Color Image Retrieval Using a Fuzzy Dominant Color Selection Clustering Algorithm

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ABSTRACT

This paper presents a fuzzy dominant color selection clustering algorithm to reduce the dimensionalities and the quantization errors of color histogram. To improve the exactness of retrieving, we also combine the region-based shape feature and texture feature. Experimental results show that the average hit ratio of the proposed algorithm is 88.8% which is superior to 77.1% of color histogram quantization methods and 58.8% of look-up-table method. Furthermore, the CIE LAB color space is less affected than RGB and HSV color spaces with various luminance, and the hit ratios of region-based image retrieval are higher than those of full image retrieval.

Keywords: content-based image retrieval (CBIR), color histogram, fuzzy clustering, region-based image retrieval.

模糊色彩量化區域特徵選取之彩色影像檢索方法

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摘要

植基於影像內容檢索(content-based image retrieval, CBIR)之方法常使用色彩、形狀、紋理等各種不同特徵，作為影像檢索比對之依據。其中色彩尤為重要，但必須正確且有效的對色彩直方圖量化。本文提出模糊色彩量化區域特徵選取之彩色影像檢索方法，其目的主要在降低因色彩量化誤差所造成之誤判，並結合區域之外形及紋理特徵，提供區域選取之檢索方式。首先利用模糊聚類(FCM, Fuzzy-C-Mean)分群法，找出彩色影像最具代表性之色彩，作為相似度比對以及區域選取之依據。接著結合區域之外形特徵及紋理特徵，作為原始影像的索引特徵值。經由實驗印證本文所提之方法，影像檢索之平均正確率 88.8%高於色彩均等量化法 77.1%與查表量化法 58.8%。並且採用 CIE LAB 之色彩空間，比採用 RGB、及 HSV 色彩空間較不受亮度變化誤判之影響。同時，以區域檢索方式正確率會高於以全影像檢索之方式。

關鍵詞：影像檢索，色彩直方圖，模糊聚類分群法，區域檢索

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1. INTRODUCTION

For the ever-increasing amount of digital images, a systematic approach of retrieving image data is needed. The early image retrieval approaches are based on text retrieval [1]. High-level features represented by keywords are manually annotated to images, previously. The major problems are that the contents of image can not be completely represented only by keywords, and different persons could select different keywords for a same image. In the past decade, content-based image retrieval (CBIR) is expected to provide high percentage of relevant images in response to user query via low-level features such as color, shape, or texture features. Furthermore, the relevance feedback mechanism [2] and the region of interest approaches [3] have been proposed to bridge the gap between low-level features and high-level features.

Color histogram is one of the most frequently used features in the field of color-based image retrieval. However, it has the problem of high-dimensionality. Furthermore, RGB color features are sensitive to the various luminance of image, and the performance of full image indexing is not good enough. To address these problems, we proposed a fuzzy dominant color selection clustering algorithm for the three purposes as follows.

- To reduce the color quantization errors, the fuzzy c-means (FCM) clustering method is used to select dominant colors, and the retrieval performance is also compared with the equal quantized and table-look-up approaches.
- To analyze the influence on various luminance of the same image, the adaptation of RGB, HSV, and CIE LAB color spaces are investigated.
- To examine the effect of region, a semi-automatic region selection method is provided, and the retrieval performance of the region and full image is compared for the combination of color, shape, and texture features.

Experimental results show that our method could obtain higher accuracy and save more memory space than equal quantization methods and table-look-up methods, and the hit ratio of the region-based image retrieval is higher than the full image retrieval.

In the following sections, existing CBIR approaches are examined. The fuzzy dominant color selection clustering algorithm and similarity measures are detailed in Sec III. In Sec. IV, the experimental results are presented and analyzed. In the last section, we conclude this paper with possible research directions.

2. LITERATURE REVIEW

In this section, low-level features for existing image retrieval algorithms or systems are described. Also, the related popular CBIR systems are outlined.

2.1. Image Features

2.1.1. Color Features

Color constitutes a powerful visual information and is one of the most salient and commonly used features in color image retrieval systems [4]. It can not only provide regional information but also be robust to scaling, orientation, translation, and rotation of images. Color histogram is one of the most frequently used features in the field of color-based image retrieval [5]. The advantage of color histogram is simple and quick to process. However, it has the problem of high-dimensionality. To address this problem, there are three general color histogram quantization techniques to reduce color bins: equal quantization, table-look-up, and clustering methods. An equal quantization method reduces color histogram bins by partitioning the color space into rectangular bins with the same width [6]. For a table-look-up method, the color space is grouped into predefined perceptual color bins for some specific image databases [7]. Prasad et al. [7] apply a color table with 25 color bins, and select 3 dominant color bins of each image. However, they do not mention how to get the table of 25 color bins and why to select 3 dominant color bins. For a clustering method, a color is quantized to the centroid of its nearest cluster. Though Han and Ma [8] use FCM to cluster color bins, they equally quantize color bins to a number of pre-defined color bins before using FCM clustering algorithm. Therefore, there are still some quantization errors in this approach. Both the equal quantization methods and the table-look-up methods, however, contain large quantization errors resulting in low performance of retrieving. Also, to reduce the computational time and obtain the high performance of retrieval, the proper number of clusters is needed for clustering methods. Furthermore, RGB color feature is more sensitive to the variation of luminance than HSV or CIE LAB color features. Therefore, HSV or CIE LAB color feature could be more adapted to CBIR than RGB while the color image database contains lots of images with the same content but different luminance, especially.

2.1.2. Shape Features

Another important feature used for CBIR is the shape of regions of interest [9]. To acquire effective shape features, a good image segmentation method is required to detect regions, previously. Shape similarity needs a representation that is invariant to translation, rotation, and scaling. Two types of shape descriptors are used: region-based descriptor [7] and boundary-based descriptor [10]. Region-based features include statistical moments and grid-based approach. Boundary-based shape features include rectilinear shapes, polygonal approximation, finite element model, and Fourier-based shape descriptors for various applications [11].

2.1.3. Texture Features

Three principle approaches used to describe the texture of images or regions are statistical, structural, and spectral [11]. For the statistical approach, the co-occurrence matrix, the compound Gauss-Markov random fields, and histogram feature can yield characterizations of textures as smooth, coarse, grainy, and so on, which are matched to the human perception. For the structural approach, the periodic texture can be described by symbols and rules like a grammar description. For the spectral approach, the Gabor filter, Fourier transform, and Wavelet transform are widely used [12, 13].

2.2. CBIR Systems

In the last decade, lots of CBIR systems are developed for various applications. QBIC [n14], Visual SEEK [15], PhotoBook [16], and Blobworld [17] are the popular CBIR systems. Color, shape, and texture features are concerned in these systems. For a specific application, [18] designs a butterfly image retrieval system which predefines 18 colors, 7 shapes, and 17 textures for the image database of butterfly. [19] conceives a fish image retrieval system which defines 236 shapes to recognize fishes.

3. COLOR IMAGE RETRIEVAL

In this section, we describe the two major schemes for color image retrieval: the image indexing process, and the similarity measures. Image features are extracted by the image indexing process, and the similarity matching functions are considered by the similarity measure scheme.

3.1. Image Indexing

Fig. 1 shows the architecture of the proposed image indexing. First, dominant colors are selected by the fuzzy dominant color selection clustering algorithm. Second, the dominant region is decided, manually, according to the distribution of dominant colors. Finally, the color, shape, and texture features of the dominant region and the full image are extracted to the image feature database for image matching. Detail processes are described as follows.

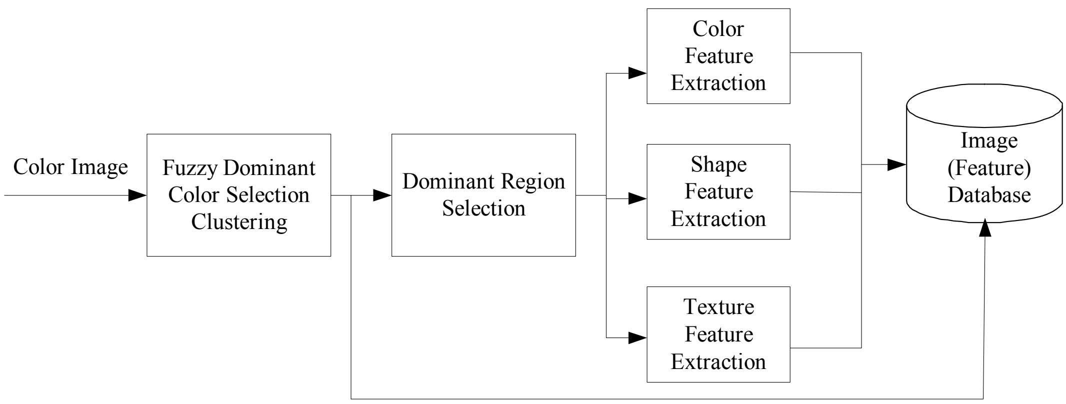

Fig. 1. The architecture of the proposed image indexing.

3.1.1. Fuzzy dominant color selection clustering

Dominant colors are selected by applying color quantization when the color information of an image is reduced. In this paper, we apply the FCM clustering algorithm to select dominant colors. As illustrated in Fig. 2, the fuzzy dominant color selection clustering algorithm is composed of three phases: the attribute extraction phase, the clustering phase, and the dominant color selection phase.

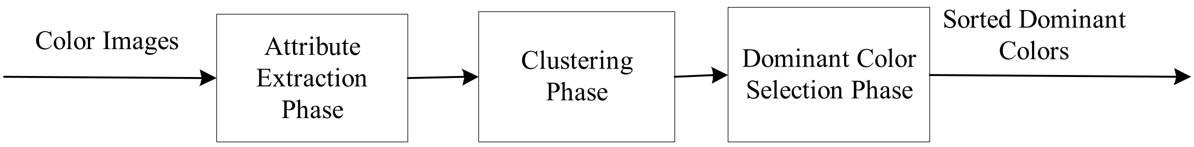

Fig. 2. The phases of the fuzzy dominant color selection clustering.

In the attribute extraction phase, to analyze the adaptation of different color space for the proposed method, RGB, HSV, and CIE LAB three color spaces will be concerned in comparison with different color quantization methods. In RGB color space, three components of RGB are direct extracted from pixels for the purpose of generality and simplicity. HSV and CIE LAB color spaces can be obtained from RGB color space [11, 20]. We only use hue (H) and saturation (S), the components of A and B as the attributes of clustering for HSV and CIE LAB color spaces, respectively. The reason is that values (V) and luminance (L) are uncorrelated with the color perceptual of human. However, they need extra converting computation from RGB color space.

In the clustering phase, the FCM algorithm is used to group pixels into clusters [21] according to RGB, HS, or CIE AB color features. The FCM_based clustering procedure iteratively minimizes the criterion function as shown in (A1). Detailed description is given as follows.

The FCM Clustering Procedure

// The input values are RGB, HS, or CIE AB color features.
// The output values are clusters with pixels.
// *c* represents the number of clusters, *w* the exponential weight, and
// μ_{ik} 's ($i=1,\ldots,c$, $k=1,\ldots,n$) the membership values
1 Initialize parameters *c* and *w*; and then assign values to μ_{ik} 's using either a random function or an approximation method.
2 Do
3 For each cluster c, update center using (A3) and
4 μ_{ik} 's using (A2);
5 Until (all centers are stabilized)
6 Assign pixels to one cluster according to μ_{ik}'s.

In the simulation, *w* is 1.5, and *c* is set from 3 to 10 which will be discussed in the experimental section. To reduce the occurrence of local minimum, the initial values of $\boldsymbol{\mu_{ik}}$**'s** can be well estimated which is superior to k-mean methods.

In the color selection phase, first, the number of pixels in each cluster is calculated. Then, the clusters are sorted in the descending order according to the number of pixels. Finally, centroid colors of each cluster are selected as dominant color bins. The dominant color selection procedure is stated as follows.

The Dominant Color Selection Procedure

// The input values are the clusters with pixels.
// The output values are sorted dominate color bins.
1 Compute the color bins using the clusters with pixels.
2 Sort the color bins in the descending order, based on the cluster population.
3 Select the dominant color bins.

3.1.2. Dominant region selection

According to the distribution of dominant color automatically generated from fuzzy dominant color selection clustering algorithm, a region is selected manually. As shown in Fig. 3, (c) is the selected region according to the dominant color image of (b).

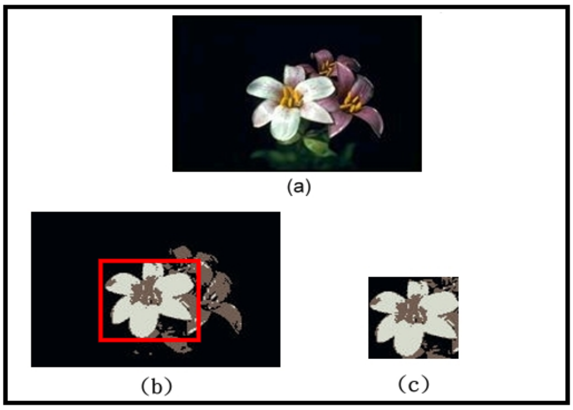

Fig. 3. (a) Original image (b) Dominant color image (c) Selected region.

3.1.3. Color feature extraction

The color feature extraction applies the aforementioned fuzzy dominant color selection clustering algorithm to extract the dominant colors of selected region or full image. RGB, HSV, and CIE LAB color spaces are also considered.

3.1.4. Shape feature extraction

We applied the region-based shape description approach [10] to extract the shape feature of image or region. First, the original color image or region is transformed to binary image and divided into grids. Second, the value of grid is 1 while the umber of black pixel is over 25% in the grid, and 0 to the other grids. Finally, the shape feature can be represented as string with 0 and 1.

3.1.5. Texture feature extraction

We used the variance of color image or selected region [11] to represent the degree of smooth or coarse texture as (1). Variance is calculated from the gray values of the color image or selected region, and normalized to the interval [0,1] as

$$R = 1 - \frac{1}{1+\sigma^2(z)} \quad (1)$$

While the image or region has smooth texture, R approaches to 0 for small values of $\sigma^2(z)$. On the contrary, while the image or region has coarse texture, R approaches to 1 for large values of $\sigma^2(z)$.

3.2. Similarity Measures

Similarity measures are proceeded between the query image or selected region (Q) and the image of database (I). In this paper, various similarity matching functions of features are considered as follows. Low value of similarity matching function represents high similarity between Q and I, and high similarity feedbacks the high important value of ranking. Though bin-by-bin measures are more sensitive to the position of bin boundaries than cross-bin measures [12], the former measure has less computational complexity than the latter measure. In this paper, therefore, the similarity matching functions of color features adopt the bin-by-bin Euclidean distance for their low complexity of sorted dominant colors.

3.2.1. Similarity measure for color features

One dominant color bin corresponds to one cluster, and the centroid of the cluster represents one color. Therefore, a color image with *n* dominant color bins in RGB, HSV, and CIE LAB color spaces can be defined as $F_i=\{R_i,G_i,B_i\}$, $F_i=\{H_i,S_i\}$, and $F_i=\{A_i,B_i\}$, respectively, where $i=1,2,\ldots,n$. The similarity between a pair of images Q and I is given by the Euclidean distance of bin-by-bin measure in (2), (3), and (4).

$$C_{RGB}(Q,I)=\sum_{i=1}^{n}\sqrt{(QR_i-IR_i)^2+(QG_i-IG_i)^2+(QB_i-IB_i)^2} \quad (2)$$

$$C_{HSV}(Q,I)=\sum_{i=1}^{n}\sqrt{(QH_i-IH_i)^2+(QS_i-IS_i)^2} \quad (3)$$

$$C_{LAB}(Q,I)=\sum_{i=1}^{n}\sqrt{(QA_i-IA_i)^2+(QB_i-IB_i)^2} \quad (4)$$

3.2.2 Similarity measure for shape feature

The similarity matching function of shape feature between Q and I [9] is described by

$$S(Q,I)=(R_d+C_d), \quad (5)$$

where $R_d=\sum_{j=1}^{m}\left|RC^Q{}_i-RC^I{}_i\right|$ represents the *m* row difference between Q and I, $C_d=\sum_{i=1}^{n}\left|CC^Q{}_j-CC^I{}_j\right|$ the *n* column difference between Q and I. RC_i and CC_j are the count of 1 in row and column of a grid image as (6) and (7), respectively.

$$RC_i=\sum_{j=1}^{m}C_{ij} \quad (6)$$

$$CC_j=\sum_{i=1}^{n}C_{ij} \quad (7)$$

3.2.3 Similarity measure for texture feature

The similarity matching function of texture feature between Q and I [11] is described by

$$T(Q,I)=\left|R^Q-R^I\right|, \quad (8)$$

where R^Q, and R^I are the normalized variances of Q and I, respectively.

3.2.4. Similarity measure for color-shape-texture feature

The similarity matching function of color-shape-texture feature between Q and I [2] is described by

$$d(C,S,T)=w_c\cdot C(Q,I)+w_s\cdot S(Q,I)+w_t\cdot T(Q,I) \quad (9)$$

where w_c, w_s, and w_t are the weights of color feature, shape feature, and texture feature of Q and I, respectively, and $w_c+w_s+w_t=1$.

4. EXPERIMENTAL RESULTS AND ANALYSIS

First, the experimental environment, the image database, and the architecture of image retrieval are detailed. Then, the performance evaluation is defined, and some experimental results are discussed.

4.1. The Experimental Environment

The experimental environment is depicted as follows.

- Personal Computer : CPU-Pentium III 3.0G，RAM=1GB，Hard Disk=200GB
- Operating System : Window XP
- Development Tool : Matlab 6.5
- Image Editing Tool : PhotoImpact 8
- Database : MS-Access

4.2. Image Database

The experimental database consists of 1500 images of flower, animal, airplane, sea, sky scene, etc. These images are selected form Berkeley Multimedia Lab. [22], the MPEG 7 core experiments [23], and FreeFoto.com [24]. The image database has the characteristics as follows.

- The sizes of all images are 192 by 128 pixels.
- 1500 selected images are grouped into 70 classes, and each class contains 10 to 25 images.
- Color is the main factor of grouping.
- All images are in JPEG format.

4.3. The Architecture of Image Retrieval

The architecture of image retrieval is depicted in Fig. 4. First, the query image is selected from the graphic user interface, and the color, shape, and texture features of full images and selected regions are extracted from image indexing as described in section 3.1. Then, the similarity matching measures the similarity of color, shape, or texture between the query image and the images of database as mentioned in section 3.2. Finally, the top *n* images are retrieved from image selection.

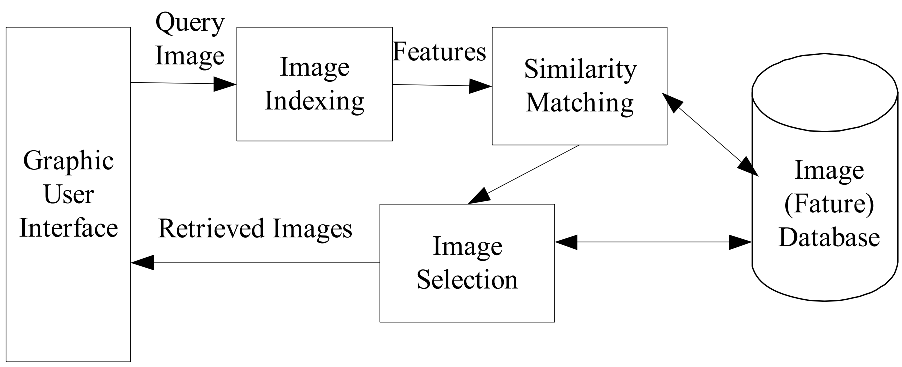

Fig. 4. The architecture of image retrieval.

4.4 Performance Evaluation

We evaluate the performance of image retrieval according to hit ratios [25]. Hit ratios measure the ability of retrieving all relevant or similar images in the database, and defined as S_i/R_i. R_i represents the number of images in class *i*, and S_i represents the number of relevant or perceptually similar images retrieved in class *i*. Though fault ratios could measure the ability of retrieving erroneous and miss images [25], we reduce the fault ratio to $1 - S_i/R_i$ that could be obtained from hit ratios. The reason is that we only consider top *n* retrieval images, where *n* is the number of images included in class *i*. Therefore, we only evaluate hit ratios.

4.5. The Experimental Results

In this subsection, the performance of cluster number of proposed method is examined, and the performance of different color quantization approaches is analyzed. Also, we discuss the effects of luminance on different color space, and compare the performance of full image retrieval with region-based image retrieval.

4.5.1. The evaluation of the cluster number

In this experiment, we evaluate the performances of cluster number of FCM clustering algorithm from 3 to 10 clusters. Test images are selected from 12 classes with outstanding color difference. The query images are selected from these 12 classes as shown in Fig. 5. Actually, lots of test cases have been evaluated. For the conciseness, we demonstrate only the test case as shown, previously. Table 1 demonstrates that the performance is improved as the increasing of color bins. However, the hit ratio does not have remarkable improvements when the number of color bins is greater than 6. For the consideration of computational complexity, therefore, we use 6 color bins for the proposed algorithm. In other words, that is the reason we extract 6 dominant colors from each image or region.

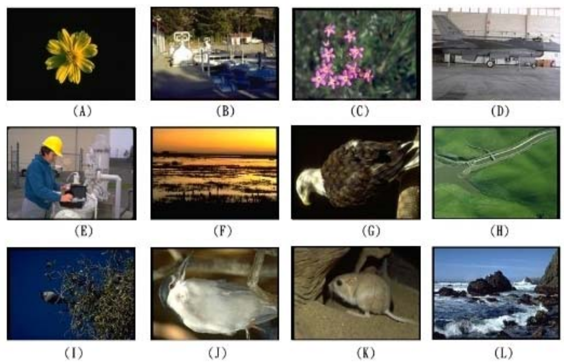

Fig. 5. The query images.

Table 1. The performance of different clusters of FCM clustering algorithm.

The number of color bins	Hit Ratio (%)											
	Examples of query images											
	A	B	C	D	E	F	G	H	I	J	K	L
3 color bins	85	75	75	85	59	75	83	71	75	80	78	56
4 color bins	92	75	88	85	65	100	83	71	100	80	78	61
5 color bins	92	75	88	85	86	100	83	79	100	100	89	61
6 color bins	92	92	88	85	86	100	83	79	100	100	89	72
7 color bins	92	92	88	85	86	100	83	79	100	100	89	67
8 color bins	92	92	88	85	86	100	83	79	100	100	89	89
9 color bins	92	92	100	85	86	100	83	79	100	100	89	89
10 color bins	92	92	100	85	86	100	83	79	100	100	89	94

Table 2. The comparison of color quantization approaches.

Methods of color quantization	Hit Ratio (%)											
	Examples of Query Images											
	A	B	C	D	E	F	G	H	I	J	K	L
3 color bins with proposed method	85	75	75	85	59	75	83	71	75	80	78	56
6 color bins with proposed method	92	92	88	85	86	100	83	79	100	100	89	72
look-up-table method (25 color bins) [7]	50	73	63	60	30	50	45	43	80	60	66	50
quantization method (64 color bins) [6]	83	92	88	75	65	75	60	58	100	80	77	72

4.5.2. The comparison of color quantization approaches

In this experiment, we compare the hit ratios of the proposed fuzzy dominant color selection clustering algorithm with those of table-look-up method [n10:5] and equal quantization method [n9:4] for RGB color feature. As shown in Table 2, it clearly demonstrates that the FCM dominant color selection clustering algorithm with 6 color bins obtains the highest hit ratios among all tested approaches.

4.5.3. The effects of luminance on different color spaces

In this experiment, we evaluate the effects of luminance on RGB, HSV, and CIE LAB color spaces. Actually, more than 50 images have been tested. For the conciseness, we demonstrate only three images as shown in Fig. 6. A1, B1, and C1 are the original images. A0, B0, and C0 are the half reducing luminance of A1, B1, and C1, respectively. A2, B2, and C2 are the half increasing luminance of A1, B1, and C1, respectively. We choose RGB, HS, and AB components from RGB, HSV, and CIE LAB color spaces, respectively. The components of each color space are normalized to the range of 0 to 1. The differences between the original image and the half reducing luminance image or the half increasing luminance image in different color spaces are depicted in Table 3. We conclude that CIE LAB color space is less affected than RGB or HSV color space with various luminance, and is suitable for the proposed method. However, extra computational effort is needed to obtain the CIE LAB color images.

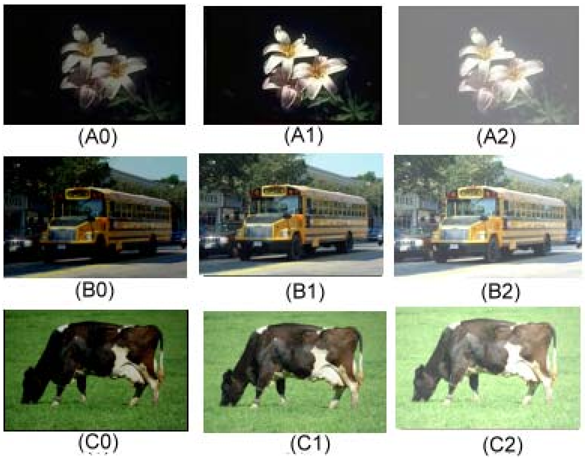

Fig. 6. Images with different luminance.

Table 3. The differences of images with various luminance in RGB, HSV, and CIE LAB color spaces.

	Differences of images					
Color spaces	A1–A0	A1–A2	B1–B0	B1–B2	C1– 0	C1–C2
RGB	2.0066	2.3673	1.3420	1.3891	1.3573	1.4092
HSV	0.6815	1.0499	0.5733	0.8416	1.2776	0.6621
CIE LAB	0.3404	0.6375	0.4326	0.6154	0.5930	0.5257

4.5.4. The comparison of full image retrieval and region-based image retrieval

In this experiment, we compare the hit ratio of full image and region-based image retrieval by using color-shape-texture features. 150 images are selected from the 12 classes of image database, and one region is elected from each image, manually. Twelve query images are selected from 12 classes as shown in Fig. 7.

Fig. 8 demonstrates the result of region-based image retrieval be more appropriate than the result of full image retrieval for the proposed method as shown in Fig. 9. Table 4 depicts that the hit ratios of region-based image retrieval is higher than those of full image retrieval.

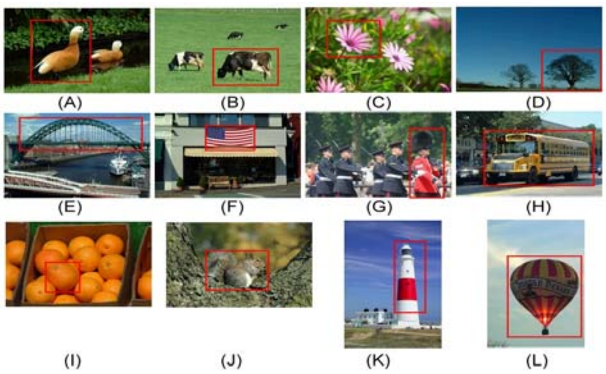

Fig. 7. The query images and regions.

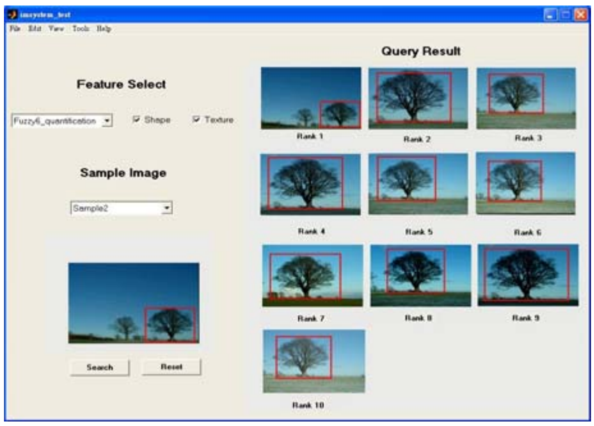

Fig. 8. The result of region-based image retrieval.

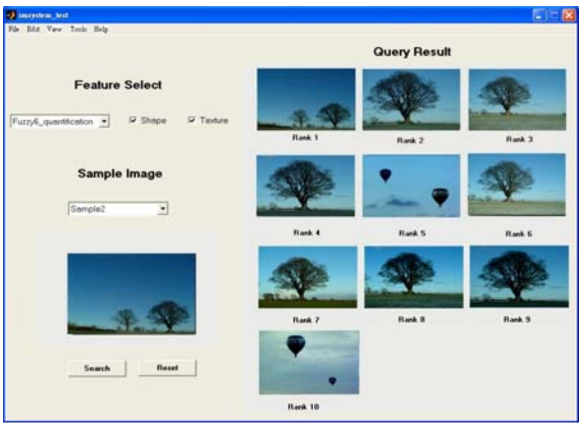

Fig. 9. The result of full image retrieval.

Table 4. The hit ratios of region-based image retrieval and full image retrieval.

Methods of retrieval	Hit Ratio (%)											
	Examples of Query Images											
	A	B	C	D	E	F	G	H	I	J	K	L
full image retrieval	80	85	75	80	85	80	90	80	75	70	90	90
region-based image retrieval	100	90	90	100	95	100	100	100	80	100	100	95

5. CONCLUSIONS

In this paper, we proposed the FCM clustering algorithm for dominant color selection. It not only outperforms other widely used color quantization methods in hit ratio for CBIR on color, but also helps users to select representative region, easily and efficiently. Furthermore, the proposed method could provide region-based or full image retrieval by the combination of color, shape, and texture features, and the former is more efficient than the latter indeed. We also verify that CIE LAB color space is suitable for CBIR while luminance is the major concerned factor.

Here we would like to mention the following areas of investigation which may merit further study.

- Adjust the weighted values of color, shape, texture features according to the characteristics of query image or region, adaptively.
- Join the mechanism of relevance feedback.
- Design an appropriate automatic region selection algorithm.
- Compare with other clustering algorithms for color quantization.

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APPENDIX

Fuzzy c-means

The purpose of FCM [21] is to minimize the object function J(U,V):

$$J(U,V)=\sum_{i=1}^{c}\sum_{k=1}^{n}\mu_{ik}^{w}\left|x_k-v_i\right|^2, \qquad \text{(A1)}$$

where, c represents the number of clusters, n the number of data items, w the exponential weight, $\mathbf{X}=\{\boldsymbol{x_1},\boldsymbol{x_2},\boldsymbol{x_3},\ldots,\boldsymbol{x_n}\}$ an n-dimensional data vector, $V=\{\boldsymbol{v_1},\boldsymbol{v_2},\ldots,\boldsymbol{v_c}\}$ a vector of dimension c, $U=(\mu_{ik})$ a $c*n$ matrix, where μ_{ik} represent the membership value of vector $\boldsymbol{x_k}$ in cluster i, and

$$0\leqq\mu_{ik}\leqq 1 \qquad i=1,2,\ldots,c;\ k=1,2,\ldots,n,$$

$$\sum_{i=1}^{c}\mu_{ik}=1 \qquad k=1,2,\ldots,n,$$

$$0\le\sum_{k=1}^{n}\mu_{ik}\le n \qquad i=1,2,..,c.$$

The minimization of the objective function with respect to membership values leads to

$$\mu_{ik}=\frac{\left[\dfrac{1}{\left|x_k-v_i\right|^2}\right]^{1/(m-1)}}{\sum_{j=1}^{c}\left[\dfrac{1}{\left|x_k-v_j\right|^2}\right]^{1/(m-1)}} \qquad \text{(A2)}$$

$i=1,2,\ldots,c;\quad k=1,2,\ldots,n.$

The minimization of the objective function with respect to the center of each cluster gives rise to the following equality

$$v_i=\frac{\sum_{k=1}^{n}\mu_{ik}^{m}x_{ik}}{\sum_{k=1}^{n}\mu_{ik}^{m}} \qquad i=1,2,\ldots,c. \qquad \text{(A3)}$$

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