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CTDCIRS: Content based Image Retrieval System based on Dominant Color and Texture Features

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ABSTRACT
There is a great need of developing efficient content based image retrieval systems because of the availability of large image databases. A new image retrieval system CTDCIRS (color-texture and dominant color based image retrieval system) to retrieve the images using three features called dynamic dominant color (DDC), Motif co-occurrence matrix (MCM) and difference between pixels of scan pattern (DBPSP) is proposed. Initially the image is divided into eight coarse partitions using the fast color quantization algorithm and the eight dominant colors are obtained from eight partitions. Next the texture of the image is represented by the MCM and DBPSP. MCM is derived using a motif transformed image. MCM is similar to color co-occurrence matrix (CCM). MCM is the conventional pattern co-occurrence matrix that calculates the probability of the occurrence of same pixel color between each pixel and its adjacent ones in each image, and this probability is considered as the attribute of the image.MCM captures third order image statistics in the local neighborhood which describes the direction of textures but not the complexity of the textures. That is why the DBPSP is also considered as one of the texture features. The three features Dominant color, MCM and DBPSP are integrated to facilitate the image retrieval system. Experimental results show that the proposed image retrieval is more efficient in retrieving the user- interested images.

General Terms
Algorithm, pattern recognition, database, image.

Keywords
Image retrieval, dominant color, texture, Co-occurrence, motif.

1. INTRODUCTION
The arrival of computer vision technology and the increase in the number of images taken by digital video devices, searching for images containing user-specified characteristics in large image databases has become more and more important and challenging than ever before [1]. The basic image searching method in olden days is the text-based image retrieval, which searches for images based on one or more keywords specified by the user. But, there are different situations in which a query request cannot be easily described by keywords. To solve this problem, the content-based image retrieval (CBIR) was come into existence for searching images based on a given query image [2]. A summary of current system architectures, techniques, and methods for feature extraction and algorithms for image matching can be found in [2].

In CBIR system model, the images are indexed by their visual contents as the features. These include the characteristics such as color, texture, shape, and color layout (both color features and spatial relations). The features are stored in an image feature database for future use. Whenever a query image is given, the features of the query image are retrieved to match the features in the feature database by a pre-established algorithm, so that related images are returned for the query image [2].

Color is one of the most commonly used low-level visual features and is invariant to image size and orientation [1]. As conventional color features used in CBIR, there are color histogram, color correlogram, and dominant color descriptor (DCD). Color histogram is the most widely used color representation, but it does not include any spatial information. Li et al. [3] proposed a new algorithm based on running sub blocks with different similarity weights for object-based image retrieval. First split the image into certain sub blocks, similarity matrix analysis and the color region information are used to retrieve images under the query of special object. Color correlogram describes the probability of finding color pairs at a fixed pixel distance and provides spatial information. Hence color correlogram yields better retrieval accuracy in comparison to color histogram. Color autocorrelogram is a subset of color correlogram, which captures the spatial correlation between identical colors only. Although it provides much computational benefits over color correlogram, it is more suitable for image retrieval. DCD is MPEG-7 color descriptors [4]. DCD describes the salient color distributions in an image or a region of interest, and provides an effective, compact, and intuitive representation of colors presented in an image. However, DCD similarity matching does not fit human perception very well, and it will cause incorrect ranks for images with similar color distribution [5,6]. In [7], Yang et al. presented a color quantization method for dominant color extraction, called the linear block algorithm (LBA), and it has been shown that LBA is efficient in color quantization and computation. For the purpose of effectively retrieving more similar images from the digital image databases (DBs), Lu et al. [8] uses the mean value, the color distributions and the standard deviation, to represent the global characteristics of the image, and the image bitmap is used to represent the local characteristics of the image for increasing the accuracy of the retrieval system. Dominant colors describe color features with a smaller number of features. This method is expected to effectively shorten image retrieval time and enhance retrieval performance.

A single attribute is not sufficient to describe image features. Despite the extensive applications of textures [9,13,14], colors [15–18], spatial relations [16], and shapes [19] in image retrieval, the results have limited effects on discrimination. For describing image features, the relations between colors and textures are problematic. Hence, in this study, colors and textures are used as attributes in similarity retrieval to develop an innovative and effective image retrieval system (CTDCIRS).

Whenever we are describing the image features, we consider the relations between colours and textures are critical. Huang and Dai [9] proposed a texture based image retrieval system which combines the wavelet decomposition [10] and gradient vector [11]. The system consists a coarse feature descriptor and a fine feature descriptor with each image. Both descriptors are derived from the wavelet coefficients of the original image. The coarse feature descriptor is used at the first stage to quickly screen out non-promising images; the fine feature descriptor is subsequently employed to find the truly matched images.

In Jhanwar et al. [12] the image retrieval system introduced is based on motif co-occurrence matrix (MCM), which converts the difference between pixels into a basic graphic and computes the probability of its occurrence in the adjacent area as an image feature. The color difference between adjacent pixels by our proposal, a better technique integrated with Motif co-occurrence matrix (MCM) and difference between the pixels of a scan pattern (DBPSP) to improve texture description.

For the description of properties of image, Dynamic dominant color, MCM and DBPSP are available. To enhance retrieval performance, MCM, DBPSP, and Dynamic dominant Color are integrated to develop an image retrieval system based on texture distribution and color features. The remaining paper consists of: Section 2 presents dynamic dominant color extraction. Section 3 describes the Motif co-occurrence matrix representation. In Section 4, computation of DBPSP is given. Section 5 contains the description of similarity measure used in image retrieval system. Simulation results in Section 6 will show the performance of our scheme. Finally, Section 7 concludes this presentation.

2. COLOR REPRESENTATION

The most probable and differentiable low-level visual features in describing image is color. Now a days Many CBIR systems employ color to retrieve images, such as QBIC system and Visual SEEK. In theory, it will lead to minimum error by extracting color feature for retrieval using real color image directly, but the problem is that the computation cost and storage required will expand rapidly. So it goes against practical application. In fact, for a given color image, the number of actual colors only occupies a small proportion of the total number of colors in the whole color space, and further observation shows that some dominant colors cover a majority of pixels. Consequently, it won't influence the understanding of image content though reducing the quality of image if we use these dominant colors to represent image.

Several color descriptors have been approved including number of histogram descriptors and a dominant color descriptor (DCD) [4] in the MPEG-7 Final Committee Draft. DCD contains two main components: 1.representative colors 2.the percentage of each color. DCD can provide an effective, compact, and intuitive salient color representation, and describe the color distribution in an image or a region of interesting. But, for the DCD in MPEG-7, the representative colors depend on the color distribution, and the greater part of Representative colors will be located in the higher color distribution range with smaller color distance. because of human eyes cannot distinguish exactly, it may be not consistent the colors with close distance. Moreover, DCD similarity matching does not fit human perception very well, and it will cause incorrect ranks for images with similar color distribution. We will adopt a new and efficient dominant color extraction scheme to address the above problems [7].

The selection of color space is not a critical issue for DCD extraction According to numerous experiments. Therefore, for simplicity and without loss of generality, the RGB color space is used. First, the RGB color space is divided equally into 8 coarse partitions, as shown in Fig. 1. If there are several colors located on the same partitioned block, they are assumed to be similar. After the above coarse partition, the centroid of each partition ("colorBin" in MPEG-7) is selected as its quantized color. Let X=(XR,XG,XB) represent color components of a pixel with color components

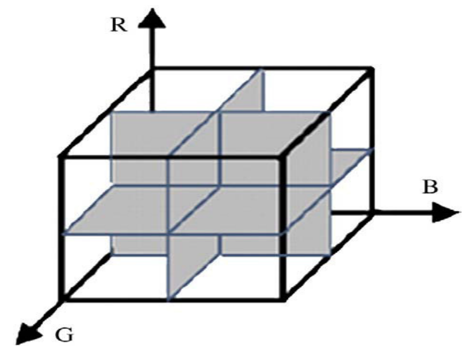


Fig. 1. The coarse division of RGB color space.

Red, Green, and Blue, and Ci be the quantized color for partition i. The average value of color distribution for each partition centre can be calculated by

$$\overline{X}_i = \frac{\sum_{X \varepsilon Ci} X}{\sum_{X \varepsilon Ci} 1} \tag{1}$$

After the average values are obtained, each quantized color can be determined. i.e.

$$C_i = \left(\overline{X}_i^R, \overline{X}_i^G, \overline{X}_i^B\right)\left(1 \le i \le 8\right) \tag{2}$$

Where C_i is a 3D dominant color vector. Eight dominant colors are obtained per an image.

3. MOTIF CO-OCCURRENCE MATRIX

CTDCIRS uses a Motif Co-occurrence Matrix (MCM) to represent the traversal of adjacent pixel color difference in an image. As each pixel corresponds to four adjacent pixel colors, each image can be presented by four images of motifs of scan pattern, which can be further constructed into four two-dimensional matrices of the image size. Based on these four matrices, the attribute of the image will then be computed with the motifs of scan pattern and a Motif Co-occurrence Matrix (MCM) can be obtained, which is the feature used in the image retrieval.

A 3x3 convolution mask for each pixel G(x, y) can be generated as shown in Fig. 2. This 3x3 convolution mask can be further divided into four blocks of 2x2 grids (pixels) with each including pixel G(x, y).

There are 25 different scan patterns in a grid if the traversal goes from four angles generally. Here, we only consider the scan starting from the top left corner pixel p1 as shown in Fig. 2(a), because it represents a complete family of space filling curve, reducing the number of patterns to only 7 as shown in Fig. 3. Among them motif number 0 signifies theThis paper proposes a Motif Co-occurrence Matrix (MCM) to represent the traversal of adjacent pixel color difference in an image. As each pixel corresponds to four adjacent pixel colors, each image can be presented by four images of motifs of scan pattern, which can be further constructed into four two-dimensional matrices of the image size. Based on these four matrices, the attribute of the image will then be computed with the motifs of scan pattern and a Motif Co-occurrence Matrix (MCM) can be obtained, which is the feature used in the image retrieval.

For each pixel G(x, y), a 3x3 convolution mask can be generated as shown in Fig. 2. This 3x3 convolution mask can be further divided into four blocks of 2x2 grids (pixels) with each including pixel G(x, y).

In general, there are 25 different scan patterns in a grid if the traversal goes from four angles. Here, we only consider the scan starting from the top left corner pixel p1 as shown in Fig. 2(a), because it represents a complete family of space filling curve, reducing the number of patterns to only 7 as shown in Fig. 3. Among them motif number 0 signifies the situation wherein a motif cannot be formed due to the equivalence.

These 2x2 grids are then replaced by motifs of scan pattern which would traverse the grid in an optimal sense. The optimality of the scan is related to the incremental difference in intensity along the scan line minimizing the variation in the intensities in a local neighbourhood.

Let G(x, y): Nx x Ny→Z be the gray levels of an Nx x Ny image I for Z = {0, 1, . . ., 255}. Pixel G(x, y) is divided into four blocks, each of which has 2x2 grids (pixels), to form four different motifs shown by number m of motif.

1	2	3
4 6	G(x,y) 7	5 8

(a) 3x3 convolution mask of Pixel G(x,y)

A	B
C	D

(b) A block of 2x2 grids including G(x,y) in the 3x3 convolution mask

1	2
4	G(x,y)

(c) The 2x2 grids of A Block

2	3
G(x,y)	5

(d) The 2x2 grids of B Block

4	G(x,y)
6	7

(e) The 2x2 grids of C Block

G(x,y)	5
7	8

(f) The 2x2 grids of D Block

Fig.2 The 3 X 3 convolution masks are divided into four 2 X 2 grids

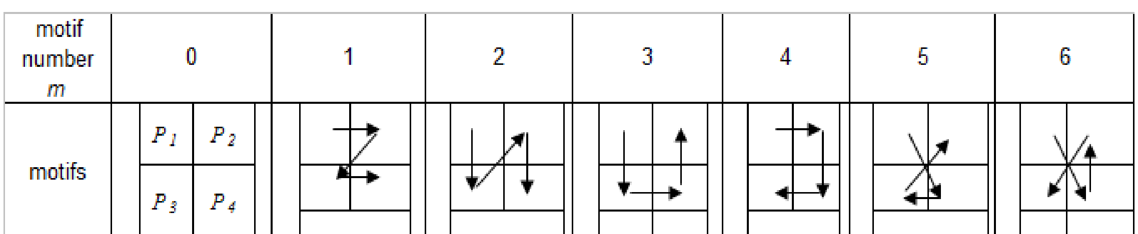


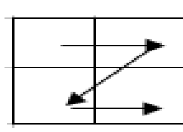
Fig.3. The seven scan patterns

0	5
10	15

(a) 2x2 grids(pixel)

0	50
100	150

(b) 2x2 grids(pixel)



(c) The motifs of scan pattern for (a) and (b)

Fig. 4. The motifs of scan pattern for 2 X 2 grids

These four motifs will be saved in four Nx x Ny two-dimensional motifs of scan pattern matrix Pi[x, y], in which i=1, 2, 3, 4, x = 1, 2, . . ., Nx, y = 1, 2, . . ., Ny, and Pi[x, y]: Nx x Ny→W denotes an Nx x Ny matrix for W= {0, 1, . . ., 6}. The Motif co-occurrence matrix (MCM) calculates the distribution within the two-dimensional motifs of scan pattern matrix Pi[Nx, Ny]. That is, it takes into account the probability of the co-occurrence between the two motifs respectively corresponding to (x, y) and its adjacent (x + dx, y + dy). This probability is then the attribute of image color variation used. The coordinate that distances from (x, y) on the x axis in dx and on y axis in dy, then the total number of co-occurring motifs of scan pattern pairs (u, v) (where u = 0, 1, . . ., 6 and v = 0, 1, . . ., 6) is determined by

$$M_i(u,v)=M_i(u,v|\delta_x,\delta_y)=M_i(P_i[x,y],P_i[x+\delta_x,y+\delta_y]) \tag{3}$$

where Pi[x, y] = u, Pi[x + dx, y + dy] = v, 1≤ i≤ 4, 1≤ x≤ Nx, 1≤y≤Ny, 1≤x + dx≤Nx, and 1≤ y + dy ≤ Ny. The co-occurring probabilities of the number i motifs of scan pattern matrix are determined by dividing Mi (u, v) by the total number of counts across all u and v, as shown below

$$m(u,v)=\frac{M_i(u,v)}{N_i} \tag{4}$$

Where

$$N_i=\sum_{u=0}^{6}\sum_{v=0}^{6}M_i(u,v) \tag{5}$$

and 1 ≤ i ≤ 4. As a result, there will be a 7 x 7 two-dimensional grids in total, which amounts to 7 x 7 = 49, with N_f = 49 is the total number of MCM attributes to be considered.

4. DIFFERENCE BETWEEN PIXELS OF SCAN PATTERN (DBPSP)

The MCM feature proposed in the previous section could effectively describe the direction of textures but not the complexity of textures. As shown in Fig. 4, the motif number in both Fig. 4(a) and (b) is 2, but the differences among the four pixels values are large. Therefore, we take the difference between pixels of scan patterns (DBPSP) as one of the texture features.

Six basic motifs can be derived from MSPM as features of an image. However, it does not mean that each motif of a scan pattern represents the same feature. Therefore, this paper specifically takes the difference between the pixels of a scan pattern (DBPSP) as one of the image retrieval features. Since DBPSP calculates the difference among all pixels within the motifs of a scan pattern, the adopted motifs of a scan pattern do not take motif number 0 as shown in Fig. 3 into account.

The feature of DBPSP is mainly intended to calculate the differences among all pixels within motifs of a scan pattern. In other words, it records the pixel value differences among all scan directions within motifs of scan pattern and then takes the appearance rate of the total pixel value differences in the whole image as the feature of DBPSP. The total pixel value difference of any coordinates (x, y) within the image is Δ(x, y). It is possible to generate six motifs of a scan pattern which can be respectively shown as Δ^1(x, y), Δ^2(x, y), . . ., Δ^6(x, y) in the following formulae:

$$\begin{aligned}
\Delta^1(x,y)&=|p1-p2|+|p2-p3|+|p3-p4|\\
\Delta^2(x,y)&=|p1-p3|+|p3-p2|+|p2-p4|\\
\Delta^3(x,y)&=|p1-p3|+|p2-p4|+|p4-p2|\\
\Delta^4(x,y)&=|p1-p2|+|p2-p4|+|p4-p3|\\
\Delta^5(x,y)&=|p1-p4|+|p4-p3|+|p3-p2|\\
\Delta^6(x,y)&=|p1-p4|+|p4-p2|+|p2-p3|
\end{aligned} \tag{6}$$

where Δ^1(x, y) represents the total pixel value difference of all scan directions of ith motif number of any coordinates (x, y) within the image. The formula of i's motif number and p is shown in Fig. 3. Finally, we calculate the appearance rate of Δ(x, y) within the whole image as shown below:

$$f_i=\frac{1}{N_i}\sum_{j=1}^{N_i}\Delta_j^i(x,y) \tag{7}$$

Where i is the motif number and N_i is the total appearance of i^{th} motif number within the whole image. Therefore, six DBPSP feature values can be obtained.

5. IMAGE RETRIEVAL SYSTEM

MCM and DBPSP are useful for describing the relationship between colors and textures in an image. However, they are sensitive to the noise variation in images. Given the color information of an image, Dynamic Dominant Color (DDC) is simple and easy to compute. DDC includes only eight values which reduces the size of the feature vector. This feature is also indifferent to image size variant and rotation variant of objects in image. Due to significantly complementary, these two features are integrated to establish a color–texture and Dominant-color based image retrieval system (CTDCIRS).

MCM of the query image Q and one database image D as $\left(m_1^q,m_2^q,...m_{49}^q\right)$ and $\left(m_1^d,m_2^d,...m_{49}^d\right)$ are obtained from Eq.(4). Here, the superscripts q and d stand for the query Q and database image D. The image matching distance Δ^{MCM} between Q and D based on the CCM can be calculated via the following equation:

$$\Delta^{MCM}=\sum_{k=1}^{49}\left|\frac{m_k^q-m_k^d}{m_k^q+m_k^d+v}\right| \tag{8}$$

Where m is any small number that avoids denominator = 0.

Considering DBPSP $\left(f_1^q,f_2^q,...f_6^q\right)$ and $\left(f_1^d,f_2^d,...f_6^d\right)$ of images Q and D are obtained from Eq. (7), the image matching distance Δ^{DBPSP} of Q and D based on DBPSP is formulated as the following:

$$\Delta^{DBPSP}=\sum_{k=1}^{6}\left|\frac{f_k^q-f_k^d}{f_k^q+f_k^d+v}\right| \tag{9}$$

Considering DDC $\left(c_1^q,c_2^q,...c_8^q\right)$ and $\left(c_1^d,c_2^d,...c_8^d\right)$ of images Q and D are obtained from Eq.(2), the image matching distance Δ^{DDC} of Q and D based on DDC is formulated as following:

$$\Delta^{DDC} = \sum_{k=1}^{8} \left| \frac{c_k^q - c_k^d}{c_k^q + c_k^d + v} \right| \quad (10)$$

The proposed CTDCIRS system combines the MCM, DBPSP and DDC to quantize the similarity between Q and D. Using such retrieval system, one can define the image matching distance $\Delta^{CTDDCIR}$ between Q and D as

$$\Delta^{CTDCIRS} = W_1 X \Delta^{MCM} + W_2 X \Delta^{DBPSP} + W_3 X \Delta^{DDC}$$

Where W_1, W_2 and W_3 are the weights for MCM, DBPSP and DDC. Generally, $\Delta^{CTDDCIRS}$ decreases with the increase of similarity between Q and D. Hence, the CTDCIRS system can deliver the image with the minimal $\Delta^{CTDDCIRS}$ from the database.

6. THE PERFORMANCE OF CTDCIRS

An experiment is conducted to explore the performance of the CTDCIRS system on image Set downloaded from http://wang.ist.psu.edu/docs/related/. Image Set consists of 1000 images. These images are grouped into 10 clusters with each containing 100 images. The images in the same cluster are considered as similar images. Fig. 7 shows some of these images. The images in the same row in Fig. 7 belong to the same cluster. In this experiment, the values of the parameters are: spatial offset $(\delta_x,\delta_y) = (0, 1)$ and $W_1 = 0.2$, W2 = 0.4, and $W_3 = 0.4$. Classes names are listed in Table 1.

This experiment used each image in each class as a query image. The experiment was carried out with the number L of retrieved images set as 20 to compute the precision P of each query image and finally obtain the average precision P/100 (100 images of a class).

The experimental results from proposed method and the other two methods are shown in Table 1. It is obvious that this proposed method has achieved a better average precision of various images than the other two methods.

The precision and recall measurements of Mehtre et al.[20] are often used to describe the performance of an image retrieval system. The precision (P) and recall (R) are defined as follows:

$$P(k)=n_k/L \quad \text{and} \quad R(k)= n_k/N \quad (11)$$

Where L is the number of retrieved images; nk is the number of relevant images in the retrieved images and N is the number of all relevant images in the database.

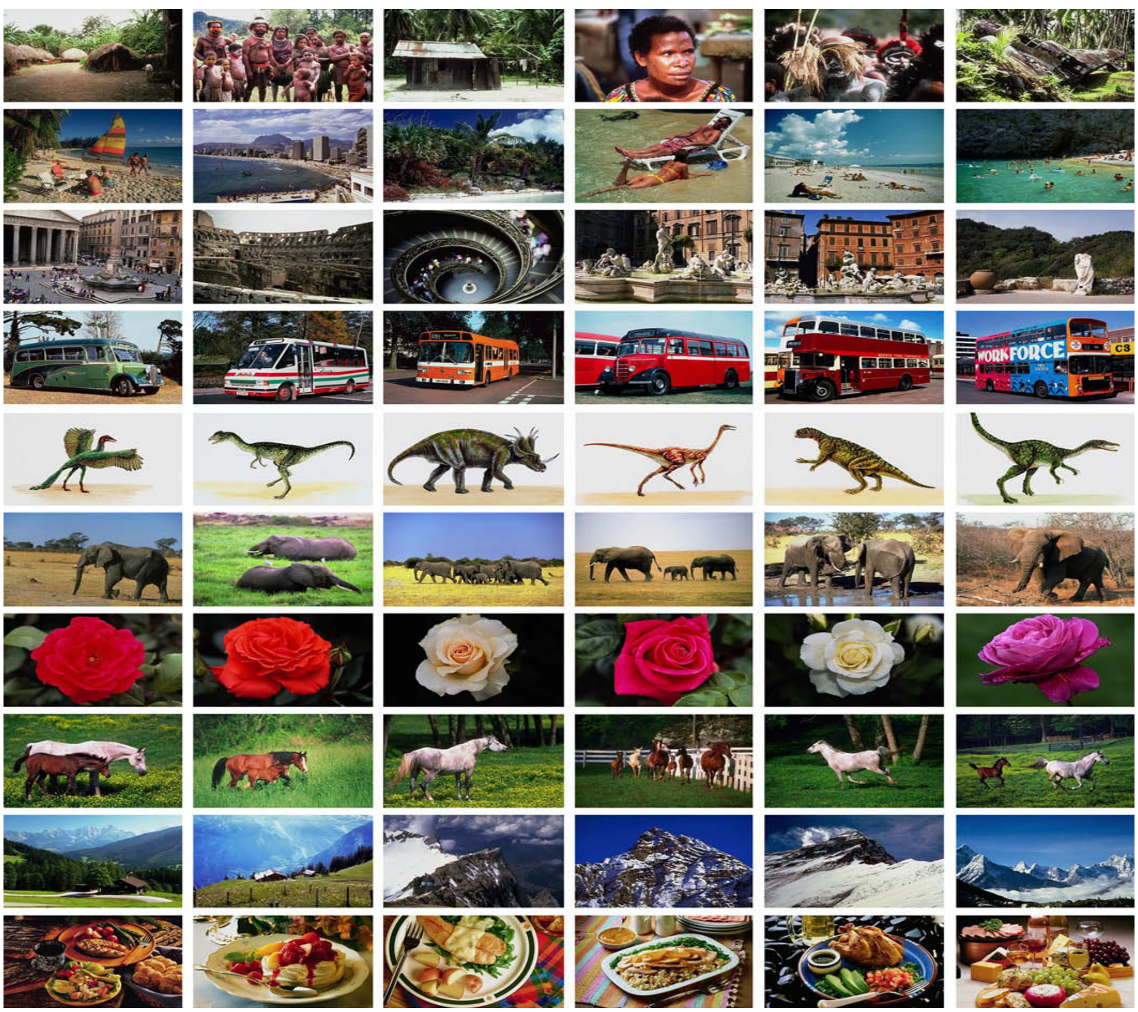


Fig.5 Some examples of image set

Table 1 Ten classes of image set

Classes	Semantic name
1	African people and village
2	Beach
3	Building
4	Buses
5	Dinosaurs
6	Elephants
7	Flowers
8	Horses
9	Mountains and glaciers
10	Food

are: spatial offset $(\delta_x,\delta_y) = (0, 1)$ and $W_1 = 0.2$, W2 = 0.4, and $W_3 = 0.4$. Classes names are listed in Table 1.

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$$P(k)=n_k/L \quad \text{and} \quad R(k)= n_k/N \qquad (11)$$

Where L is the number of retrieved images; nk is the number of relevant images in the retrieved images and N is the number of all relevant images in the database.

The quantitative measure is given below

$$p(i) = \frac{1}{100} \sum_{1\le j\le 1000, r(i,j)\le 100, ID(j)=ID(i)} 1$$

Where *p(i)* is precision of query image I, ID(i) and ID(j) are category ID of image i and j respectively, which are in the range of 1 to 10. the r(i, j) is the rank of image j. This value is percentile of images belonging to the category of image i , in the first 100 retrieved images.

The average precision p_t for category t(1≤t≤10) is given by

$$= \frac{1}{100} \sum_{1\le i\le 1000, ID(i)=t} p(i)$$

The experiments were carried out on a Core i3, 2.4 GHz processor with 4GB RAM using MATLAB. Image retrieval results with different methods are shown in Fig.7. The image at the top left- hand corner is the query image and the other 19 images are the retrieval results. The number of retrieved images is more with our proposed system than the other methods.

Table 2: The average precision of these methods on image

Semantic name	proposed method	Jhanwar et.al.[12]	Hung and Dai's[9]
African people and village	0.562	0.4525	0.424
Beach	0.536	0.3975	0.4455
Building	0.61	0.3735	0.4105
Buses	0.893	0.741	0.8515
Dinosaurs	0.984	0.9145	0.5865
Elephants	0.578	0.304	0.4255
Flowers	0.899	0.8515	0.8975
Horses	0.78	0.568	0.589
Mountains and glaciers	0.512	0.2925	0.268
Food	0.694	0.3695	0.4265
Average	0.7048	0.52645	0.53245

Fig.6. The image retrieval results (dinosaurs) using different techniques (a) N.Jhanwar et.al [12] (b) Hung and Dai et.al[9] (c) proposed method

The Fig7. is a graph showing the Comparison of average precision obtained by proposed system with other retrieval systems.

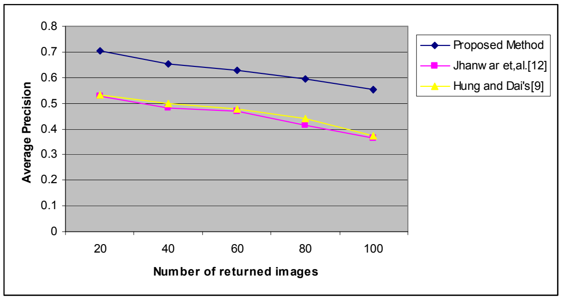

Fig. 7 The average precision of different methods

7. CONCLUSION

The proposed system uses three image features namely MCM, DBPSP and DDC to characterize a color image for image retrieval. MCM and DBPSP can describe texture distribution, while DDC can describe color features of the pixels in an image. DDC is invariant to translation and rotation. Since these features can describe different properties of an image, the CTDCIRS system integrates these three features to retrieve the images. The experimental results show that the proposed system outperforms Hung's and Jhanwar's methods.

REFERENCES

[1] Ritendra Datta, Dhiraj Joshi, Jia Li, James Z. Wang, Image retrieval: ideas, influences, and trends of the new age, ACM Computing Surveys 40 (2) (2008) 1–60.

[2] Y. Rui, T.S. Huang, S.F. Chang, Image retrieval: current techniques, promising directions, and open issues, J. Visual Commun. Image Representation 10 (1999) 39–62.

[3] Xuelong Li, Image retrieval based on perceptive weighted color blocks, Pattern Recognition Letters 24 (12) (2003) 1935–1941.

[4] ISO/IEC 15938-3/FDIS Information Technology—Multimedia Content Description Interface—Part 3 Visual Jul. 2001, ISO/IEC/JTC1/SC29/WG11 Doc. N4358.

[5] L.M. Po, K.M. Wong, A new palette histogram similarity measure for MPEG-7 dominant color descriptor, Proceedings of the 2004 IEEE International Conference on Image Processing (ICIP'04), Singapore, October 2004, pp. 1533–1536.

[6] Rui Min, H.D. Cheng, Effective image retrieval using dominant color descriptor and fuzzy support vector machine, Pattern Recognition 42 (1) (2009) 147–157.

[7] Nai-Chung Yang, Wei-Han Chang, Chung-Ming Kuo, Tsia-Hsing Li, A fast MPEG-7 dominant color extraction with new similarity measure for image retrieval, Journal of Visual Communication and Image Representation 19 (2) (2008) 92–105.

[8] Tzu-Chuen Lu, Chin-Chen Chang, Color image retrieval technique based on color features and image bitmap, Information Processing and Management 43 (2) (2007) 461–472.

[9] P.W. Huang, S.K. Dai, Image retrieval by texture similarity, Pattern Recognition 36 (3) (2003) 665–679.

[10] I. Daubechies, Orthonormal bases of compactly supported wavelets, Communications on Pure and Applied Mathematics 41 (1998) 909– 996.

[11] R.M. Haralick, L.G. Shapiro, Computer and Robot Vision, vol. I, Addison-Wesley, Reading, MA, 1992.

[12] N. Jhanwar, S. Chaudhuri, G. Seetharaman, B. Zavidovique, Content based image retrieval using motif co-occurrence matrix, Image and Vision Computing 22 (2004) 1211–1220.

[13] H. Abrishami Moghaddam, T. Taghizadeh Khajoie, A.H. Rouhi, M. Saadatmand Tarzjan, Wavelet correlogram: a new approach for image indexing and retrieval, Pattern Recognition 38 (2005) 2506–2518.dbfbfn

[14] S. Liapis, G. Tziritas, Color and texture image retrieval using chromaticity histograms and wavelet frames, IEEE Transactions on Multimedia 6 (5) (2004) 676–686.

[15] B.C. Ko, H. Byun, FRIP: a region-based image retrieval tool using automatic image segmentation and stepwise Boolean and matching, IEEE Transactions on multimedia 7 (1) (2005) 105–113.

[16] Y.K. Chan, C.Y. Chen, Image retrieval system based on color-complexity and color-spatial features, The Journal of Systems and Software 71 (1–2) (2004) 65–70.

[17] C.C. Chang, Y.K. Chan, A fast filter for image retrieval based on color features,SEMS2000, Baden-Baden, German, 2000, pp. 47–51.

[18] H. Nezamabadi-Pour, E. Kabir, Image retrieval using histograms of uni-color and bi-color blocks and directional changes in intensity gradient, Pattern Recognition Letters 25 (14) (2004) 1547–1557.

[19] B.M. Mehtre, M. Kankanhalli, W.F. Lee, Shape measures for content-based image retrieval: comparison info, Processing and Management 33 (1997) 319–337.

[20] G.P. Babu, B.M. Mehtre, M.S. Kankanhalli, Color indexing for efficient image retrieval, Multimedia Tools and Applications 1 (4) (1995) 327–348.