor color. We set threshold τ_q for color classification. If the occurrence frequency of one color C_i ($i=1,2,\cdots,256$) is larger than or equal to τ_q, we define it as main color; on the contrary, we define it as minor color. The discrimination formula is:

$$C_i = \begin{cases} \text{main color}, & \boldsymbol{h}(i) \ge \tau_{\text{q}}, \\ \text{minor color}, & \boldsymbol{h}(i) < \tau_{\text{q}}. \end{cases} \quad (11)$$

If we interpret color value at point (x, y) as random variable and assume that the occurrence of 256 kinds of colors is equiprobable, we can preliminary set threshold $\tau_{\text{q}} = \frac{1}{256} \approx 0.004$.

Step 3. Find main color intervals. If the most colors in one interval are main colors, we define it as main color interval; on the contrary, we define it as minor color interval. An image may have several main color intervals, as shown in Fig. 5. It can be seen from Fig. 5 that the occurrence frequency of colors in area L_2 and L_4 is higher than colors in area L_1, L_3 and L_5. Thus, we can define area L_2 and L_4 as main color intervals and define L_1, L_3 and L_5 as minor color intervals. In this paper, we assume that an image has one main color interval or two main color intervals due to that it will be difficult to conduct similarity measure if we partition the color space too elaborate. We set a flag f_{m}, if $f_{\text{m}} = 1$, it indicates that the image has two main color quantization intervals; if $f_{\text{m}} = 0$, it indicates that the image has one main color quantization interval. In addition, we need to notice that minor color intervals may contain some main colors, we choose to ignore them because the number of main colors in minor intervals is small.

(a)



(b)

Fig. 5. Zebra image: (a) Original image, (b) Color distribution.

Step 4. Quantization intervals partition. The colors in main color intervals have a greater effect on similarity measure. Thus, we should choose a smaller interval for the main color intervals to improve retrieval accuracy. In the same way, we should choose a bigger interval for minor color intervals to reduce store memory and improve retrieval efficiency. In this paper, the intervals respectively are 4 and 8. Thus, starting points must be a multiple of 8, both main color intervals and minor color intervals. For example, in Fig. 5, if we have found main color intervals and minor color intervals and s_1, s_2, s_3, s_4, s_5 respectively are the starting points of L_1, L_2, L_3, L_4, L_5, they may be not the multiple of 8. We need to deal with these starting points to make them to be divisible by 8:

$$s_i = ceil(s_i / 8) \times 8 \quad (12)$$

where $ceil()$ function returns a value of number rounded upwards to the nearest integer. In addition, we should set a fixed length of main color intervals in order to make different images have same dimension of color histogram. We count the number of color whose occurrence frequency is greater than threshold τ_{q} in different images and the value are 104 mainly. Thus, the total length of main color intervals is 104 in this paper. In this way, the image has $\frac{104}{4} + \frac{256-104}{8} = 45$ quantization intervals.

Step 5. Calculate the second level feature vector. If s_i and e_i are the starting point and the ending point of the i-th quantization interval respectively, the frequency of the i-th quantization interval is:

$$h(i) = \sum_{n=s_i}^{e_i} h(n), \; i = 1, 2, \cdots, 45 \quad (13)$$

2) Similarity measure

If we use the dynamic algorithm above-mentioned to conduct color space quantization for different images, the components of color feature vector in the same place may not correspond to the same color.

For example, we quantize color space for a Lake image and a Cherry image respectively, as shown in Fig. 6. We list only starting points of quantization intervals to represent quantization intervals.

(a) (b)

Fig. 6. (a) Lake image, (b) Cherry image.

Lake image: [1, 5, 9, 13, 17, 21, 25, 29, 33, 37, 41, 45, 49, 53, 57, 61, 65, 69, 73, 77, 81, 85, 89, 93, 97, 101,105, 113, 121, 129, 137, 145, 153, 161, 169, 177, 185, 193, 201, 209, 217, 225, 233, 241, 249];

Cherry image: [1, 9, 17, 25, 33, 37, 41, 45, 49, 53, 57, 61, 65, 69, 73, 77, 81, 85, 89, 93, 97, 101, 105, 109, 113, 117, 121, 125, 129, 133, 137, 145, 153, 161, 169, 177, 185, 193, 201, 209, 217, 225, 233, 241, 249].

In order to solve this problem, we only consider the overlapping quantization intervals between images. For example, we could see that the quantization intervals of these two images in Fig. 5 are different, but they have overlapping quantization intervals: [33,36], [37,40], [41,44], [45,48], [49,52], [53,56], [57,60], [61,64], [65,68], [69,72], [73,76], [77,80], [81,85], [89,92], [93,96], [97,100], [101,104], [137,144], [145,152], [153,160], [161,168], [168,176], [177,184], [185,192], [193,200], [201,208], [209,216], [217,224], [225,232], [233,240], [241,248], [249,256].

Thus, we can use the color histogram of overlapping parts to calculate distance between images. The concrete steps of similarity measure are as follows:

Step 1. Compare flags of different images. We use f_m whose value represents the number of color intervals of an image to screening. If flags f_m are equal, we can take next step; on the contrary, we should discard image directly.

Step 2. Calculate the overlapping quantization intervals between images. Thus, we should save the starting points of quantization intervals into 45-dimensional vector $\boldsymbol{S}$ when calculating color histogram of an image. In this paper, we save only the starting points of quantization intervals of Y component due to that the quantization of three components: Y, Cb, Cr, are the same.

Step 3. Calculate distance between images. We use histogram intersection to calculate distance between images:

$$D(I,M)=\sum \min(I_j, M_j),\ j\in \boldsymbol{A} \tag{14}$$

Set $\boldsymbol{A}$ save the number of the overlapping quantization intervals. We assign different weights to each color channel given that we are more sensitive to Y channel than Cb channel and Cr channel. The weights ω_1, ω_2, ω_3 are 0.6, 0.2 and 0.2, respectively. Fig. 7 shows the diagram of similarity measure.

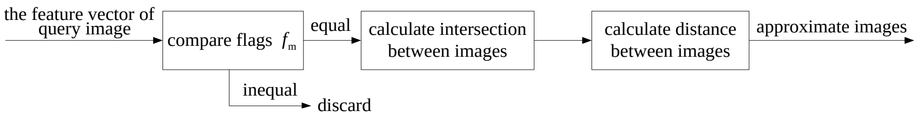


Fig. 7. The diagram of similarity measure.

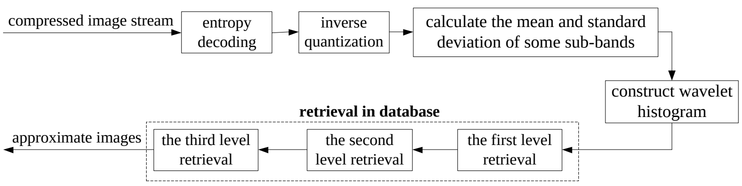


Fig. 8. Retrieval based on DWT compressed domain diagram.

IV. Image Retrieval Based on DWT Compressed Domain

We propose 3-level grading image retrieval algorithm to realize image retrieval based on DWT compressed domain. We use texture features: the mean and standard deviation of wavelet sub-band and wavelet histogram, to describe content of images. In addition, we propose using the mean, standard deviation of low frequency sub-band and the mean, standard deviation of high frequency sub-bands as two level feature vectors. Fig. 8 shows retrieval based on DWT compressed domain diagram.

A. The First Level Retrieval

1) The first level feature vector

The low frequency of wavelet sub-band describes the outline of images. Thus, we can use the mean and standard deviation of low frequency information as the texture feature vector. Formula (3) shows their definitions. In this way, for color images which have three color channels, the first level feature vector is:

$$[E_1,\sigma_1,E_2,\sigma_2,E_3,\sigma_3] \tag{15}$$

2) Similarity measure

Like the first level feature vector in DCT domain, we use block distance to measure the similarity between the first level feature vectors in DWT domain and assign different weights 0.6, 0.2, 0.2 to Y channel, Cb channel and Cr channel, respectively.

B. The Second Level Retrieval

1) The second level feature vector

The high frequency of wavelet sub-bands describes the details of images: horizontal edge, vertical edge and diagonal edge. Thus, we can use the mean and standard deviation of high frequency information as the texture feature vector to improve retrieval accuracy further.

For an image decomposed by 3-level wavelet transform, it has one low frequency sub-band LL_3 and 9 high frequency sub-bands LH_3, HL_3, HH_3, LH_2, HL_2, HH_2, LH_1, HL_1, HH_1. Thus, the feature vector of low frequency sub-band has $3\times 2=6$ dimensions and the feature vectors of high frequency sub-bands have $3\times 2\times 9=54$ dimensions. The former algorithm uses the mean and standard deviation of all sub-bands as the same level feature vector. The feature vector will have 60 dimensions and the retrieval time is longer. We can see that the dimension of the high frequency sub-bands is higher and the dimension of the low frequency sub-band is lower. Thus, we propose that after the preliminary screening by the feature vector of low frequency wavelet sub-band, we can conduct further screening by the feature vectors of high frequency wavelet sub-bands. Because lots of images which do not meet the conditions are discarded according to the lower dimension feature vector, we only need to measure the similarity between images which meet the conditions of the first level retrieval and the retrieval time is shorter. In addition, we can set different thresholds to these two level feature vectors, the retrieval accuracy can be improved.

As we know, sub-bands LH_n, HL_n, HH_n describe the horizontal edge, vertical edge and diagonal edge of images, respectively. Taking horizontal edge information as example, we can choose only sub-bands LH_3, LH_2 to describe. In addition, if level n is lower, the sub-band coefficients correspond to it are quantized as 0 mainly and they have less effect on retrieval result. Thus, in order to reduce feature space, we can use only the means and standard deviations of sub-bands LH_3, HL_3, HH_3, LH_2, HL_2, HH_2 as second level feature vectors. Fig. 9 shows the difference between these two algorithms.

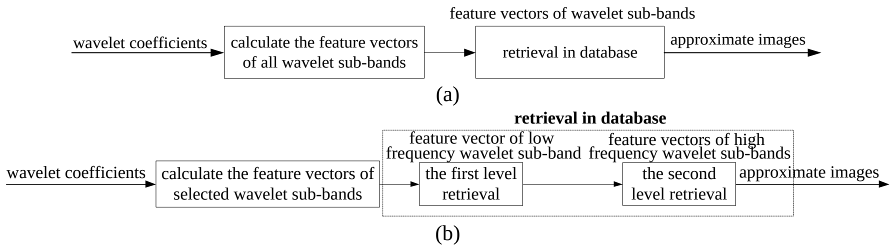


Fig. 9. (a) Retrieval algorithm in reference [12], (b) Retrieval algorithm in this paper.

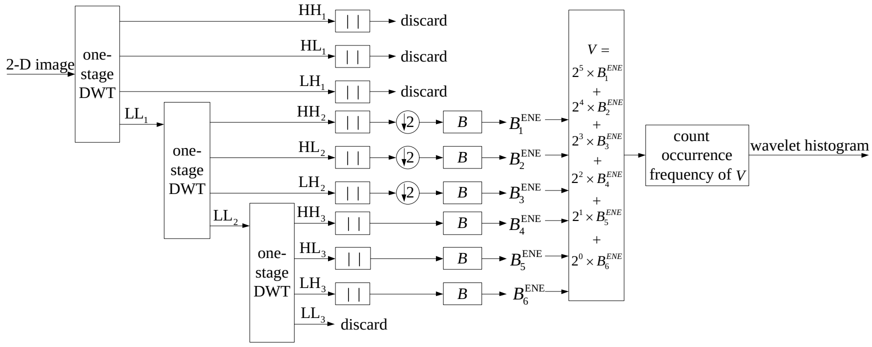


Fig. 10. Schematic of fast wavelet histogram at level 3.

2) Similarity measure

We use block distance to measure the similarity between the second level feature vectors and assign different weights 0.6, 0.2, 0.2 to Y channel, Cb channel and Cr channel, respectively.

C. The Third Level Retrieval

1) The third level feature vector

In order improve retrieval accuracy, we use fast wavelet histogram techniques to construct wavelet histogram to describe texture feature of images further.

As we mentioned in Section II, we assume that images are decomposed by 3-level wavelet transform during image coding. In order to minimize calculation, we set level $k=3$, in other words, 1-level wavelet sub-bands and 2-level wavelet sub-bands should be down-sampled to have the same size with 3-level wavelet sub-band, and the sample rates are 4×4 and 2×2, respectively.

In order to reduce feature space, sub-band LL_3 is not included in calculation range due to that the first level feature vector which extracted by low frequency coefficients is sufficient to describe the low frequency information of images, so we have no need to consider sub-band LL_3 repeatedly. Thus, as the second level feature vectors, we can consider only sub-bands LH_3, HL_3, HH_3, LH_2, HL_2, HH_2 to construct wavelet histogram. Fig. 10 shows the diagram of constructing wavelet histogram.

2) Similarity measure

We use block distance to measure the similarity between the third level feature vectors and assign different weights 0.6, 0.2, 0.2 to Y channel, Cb channel and Cr channel, respectively.

V. Experimental Results and Analysis

In order to verify the validity of the algorithms we proposed, we download 600 images from http://www.cs.washington.edu/research/imagedatabase and http://wang.ist.psu.edu/docs/related, including 300 JPG images and 300 BMP images. Our database contains 10 kinds of images, like Polar bear, Lake, Football field; each contains 30 JPG images and 30 BMP images. Due to the lack of wavelet compressed images, we use BMP images to simulate the wavelet coefficients. The BMP images are transformed by 3-level wavelet decomposition using "bior4.4". So we get the wavelet coefficients. Our software environment of experiment is MATLAB 7.0.

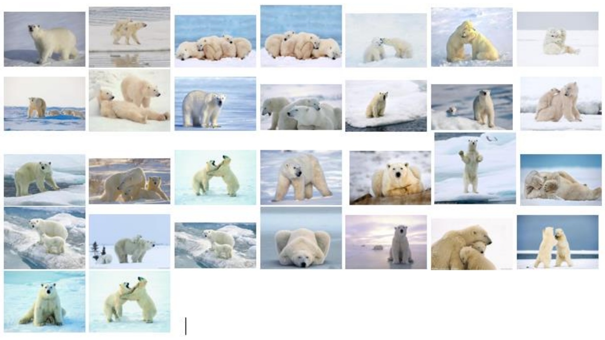
We use the recall ratio [20] and the precision ratio [20] to evaluate retrieval results. Recall ratio R is the ratio between the number of the right approximate images in retrieval result n_M and the number of right approximate images in database n_I; Precision ratio P is the ratio between the number of the right approximate image in retrieval result n_M and the number of all images in retrieval result n_R. They can be respectively expressed as:

$$R = \frac{n_M}{n_I},\ P = \frac{n_M}{n_R} \tag{16}$$

A. Experimental Results and Analysis Based on DCT Compressed Domain

In Section III, we propose a dynamic color space quantization algorithm to reduce the dimension of color histogram. Firstly, we only use histogram as feature vector to conduct retrieval to verify the validity of the quantization algorithm. Selecting a Polar bear image at random as an example, we use the quantization algorithm and the similarity measure mentioned to conduct retrieval. Fig. 11(a) shows the result, and the first image is query image. In reference [16], the color space is quantized by uniform-quantization algorithm and we set quantization interval as 4. Fig. 11(b) shows the retrieval result based on the algorithm we proposed.

(a)



(b)

Fig. 11. (a) Retrieval result based on reference [16], (b) Retrieval result based on the algorithm we proposed.

As shown in Fig. 11(a), the recall ratio R is:

$$\frac{24}{30} \times 100\% = 80\% \tag{17}$$

The precision ratio P is:

$$\frac{24}{30} \times 100\% = 80\% \tag{18}$$

As shown in Fig. 11(b), the recall ratio R is:

$$\frac{30}{30} \times 100\% = 100\% \tag{19}$$

The precision ratio P is:

$$\frac{30}{30} \times 100\% = 100\% \tag{20}$$

Thus, the algorithm we proposed can improve retrieval accuracy. In addition, the second level feature vectors have $1+45+45\times3=181$ dimensions in our algorithm; if we use uniform-quantization algorithm and set interval as 4, the second feature vectors have $(256/4)\times3=192$ dimensions. Thus, the algorithm we proposed also saves store memory.

Secondly, we use 2-level grading image retrieval algorithm based on DCT compressed domain mentioned in Section III to conduct grading retrieval. Selecting a Football field and a Lake image at random as example, Fig. 12(a) and Fig. 12(b) show their retrieval results respectively, and the first image is query image.

We count the recall and precision ratios of 10 kinds of JPG images, respectively, as shown in Table I.

(a)

(b)

Fig. 12. (a) Retrieval result of Football field image, (b) Retrieval result of Lake image.

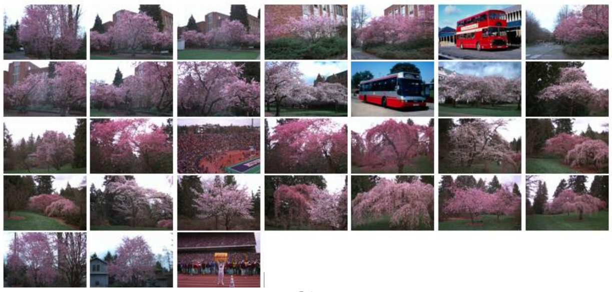
TABLE I: RECALL AND PRECISION RATIOS OF 10 KINDS OF JPG IMAGES

Images	Recall ratio (%)	Precision ratio (%)
Cherry	80	90
Lake	70	95
Sky	40	85
Zebra	55	97
Lion	60	90
Elephant	30	88
Dinosaur	90	95
Polar bear	80	95
Football field	85	93
Bus	40	85

B. Experimental Results and Analysis Based on DWT Compressed Domain

In Section IV, we propose to use the mean, standard deviation of low frequency wavelet sub-bands LL_3 and the means and standard deviations of high frequency wavelet sub-bands LH_3, HL_3, HH_3, LH_2, HL_2, HH_2 as two level feature vectors. In reference [12], they used the mean and deviation of all wavelet sub-bands as the same level feature vector. Selecting Cherry images at random as example, Fig. 13 shows the retrieval results of these two algorithms, respectively.

(a)



(b)

Fig. 13. (a) Retrieval result based on reference [12], (b) Retrieval result based on the algorithm we proposed.

As shown in Fig. 13(a), the recall ratio R is:

$$\frac{21}{30} \times 100\% = 70\% \tag{21}$$

The precision ratio P is:

$$\frac{21}{30} \times 100\% = 70\% \tag{22}$$

As shown in Fig. 13(b), the recall ratio R is:

$$\frac{26}{30} \times 100\% = 86.7\% \tag{23}$$

The precision ratio P is:

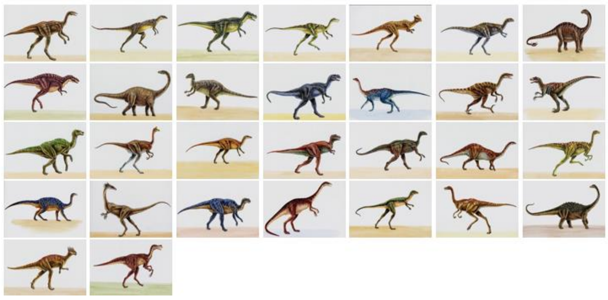
$$\frac{26}{31} \times 100\% \approx 84\% \tag{24}$$

Thus, the algorithm we proposed can improve retrieval accuracy. In addition, the retrieval time of the algorithm in reference [12] is 23.76s; the retrieval time of the algorithm we proposed is 20.12s. Besides, the dimension of feature vector used the algorithm in reference [12] to extract is $1\times3\times2+9\times3\times2=60$; the dimension of feature vector used the algorithm to extract is $1\times3\times2+6\times3\times2=42$. Thus, the algorithm we proposed also saves store memory.

Secondly, we use 3-level grading image retrieval algorithm based on DWT compressed domain mentioned in Section IV to conduct grading retrieval. Selecting a Bus and a Dinosaur image at random as example, Fig. 14(a) and Fig. 14(b) show their retrieval results respectively, and the first image is query image.

We count the recall and precision ratios of 10 kinds of BMP images, respectively, as shown in Table II.

(a)



(b)

Fig. 14. (a) Retrieval result of Bus image, (b) Retrieval result of Dinosaur image.

TABLE II: RECALL AND PRECISION RATIOS OF 10 KINDS OF BMP IMAGES

Images	Recall ratio (%)	Precision ratio (%)
Cherry	80	87
Lake	70	92.7
Sky	80	95
Zebra	40	95
Lion	66	98
Elephant	45	85
Dinosaur	90	95
Polar bear	80	100
Football field	90	97
Bus	60	96

VI. CONCLUSION

We have presented two grading retrieval algorithms based on DCT compressed domain and DWT compressed domain, respectively. Firstly, we use 2-level grading image retrieval algorithm to realize image retrieval based on DCT compressed domain. We used color features: color moment and color histogram, to describe content of images. For the second level feature vector, color histogram, instead of quantizing color space by uniform quantization algorithm, we use a new dynamic color space quantization algorithm based on color distribution to reduce dimensions of histogram. Our experimental results clearly show that the 2-level grading image retrieval algorithm works better than other algorithms: store memory is reduced and retrieval accuracy is improved. Secondly, we use 3-level grading image retrieval algorithm to realize image retrieval based on DWT compressed domain. We used texture features: the mean and standard deviation of wavelet sub-band and fast wavelet histogram, to describe content of images. Instead of using the mean and standard deviation of all wavelet sub-bands as the same level feature vector, we use the mean, standard deviation of low frequency sub-band and the means, standard deviations of some selected high frequency sub-bands as two level feature vectors. Our experimental results clearly show that the two grading image retrieval algorithms work better than other algorithms: store memory is reduced and retrieval accuracy is improved.

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