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A smart content-based image retrieval system based on color and texture feature

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ABSTRACT

In this paper, three image features are proposed for image retrieval. In addition, a feature selection technique is also brought forward to select optimal features to not only maximize the detection rate but also simplify the computation of image retrieval. The first and second image features are based on color and texture features, respectively called color co-occurrence matrix (CCM) and difference between pixels of scan pattern (DBPSP) in this paper. The third image feature is based on color distribution, called color histogram for *K*-mean (CHKM).

CCM 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. According to the sequence of motifs of scan patterns, DBPSP calculates the difference between pixels and converts it into the probability of occurrence on the entire image. Each pixel color in an image is then replaced by one color in the common color palette that is most similar to color so as to classify all pixels in image into *k*-cluster, called the CHKM feature.

Difference in image properties and contents indicates that different features are contained. Some images have stronger color and texture features, while others are more sensitive to color and spatial features. Thus, this study integrates CCM, DBPSP, and CHKM to facilitate image retrieval. To enhance image detection rate and simplify computation of image retrieval, sequential forward selection is adopted for feature selection. Besides, based on the image retrieval system (CTCHIRS), a series of analyses and comparisons are performed in our experiment. Three image databases with different properties are used to carry out feature selection. Optimal features are selected from original features to enhance the detection rate.

1. Introduction

Many contemporary scholars have been very much devoted to the design of image databases [1–6], as similarity retrieval is important for applications such as medical imaging, office automation, digital library, computer aided design, and multimedia publications. Traditional image retrieval systems are based on the features of the original data [1,3], such as file name, note title, keyword, and indexing icon. When applied to large-scale image databases, these features become troublesome and time-consuming, and even unable to adequately describe image contents. Thus, many feature-based image retrieval systems have been proposed in the academic arena [6–18].

Using a single attribute to describe image features is not enough. Despite the extensive applications of textures [6,8,16], colors [12–15], spatial relations [13], and shapes [19] in image retrieval, the results have limited effects on discrimination. When describing image features, the relations between colors and textures are critical. Hence, in this study, colors and textures are employed as attributes in similarity retrieval to develop an innovative and effective image retrieval system (CTCHIRS).

Huang and Dai [6] proposed a texture based image retrieval system which combines the wavelet decomposition [20] and gradient vector [21]. The system associates 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.

The image retrieval system introduced in Jhanwar et al. [18] 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. To obtain color difference between adjacent pixels, we propose a better technique integrated with color co-occurrence matrix (CCM) and difference between the pixels of a scan pattern (DBPSP) to improve texture description.

Color histogram [22] is one of the common techniques used in image retrieval systems. However, when directly used to describe color features, more features have to be recorded. Thus, we

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propose color histogram for K-mean (CHKM) to clearly describe color features with a smaller number of features. This method is expected to effectively shorten image retrieval time and enhance retrieval performance.

CCM, DBPSP, and CHKM are able to effectively describe various properties of an image. To enhance retrieval performance, CCM, DBPSP, and CHKM are integrated to develop an image retrieval system based on texture distribution and color features (CTCHIRS system). The integration of multiple features may certainly reduce retrieval performance. For the highest detection rate and a simplified image retrieval process, we apply a feature selection technique (SFS) in the image retrieval system to shorten the computation time.

2. Proposed features

2.1. Color co-occurrence matrix (CCM)

This paper proposes a color co-occurrence matrix (CCM) 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 color co-occurrence matrix (CCM) can be obtained, which is the feature proposed in this paper.

For each pixel $G(x, y)$, a 3×3 convolution mask can be generated as shown in Fig. 1. This 3×3 convolution mask can be further divided into four blocks of 2×2 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 p_1 as shown in Fig. 1(a), because it represents a complete family of space filling curve, reducing the number of patterns to only 7 as shown in Fig. 2. Among them motif number 0 signifies the situation wherein a motif cannot be formed due to the equivalence.

These 2×2 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 neighborhood.

Let $G(x, y)$: $N_x \times N_y \to Z$ be the gray levels of an $N_x \times N_y$ image I for $Z = \{0, 1, \ldots, 255\}$. Pixel $G(x, y)$ is divided into four blocks, each of which has 2×2 grids (pixels), to form four different motifs shown by number m of motif. These four motifs will be saved in four $N_x \times N_y$ two-dimensional motifs of scan pattern matrix $P_i[x, y]$, in which $i = 1, 2, 3, 4$, $x = 1, 2, \ldots, N_x$, $y = 1, 2, \ldots, N_y$, and $P_i[x, y]$: $N_x \times N_y \to W$ denotes an $N_x \times N_y$ matrix for $W = \{0, 1, \ldots, 6\}$.

The color co-occurrence matrix (CCM) calculates the distribution within the two-dimensional motifs of scan pattern matrix $P_i[N_x, N_y]$. That is, it takes into account the probability of the co-occurrence between the two motifs respectively corresponding to (x, y) and its adjacent $(x + \delta_x, y + \delta_y)$. This probability is then the attribute of image color variation used in this paper. The coordinate that distances from (x, y) on the x axis in δ_x and on y axis in δ_y, then the total number of co-occurring motifs of scan pattern pairs (u, v) (where $u = 0, 1, \ldots, 6$ and $v = 0, 1, \ldots, 6$) is determined by

$$M_i(u, v) = M_i(u, v|\delta_x, \delta_y) = M_i(P_i[x, y], P_i[x + \delta_x, y + \delta_y]) \tag{1}$$

where $P_i[x, y] = u$, $P_i[x + \delta_x, y + \delta_y] = v$, $1 \leqslant i \leqslant 4$, $1 \leqslant x \leqslant N_x$, $1 \leqslant y \leqslant N_y$, $1 \leqslant x + \delta_x \leqslant N_x$, and $1 \leqslant y + \delta_y \leqslant N_y$. The co-occurring probabilities of the number i motifs of scan pattern matrix are determined by dividing $M_i\ (u, v)$ by the total number of counts across all u and v, as shown below

$$m[u, v] = \frac{M_i(u, v)}{N_i} \tag{2}$$

where

$$N_i = \sum_{u=0}^{6} \sum_{v=0}^{6} M_i(u, v) \tag{3}$$

and $1 \leqslant i \leqslant 4$. As a result, there will be a 7×7 two-dimensional CCM grids in total, which amounts to $7 \times 7 = 49$, with $N_f = 49$ is the total number of CCM attributes to be discussed in this paper.

2.2. Difference between pixels of scan pattern (DBPSP)

The CCM feature proposed in the previous section could effectively describe the direction of textures but not the complexity of textures. As shown in Fig. 3, the motif number in both Fig. 3(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.

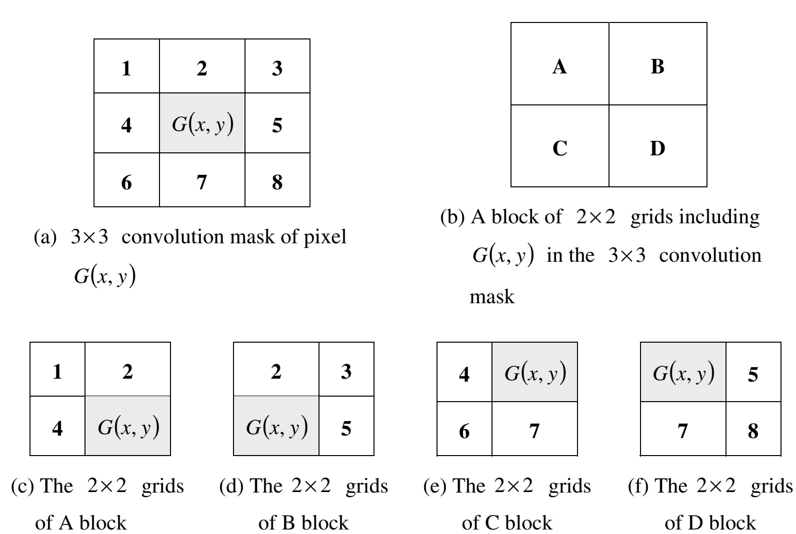


Fig. 1. The 3×3 convolution masks are divided into four 2×2 grids.

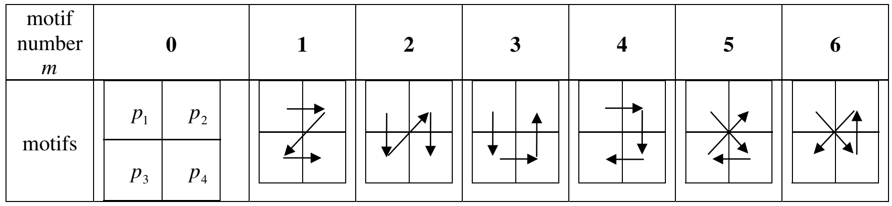
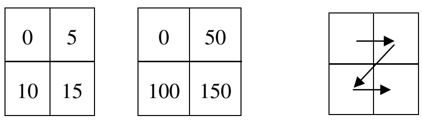


Fig. 2. The seven scan patterns.



(a) 2×2 grids(pixel) (b) 2×2 grids(pixel) (c) The motifs of scan pattern for (a) and (b)

Fig. 3. The motifs of scan pattern for 2 × 2 grids.

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. 2 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 $\Delta(x, y)$. It is possible to generate six motifs of a scan pattern which can be respectively shown as $\Delta^1(x, y), \Delta^2(x, y), \ldots, \Delta^6(x, y)$ in the following formulae:

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

where $\Delta^i(x, y)$ 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. 2. Finally, we calculate the appearance rate of $\Delta(x, y)$ within the whole image as shown below:

$$f_i = \frac{1}{N_i}\sum_{j=1}^{N_i} \Delta_j^i(x,y) \tag{5}$$

where i is the motif number and N_i is the total appearance of ith motif number within the whole image. Therefore, six DBPSP feature values can be obtained.

2.3. Color histogram for K-mean

There are 2^{24} different possible colors of a color pixel. Before defining and computing the color histogram for K-mean (CHKM) features of an image, the pixels of all database images are categorized into K clusters using the K-mean clustering algorithm [23]. This algorithm calculates the mean of all pixels in each cluster and uses it as the new initial value for further training. Color histogram shows the color distribution of an image. The CHKM feature of the kth color bin can be defines as

$$g^k = \frac{N_k}{N} \tag{6}$$

where N is total pixel numbers and N_k be the number of the pixels in the kth cluster. This paper evenly divides colors into 16 groups. Therefore, 16 CHKM feature values can be obtained from a full-color image.

3. Image retrieval system

CCM 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, CHKM is simple and easy to compute. 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 color-histogram based image retrieval system (CTCHIR system).

CCM of the query image Q and one database image D as $(m_1^q, m_2^q, \ldots, m_{49}^q)$ and $(m_1^d, m_2^d, \ldots, m_{49}^d)$ are obtained from Eq. (2). Here, the superscripts q and d stand for the query Q and database image D. The image matching distance Δ^{CCM} between Q and D based on the CCM can be calculated via the following equation:

$$\Delta^{\mathrm{CCM}} = \sum_{k=1}^{49}\left|\frac{m_k^q - m_k^d}{m_k^q + m_k^d + \upsilon}\right| \tag{7}$$

where υ is any small number that avoids denominator = 0.

Considering DBPSP $(f_1^d, f_2^d, \ldots, f_6^d)$ and $(f_1^q, f_2^q, \ldots, f_6^q)$ of images Q and D are obtained from Eq. (5), the image matching distance Δ^{DBPSP} of Q and D based on DBPSP is formulated as the following:

$$\Delta^{\mathrm{DBPSP}} = \sum_{k=1}^{6}\left|\frac{f_k^q - f_k^d}{f_k^q + f_k^d + \upsilon}\right| \tag{8}$$

Considering CHKM $(g_1^d, g_2^d, \ldots, g_{16}^d)$ and $(g_1^q, g_2^q, \ldots, g_{16}^q)$ of images Q and D are obtained from Eq. (6), the image matching distance Δ^{CHKM} of Q and D based on CHKM is formulated as the following:

$$\Delta^{\mathrm{CHKM}} = \sum_{k=1}^{16}\left|\frac{g_k^q - g_k^d}{g_k^q + g_k^d + \upsilon}\right| \tag{9}$$

The proposed CTCHIRS system combines the CCM, DBPSP and CHKM to quantize the similarity between Q and D. Using such retrieval system, one can define the image matching distance $\Delta^{\mathrm{CTCHIRS}}$ between Q and D as

$$\Delta^{\mathrm{CTCHIRS}} = w_1 \times \Delta^{\mathrm{CCM}} + w_2 \times \Delta^{\mathrm{DBPSP}} + w_3 \times \Delta^{\mathrm{CHKM}} \tag{10}$$

where w_1, w_2 and w_3 are the weights for CCM, DBPSP and CHKM. Generally, $\Delta^{\mathrm{CTCHIRS}}$ decreases with the increase of similarity between Q and D. Hence, the CTCHIRS system can deliver the image with the minimal $\Delta^{\mathrm{CTCHIRS}}$ from the database.

4. Feature selection

It is generally believed that a better image recognition effect can be achieved with more features descriptors used, but this is not absolutely true. Not all features are helpful for image recognition. Ill features are actually interfering signals and cause a drop in the recognition rate, especially if the effect of the ill features exceeds that of the effective ones. The features adopted by this paper include CCM and DBPSP for the relationship between color and texture, and CHKM for the color information of an image. The combinations of these features can help us manage retrieval for an image with a large feature area. However, different ill features can be found in different image data, such as natural images, cartoon images, texture images, colorized or gray texture images, and categorized images.

The goal of feature selection is to select the best features from the original ones. It can not only achieve maximum recognition rate but can also simplify the calculation of image retrieval. This paper has adopted sequential forward selection (SFS) introduced by Whitney in 1971 [24]. SFS is a stepwise search technique that can avoid over-consumption of calculation time. This method searches the best combination with the next feature but cannot ensure that the selected is the best combination. It is assumed that there are M features such as $x_1, x_2, \ldots, x_M$, the acceptable recognition rate threshold R, the best feature aggregate $\mathbf{Y}$, the best feature number L and the selected feature number i. Here, the reverse produces the following algorithm:

INPUT M, R, $x_1, x_2, \ldots, x_M$, and $\mathbf{Y} \in \phi$
OUTPUT L and $\mathbf{Y}$
Step 1 For $i = 1, 2, \ldots, M$(selected feature number) do Steps 2–5
Step 2 For $j = 1, 2, \ldots, M$(feature number) do Steps 3–5
Step 3 If $x_j \not\subset \mathbf{Y}$ (leave-one-out error) then set
Use the selected feature and NN decision rule to calculate the recognition rate l
Step 4 Select the feature x_j with maximum recognition rate $l_i = l$ among M features in the ith best feature number to join the best feature aggregate $\mathbf{Y}$ (Next selected feature certainly combines with the originally selected feature)
Step 5 If $l_i \geqslant R$ do Step 6
Step 6 OUTPUT (L and $\mathbf{Y}(y_1, y_2, \ldots, y_L)$);
STOP

5. Experiments

This paper adopts image features including texture of color, spatial texture of color, and color feature. To validate the effect of the proposed method, three commonly used image databases for research purposes are employed, and the proposed results are compared with the results of Huang and Dai [6] and Jhanwar et al.[18] in our experiment. The three image databases are: image set 1 of a 1051 pair natural image database, image set 2 of a 111 gray texture image database, and image set 3 of a 1000 ten-category natural image database. Another experiment is to apply feature selection to the original image features, and analyze the influences of various features on image retrieval accuracy as well as on the reduction of computation effort in different image databases.

5.1. The performance of CTCHIRS system on image set 1

In this section, the performance of the CTCHIRS system is evaluated using image set 1. There are two sets of images Set$D = \left\{I_1^d, I_2^d, I_3^d, \ldots, I_{1051}^d\right\}$ and Set$Q = \{I_1^q, I_2^q, I_3^q, \ldots, I_{1051}^q\}$. Each contains 1051 full color images. The images in Set$D$ are employed as the database images and those in Set$D$ are used as the query images. Some parts of them are drawn out from animations, where each image pair (I_i^d, I_i^q) are randomly picked up from the same animation. Most of the animations were downloaded from the websites http://www.mcsh.kh.edu.tw and http://co25.mi.com.tw. Some other images were downloaded from http://wang.ist.su.du/IMAGE. The rest of images were scanned from natural images and trademark pictures. Fig. 4 shows some of the query and database images.

In each experiment, each I_i^q is used as the query image. For each query, the system responds to the user L database images with the shortest image matching distances opposite to I_i^q. If I_i^d exists among the L database images, we say the system has correctly found the expected image. Otherwise, the system has failed to find the expected image. In the following, the accuracy rate of replying a query will be explained with accuracy (ACC, %).

The first experiment is to compare the retrieval accuracy of CTCHIRS system with Huang and Dai's [6] and Jhanwar et al.'s [18] approaches. In this test, the spatial offset $(\delta_x, \delta_y) = (0, 1)$ and the weight are $w_1 = 0.2$, $w_2 = 0.4$, and $w_3 = 0.4$. Table 1 shows the result of comparison between CTCHIRS and the other two ap-

Table 1
Comparison of accuracy (ACC, %) of retrieved images

ACC (%)	L									
	1	2	3	4	5	10	20	30	50	100
Huang and Dai's [6]	65.3	72.2	74.7	77.0	78.1	83.5	86.2	88.4	92.0	94.7
Jhanwar et al. [18]	62.4	70.7	74.8	76.6	79.0	84.0	87.7	90.2	92.3	94.6
Present method	**85.5**	**90.5**	**92.3**	**93.2**	**93.6**	**95.1**	**96.7**	**97.7**	**98.9**	**99.2**

(a) Some query images
(b) The database images corresponding to the images in (a)

Fig. 4. Some examples of image set 1.

proaches. Since CTCHIRS considers the adjacent pixel difference, better result for L can be resulted.

5.2. The performance of CTCHIRS system on image set 2

The next experiment is to scrutinize the performance of the CTCHIRS system on another image set, image Set 2. Image Set 2 contains hundred and eleven 512×512 pixel gray level images downloaded from http://www.ux.his.no/~tranden/brodatz.html. Each image is then partitioned into 16 non-overlapping images each with 128×128 pixels. Fig. 5 shows some examples of the images in Set 2.

The precision and recall measurements of Mehtre et al.[25] are often used to describe the performance of an image retrieval system. The precision (P) and recall (R) are defined as follows:

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

where L is the number of retrieved images; n_k is the number of relevant images in the retrieved images and N is the number of all relevant images in the database.

The most suitable values of the parameters in the CTCHIRS system are the spatial offset $(\delta_x, \delta_y) = (0, 1)$ and $w_1 = 0.2$, $w_2 = 0.4$, and $w_3 = 0.4$ in experiments based on image Set 2. In image Set 2, each query image corresponds to N (=15) related images in the database; hence, in the second experiment, the precision P and recall R are taken to measure the performance of an image retrieval system. Table 2 shows the average precisions of the CTCHIRS system, Huang's method, and Jhanwar's method. The experimental results tell that the CTCHIRS system provides much higher accuracy than the Huang's method and Jhanwar's method.

5.3. The performance of CTCHIRS system on image Set 3

Experiment 3 is to explore the performance of the CTCHIRS system on image Set 3 downloaded from http://wang.ist.psu.edu/docs/related/. Image Set 3 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. 6 shows some of these images. The images in the same row in Fig. 6 belong to the same cluster. In this experiment, the values of the parameters are: spatial offset $(\delta_x, \delta_y) = (0, 1)$ and $w_1 = 0.2$, $w_2 = 0.4$, and $w_3 = 0.4$. Classes names are listed in Table 3.

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 this paper's method and the other two methods are shown in Table 4. It is obvious that this paper's method has achieved a better average precision of various images than the other two methods, except for the smaller image

Table 2
Comparison of retrieval precision

P (%)	L					
	2	3	4	5	10	16
Huang and Dai's [6]	84.7	80.3	77.0	74.6	66.2	57.0
Jhanwar et al. [18]	89.5	84.5	80.8	78.0	68.7	59.4
Present method	**97.0**	**95.4**	**93.8**	**92.2**	**84.2**	**74.1**

of flowers (the difference between this paper (0.8910) and [6] (0.8975) is 0.065). Besides, the recall of each retrieval image and the average recall of the various images were calculated. The average precision of the retrieval results of the various images with the number of returned images, and the average recall are shown in Figs. 7 and 8. The experimental results clearly reveal that for the first 20–100 returned images of the 1000 ten-category natural image database, the present method is significantly superior to the methods of Jhanwar et al. [18] and Hung and Dai' [6]. In the average recall experiment, image retrieval precision increases with the number L of returned images. The present method is more superior to the methods of Jhanwar et al. [18] and Hung and Dai [6].

5.4. The performance of feature selection

This above experiments adopted image features including CCM, DBPSP, and CHKM, and used 49, 6, and 16 features, respectively. The proposed CTCHIRS system used 71 features. The section experiment was based on image Set 1–3 of image databases with different characteristics to carry out feature selection, select the best features from the original ones to improve the recognition rate, and further discuss the relationships among recognition rate, feature, and image database. In this experiment, the values of the parameters are: spatial offset $(\delta_x, \delta_y) = (0,1)$ and $w_1 = 0.2$, $w_2 = 0.4$, and $w_3 = 0.4$.

We first used image Set 1 of a 1051 pair natural image database to carry out the methods and steps described in Section 4. There was the CTCHIRS system accuracy (ACC, %) distribution for various feature numbers, and we used the number of retrieval images $L = 1$, 10, 50, and 100 to obtain the accuracy (ACC, %) distribution results as shown in Fig. 9. The results clearly show that the maximum accuracy (ACC, %) appeared when the feature number reached 35, and the accuracy (ACC, %) dropped slightly when the feature number was above 50. It can be inferred that the feature with a higher recognition level can reach the expected recognition effect while that with a lower recognition level not only cannot improve the recognition rate but will also lower the recognition effect.

In the feature selection experiment of image Set 2 of a 111 gray texture image database, we used different feature numbers and the number of retrieval images $L = 1$, 10, 50, and 100 to obtain the precision (P) of the CTCHIRS system with its distribution results as

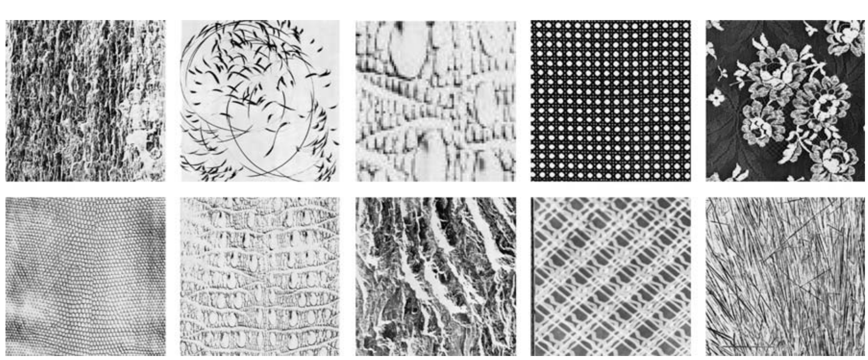


Fig. 5. Some of testing texture images.

Fig. 6. Some examples of image set 3.

Table 3
Ten classes of image set 3

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

Table 4
The average precision of these methods on image set 3

Semantic name	**Present method**	Jhanwar et al. [18]	Hung and Dai's [6]
African people and village	**0.6830**	0.4525	0.4240
Beach	**0.5400**	0.3975	0.4455
Building	**0.5615**	0.3735	0.4105
Buses	**0.8880**	0.7410	0.8515
Dinosaurs	**0.9925**	0.9145	0.5865
Elephants	**0.6580**	0.3040	0.4255
Flowers	0.8910	0.8515	**0.8975**
Horses	**0.8025**	0.5680	0.5890
Mountains and glaciers	**0.5215**	0.2925	0.2680
Food	**0.7325**	0.3695	0.4265
Average	**0.7270**	**0.5264**	**0.5324**

shown in Fig. 10. The figure indicates the optimal number of features used is 20, and the recognition rate achieved with 20 features is almost the same as the rate achieved with all the features. It can thus be concluded that SFS can effectively select features with a higher recognition level, and with fewer features used, the computation effort can be reduced.

Finally in the feature selection experiment of image Set 3 of 1000 10-category natural image database, we used different feature numbers and the number of retrieval images $L = 1$, 10, 50, and 100 to obtain the precision (P) of the CTCHIRS system with its distribution results as shown in Fig. 11. The maximum recognition rate can be achieved with the first 35 features selected. The

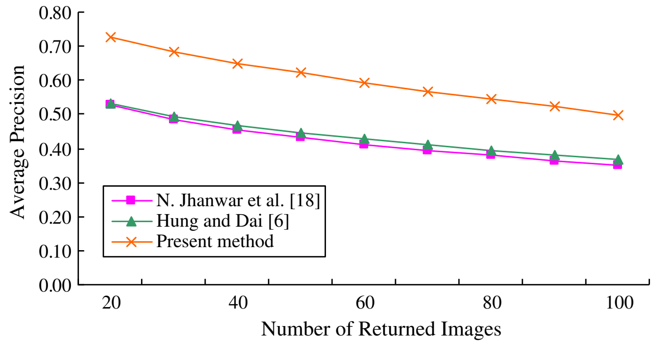


Fig. 7. The average precision of these methods on image set 3.

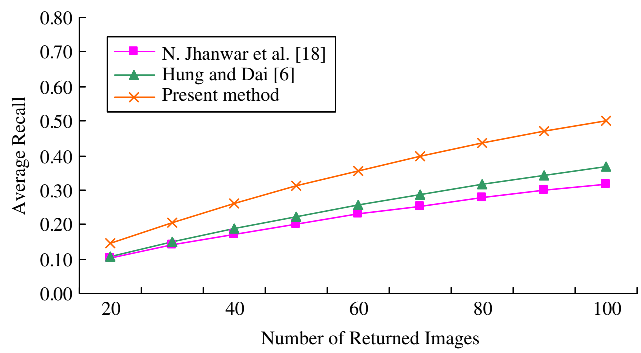


Fig. 8. The average recall of these methods on image set 3.

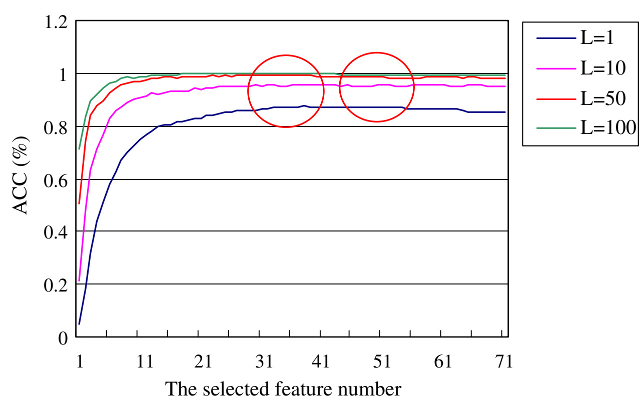


Fig. 9. The accuracy (ACC, %) for feature select on image set 1.

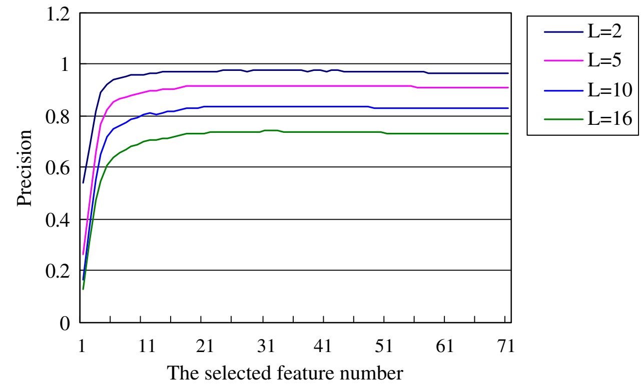


Fig. 10. The relationship between precision and number of feature selected for image set 2.

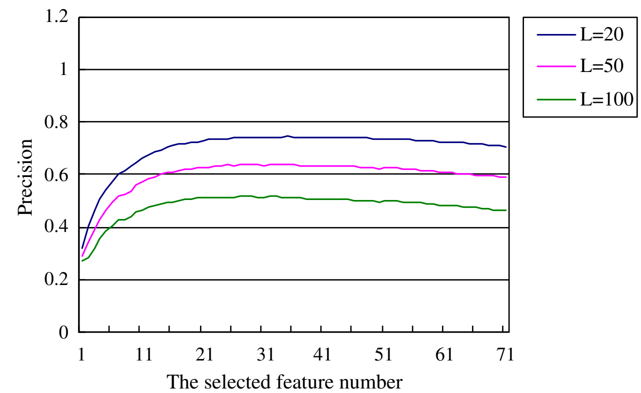


Fig. 11. The relationship between precision and number of feature selected for image set 3.

other features with poor recognition levels cannot enhance the image retrieval recognition rate, or even lower the rate.

The experimental results of the feature selection show that no matter which image database we used, SFS can effectively reduce the feature number of an image and thus reduce calculation work, or even improve the recognition rate of image retrieval.

6. Conclusions

In this paper, three image features, namely CCM, DBPSP, and CHKM, are presented to characterize a color image for image retrieval. CCM and DBPSP can effectively describe texture distribution, while CHKM can describe color features of the pixels with similar colors in an image. CHKM is not affected by image displacement and rotation and also able to resist noise-induced variations. Since these features can describe different properties of an image, this paper integrates the three features to develop the CTCHIRS system. Besides, this study further uses sequential forward selection (SFS) to select features with better discriminability for image retrieval and overcome the problem of excessive features.

The experimental results indicate that, in most cases, the proposed system can significantly outperform Huang's and Jhanwar's methods. Moreover, through feature selection, computation of image retrieval from any type of image databases can be effectively reduced. As a result, the retrieval speed can be increased. For specific image databases, the detection efficiency can also be enhanced.

The proposed image retrieval system has a high detection rate when applied to various image databases. However, multiple image features are required to achieve a high detection rate. Through feature selection, the number of features required has been significantly reduced, and a high detection rate can still be obtained.

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