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칼라 인접성과 기울기를 이용한 내용 기반 영상 검색

(Content-based Image Retrieval Using Color Adjacency and Gradient)

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요 약

본 논문에서는 칼라 인접성과 기울기를 이용한 새로운 내용 기반 영상 검색 방법을 제안한다. 칼라 영상의 특징 정보로 사용되는 칼라 히스토그램은 시점이나 영상의 회전등의 영향을 적게 받고 특징 정보의 계산이 간단하고 빠른 장점이 있지만 칼라의 위치 정보를 나타낼 수 없기 때문에 균일 양자화에 의해 비슷한 히스토그램을 가진 서로 다른 영상을 구별하지 못하고 특징 저장량이 많은 등 단점이 있다. 제안한 방법은 기존의 방법들에서 보편적으로 사용하는 양자화 대신 영상에서의 인접 화소의 칼라 변화량 즉 기울기를 계산하여 보다 정확한 색차를 구함으로써 비슷한 칼라가 서로 다르게 양자화됨으로 인한 오차를 감소시켰다. 동시에 영상의 주요 칼라 구성 특징을 나타나는 칼라 인접성 정보를 추출하여 이진 배열로 표시함으로써 특징 정보의 방대한 저장량을 줄이고 비교속도를 향상시켰다. 실험 결과 기존의 검색 방법에 비하여 제안한 방법은 적은 특징 저장 양으로 외부조건의 변화에 더욱 강건함을 보여주고 있다.

Abstract

A new content-based color image retrieval method integrating the features of the color adjacency and the gradient is proposed in this paper. As the most used feature of color image, color histogram has its own advantages that it is invariant to the changes in viewpoint and the rotation of the image etc., and the computation of the feature is simple and fast. However, it is difficult to distinguish those different images having similar color distributions using histogram-based image retrieval, because the color histogram is generated on uniformly quantized colors and the histogram itself contains no spatial information. And another shortcoming of the histogram-based image retrieval is the storage of the features is usually very large. In order to prevent the above drawbacks, the gradient that is the largest color difference of neighboring pixels is calculated in the proposed method instead of the uniform quantization which is commonly used at most histogram-based methods. And the color adjacency information which indicates major color composition feature of an image is extracted and represented as a binary form to reduce the amount of feature storage. The two features are integrated to allow the retrieval more robust to the changes of various external conditions.

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I. Introduction

An effective indexing and image retrieval from a large database became an important problem as the application of multimedia technology increases. In the traditional database system, a context-based query and retrieval scheme is usually adopted. This approach searches image on the textual keyword records and the associated target images are retrieved on the completeness of the texture search. However, a limited number of keyword is usually not sufficient to describe the visual properties of an image, such as "scattered flowers with vivid red". In addition, the detailed description will increase the storage requirements largely and require a prohibitive amount of labor for the annotation.

In this context, Content-Based Image Retrieval(CBIR) technique is improved rapidly with the growing need for effective and efficient image retrieval, and some multimedia information system that perform the storage, indexing and retrieval of multicolor images based on content have been developed consequently[1-4].

To access images based on their contents, low-level features such as colors, textures, and shapes of objects are widely used as indexing features for image retrieval. Among the features, the color information has been extensively studied because of its invariance to geometrical changes in the scene, and robustness to object transformation, including distortion, translation, rotation, occlusion and scaling.

Swain and Ballard[5] have presented a color indexing method, named histogram intersection, in 1991. In their method, the color histograms of the query image are matched with those of database images. Image retrieval based on color histograms is very fast, making a real-time implementation possible. Therefore, many studies have reported on histogram-based color image retrieval techniques[6-8].

Although this kind of approach is useful in many situations, performance may degrade significantly in such a case that images with very different appearances have similar color histograms. The reason is that the histogram itself provides a global description of the image, and the retrieval algorithms often neglect one important criteria for similarity : spatial information, which actually plays an important role in the user's perception on the chromatic contents of the image.

Recently several approaches have attempted to incorporate spatial information with color[9-11]. One common approach is to divide images or histograms into several parts refers to partitioning, an another one is to augment histograms refers to refinement. In a different way, Huang[12] proposed color correlogram for refining histogram with the consideration of distances between colors, and Park[13] proposed the graph representation, in which color adjacency information is taken into account.

However, a problem comes from the uniform quantization used as a preprocessing at most of these methods, by which two similar colors may be divided into different bins and therefore the efficiency of histogram matching degrades significantly. This problem is especially severe for large databases.

In order to cope with the above mentioned problem, the gradient is first computed for each pixel in this work, to determine whether the center color is similar or different to the neighboring colors according to the color differences. For those similar ones, we consider it as being located in a relatively homogeneous region, and record the gradient distribution of the chromatic cluster. On the other hand, those remarkably distinguishable colors with differences larger than a predetermined threshold are marked as color edges, and the adjacency information of an image is represented as binary matrix to decrease the storage of the feature. Since the calculation of gradient is carried on the original values rather than quantized values of image pixels, the problem caused by uniform quantization can be avoided.

Ⅱ. IMAGE RETRIEVAL SYSTEM

1. Image Retrieval Scheme

The basic idea of image retrieval by image example, where a query image is given by the user on input, is to extract characteristic features from query image which are then matched with those of the target images in the database.

A block schematic of a typical image archival and retrieval system is shown in Fig.1.

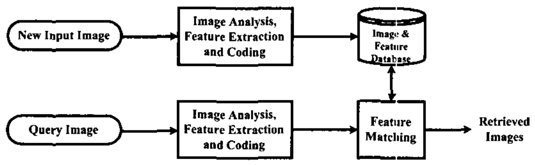


Fig. 1. Image retrieval scheme.
그림 1. 영상 검색 구성

For each image which will be added to the database, a multidimensional feature vector is generally computed and indexed into a database with the compressed image itself. The same process of feature extraction is made for a query image, then the feature vector is matched to those of each of the images in the database based on the similarities of the features. After matching, images are ordered with respect to the query image according to their similarity and in consequence a given number of images with the least differences are selected as the retrieved images.

It is desirable that the computation and the extraction of the features are performed automatically and the matching process is as fast as possible. Since the interpretation and the quantification of various features are fuzzy, emphasis is typically placed on the similarity rather than the perfect matching of the feature vectors. An important criterion for testing the efficacy of the retrieval is that the output must include as many similar images as possible. The list may have other irrelevant images as well, but it is not very important as far as all the similar ones are retrieved.

2. Color-based Image Retrieval

Color is an important attribute for image representation due to its capability of describing the global properties of an image. Especially color histogram comparison has recently become a popular technique in image and video indexing applications because of its simplicity and insensitivity to various changing conditions. The histograms of color images are generally defined in a three dimensional color space. Given a discrete color space, the color histogram is obtained by discretizing the image colors and counting the number of times each discrete color occurs in the image array. Histograms are invariant to translation and rotation about the viewing direction and changes in scale and occlusion. They provide a global description of the appearance of an image and hence is popular in image indexing.

However, the histogram-based retrieval has its drawback that histogram itself does not contain any spatial information of the image. Images with similar color histograms can have dramatically different appearances. Especially in a large database, it is common for unrelated images to have similar color histograms. To make color histogram more effective for image indexing, spatial information should be considered.

There are several techniques proposed to integrate spatial information with color histograms. Hsu et al.[9] integrates spatial information with color histograms by first selecting a set of representative colors and then analyzing the spatial information of the selected colors using maximum entropy quantization with event covering method. Stricker and Dimai[10] partition an image into five partially overlapping, fuzzy regions, extract the first three moments of the color distribution for each region, and then organize them into a feature vector of small dimension. The storage requirements for this method are low. However, the use of overlapping regions makes the feature vector relatively insensitive to small rotations or translations. Pass and Zabih[11] define the concept of color coherent vector(CCV) and use it to split a color histogram bins by the spatial coherence of pixels into two parts: a coherent vector and a non-coherent vector. A pixel is called coherent if it is a part of similar-colored and connected region. CCV are fast to compute and appear to perform better than histograms.

Huang[12] proposes color correlograms which uses a table indexed by color pairs, where the kth entry for $\langle i, j\rangle$ specifies the probability of finding a pixel of color j at a distance k from a pixel of color i in the image. A color correlogram expresses how the spatial correlation of pairs of colors changes with distances. Such an image feature is robust in large changes in appearance of the same scene caused by changing conditions such as viewing positions, changes in the background scene, partial occlusions, camera zooms, etc. Although the author chose the autocorrelogram captures spatial correlation between identical colors only, but the size of the feature is still very large.

As a special case, the color autocorrelogram with fixed distance k of value 1 captures spatial correlation between neighboring colors only, which is similar to color adjacency[14]. Color adjacency information is also used for indexing recently indicating color arrangement in an image. Park[13] proposed the Modified Color Adjacency Graph (MCAG) representation in which salient chromatic information is carried by each node, while the pixel adjacency of two chromatic regions is employed for the attribute of each edge. The node attributes that encode the pixel count of the RGB chromatic component are identical with the histograms of each color, while the edge attributes are the counting of occurrence of any two adjacent colors. Thus the method can be considered as a combination of histogram intersection with color adjacency intersection. It is obvious that MCAG performs much better than color histograms only. In addition, since the adjacency of spatial regions takes the geometrical information of an image, this method attains with quite effective retrieval performance. In the construction of MCAG, only the colors appearing in an image are counted to the nodes, but the structure of the features of the MCAG is still very large, because there usually are quite amount of dispersed colors in a natural image, even though the noise is removed before the MCAG generation. Besides, since the color adjacency counting is also taken on the quantized colors, the shortcoming caused by color quantization still remains an inevitable issue at the graph intersection method.

In addition to the MCAG, Park proposes the Spatial Variance Graph(SVG) representation as well in which self and relational variance of color classes are used. It is integrated with the MCAG to improve the performance in the graph intersection method, but in this paper only the MCAG is concerned because of the color adjacency term in it.

III. PROPOSED IMAGE RETRIEVAL INTEGRATING ADJACENCY AND GRADIENT

1. The Motive and the Mechanism of the Proposed Image Retrieval

Most of color histogram-based retrieval methods are based on the assumption that similar images have similar quantized color distributions. But it is worthwhile to emphasize that the results of quantization are so sensitive to the location of quantization boundaries that a small change in original scenes may cause a large difference in quantized images. One of the reasons is that two similar colors near to a quantization boundary may fall on the different sides since colors in RGB space are quantized uniformly. Fig. 2 depicts the quantizing process of the colors located in a line with fixed R=255 and B=0. The colors near to the boundary

G=127 are indexed to different classes with G=95 and G=159 respectively. Considering that the quantization is carried out on 3-D color space, the quantization errors will be significant. Since there are various changes in the environments during achieving, processing and transmitting images, colors in different images are affected and hence quantized differently. Provoked by this problem, we take the original color values instead of quantized ones of each pixel into account in order to classify the colors more correctly. First, for each pixel in an image we calculate the color gradient, which is defined as the maximum color distance between two pixels among all the neighboring pixels. Since the color gradient is computed before the colors are quantized, so it shows the real difference of the colors in the image. Then, we divide the neighborhood as either an edge or a homogeneous region according to the gradient. And then we extract the adjacency information if they are forming edges, or count the gradient distribution if they have similar colors. The adjacency feature has a representation with binary form and the gradient feature is represented as a kind of histograms. The same feature extraction process is carried on the query image whose features are compared with those of database images in a particular matching function and consequently a given number of images are retrieved. The block diagram of the of the proposed method is shown in Fig. 3.

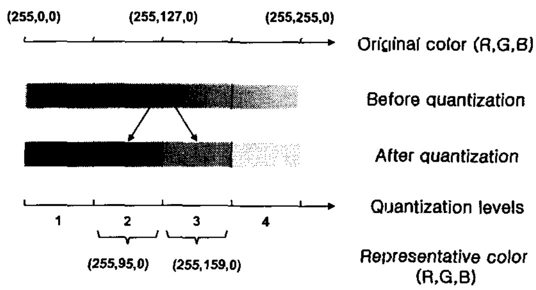


Fig. 2. Different division of two similar colors by uniform quantization on RGB space.
그림 2. 균일 양자화에 의한 RGB 색공간에서의 두 비슷한 칼라의 양자화 착오

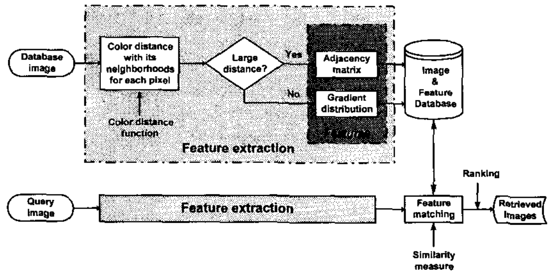


Fig. 3. Block diagram of the proposed image retrieval method.
그림 3. 제안한 영상 검색 방법의 블록도

2. Feature Extraction

1) Color Gradient

Gradient of a color pixel is defined as the maximum color difference from a pixel to its neighborhoods. It is a measure of how rapidly intensity is changing in the direction of greatest change. In this work, a 3×3 window is applied to each pixel to calculate the color distances to the neighboring pixels. The gradient magnitude at a pixel is defined as follows:

$$G(p_{ij}) = \max\{D(p_{ij}, p_{km})\}$$
$$k = i-1, i, i+1 \quad m = j-1, j, j+1 \tag{1}$$

where p_{ij} is the color value of center pixel and p_{km} is of each neighboring pixels. $D(,)$ is color distance function carried on two pixels.

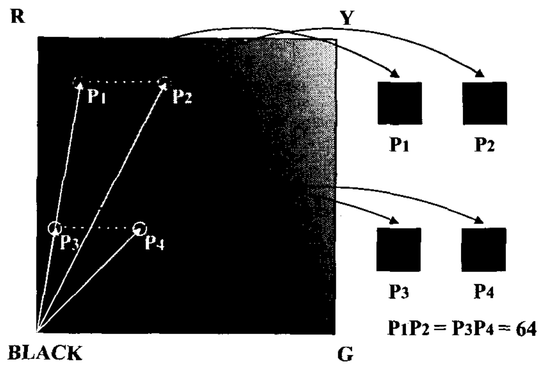


Fig. 4. Visual differences of two color pairs P_1P_2 and P_3P_4 with the same Euclidean distance in the RGB space.
그림 4. RGB 색공간에서 동일한 유클리디언 거리를 가지는 두쌍의 칼라 P1P2 와 P3P4의 시각적 차이

There are various color distance measures at different color spaces. The most commonly used color distance in RGB space is Euclidean distance which can be simply considered as the spatial distance between two color vectors. However, the spatial distances of color pairs do not correspond to equally perceptible differences of colors because RGB space is not uniform color space.

Fig. 4 is drawn to compare the perceptual differences of two color pairs P_1P_2 and P_3P_4 that have the same Euclidean distances in RGB space. Although P_1 and P_2 are part from each other with the same distance as P_3 and P_4, the latter pair appear more obviously different while the former are quite similar. It is observed from the figure that the angle of P_3P_4 is larger than that of P_1P_2. We can simply catch the information that the color differences are related to the angle of color vectors as well, that is, as the angle between two color vectors varies, the difference of the two colors changes consequently. Thus, the color difference of any two colors should be determined by both of the Euclidean distance and the angle of them.

On this account, we adopt a integrated distance measure called the vector-angular distance which is proposed by Androutsos[14]. It is based on both the vector distance and the angle between two vectors, expressed as

$$\delta(x_i, x_j) = 1-[1-\frac{2}{\pi}\cos^{-1}(\frac{x_i \cdot x_j}{|x_i|\,|x_j|})]\,[1-\frac{|x_i \cdot x_j|}{\sqrt{3 \cdot 255^2}}] \quad (2)$$

where x_i and x_j are three-dimensional color vectors at RGB space. In the function, $\cos^{-1}(\frac{x_i \cdot x_j}{|x_i|\,|x_j|})$ is the angle term and normalized by $\frac{\pi}{2}$, the maximum value of any possible angle, and $\frac{|x_i \cdot x_j|}{\sqrt{3 \cdot 255^2}}$ is the vector distance term that is identical to Euclidean magnitude normalized by $\sqrt{3 \cdot 255^2}$. Therefore the difference δ takes on possible values in the range[0,1].

The Angular measure is operated primarily on the original of the color vector in the RGB space so that it is resistant to intensity change. The integration of the two terms allows the distance function to accord with the perceptual differences of colors and more suitable for RGB color space.

2. Color Adjacency

As previously mentioned, color adjacency is successfully used for color image retrieval in the graph representation method proposed by Park. In the method, the node attributes of the Modified Color Adjacency Graph(MCAG) are equal to the color histograms, so the retrieval method can be regarded as the combination of existing color histogram matching with color adjacency matching.

Among the MCAG matrix of a natural image which contains a large amount of colors, the value of the adjacency term is usually much smaller than that of histogram term, so that the matching result is mostly affected by the latter element. Actually, it is the color adjacency information that carries the main contents of an image. We found that the information about which colors are adjacent at a image is sufficient to distinguish the image from another rather than how much colors are adjacent. The granularity provided by two dimensional graph is not necessary because the majority of the nodes and edges are found to be null and only a few number of items occupy the most amount of information. Hence we propose the binary representation indicating the rough information of adjacency.

In this work, color adjacency indicates only the information of the existence of those adjacent color pairs in an image. It is generated from the color adjacency matrix with the form similar to MCAG by the proposed binary representation.

Fig. 5 shows a 2D color adjacency histogram. The numbers marked beside each bin indicate the count of the cooccurrence of the two corresponding colors. A different thing is that the count is not based on the quantized colors but on the value of the color distances according to the previously computed gradients. Only if a color distance between two colors is larger than a predetermined threshold, the count relates to the color pairs is added to the corresponding 2D histogram bin.

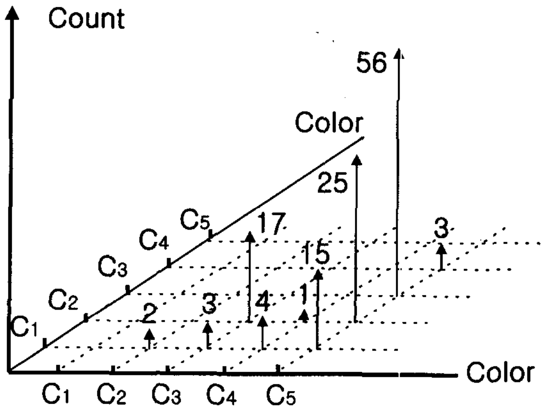


Fig. 5. Color adjacency histogram.
그림 5. 칼라 인접성 히스토그램

In the figure c_i $(i=1,2,...)$ are the representative colors. The number of the labels is variable according to the storage requirement.

Like most 2D histograms, the constructed 2D matrix have vast numbers of elements in which only a few dominant peaks capture the main edge components and the rest remained with less information, and a great portion of the elements even are empty since it is often that colors in a given image only occupy a small region of the entire color space. Therefore a detailed comparison for such features is not required. Also, there is some noise introduced during the process of scanning color images. Our observation has been that a fine comparison is not necessary and many even produce incorrect results. So we label several dominant elements with binary digit 1 while the rest with 0 to make the matrix be represented as a set of binary codes. It reduces the feature storage amount significantly and therefore improves the retrieval rate.

A node is classified into an effective one to assign the code 1 when the count of pixels in the node exceeds the given threshold. This threshold is determined to be the maximum value satisfying the need that the sum of node attributes above the threshold occupy some percent of total pixels. The binary form of the color adjacency feature is shown as Fig. 6. Four color pairs (c1,c5), (c2,c3), (c2,c5) and (c3,c5) are selected and assigned as 1.

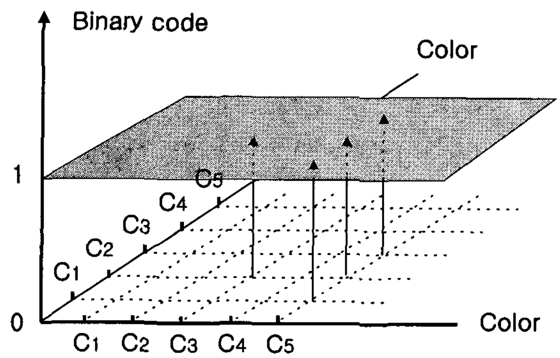


Fig. 6. Binary representation of adjacency feature.
그림 6. 인접성 특징의 이진 표시

Then the feature matrix is expressed as binary array as follows.

$$C=\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{3}$$

The binary code matrix denotes that color C1 and color C5 are adjacent to each other, likewise color C2 and color C3, and color C3 and color C5 . As a matter of convenience, only those in the half triangle of the matrix of the matrix are considered due to its symmetry.

Finally, the 2D matrix can be altered into a vector which element is each equivalent numerical number corresponding to the adjacency content of each color. Following representation is adopted from above equation.

$$C=[1\ 5\ 1\ 0\ 0] \tag{4}$$

The number of elements to be stored is the same of the number of the representative colors in the 2D matrix.

3. Feature Matching and Similarity Measure

The efficiency of the feature matching is as important as the feature extraction itself. At the color indexing method introduced by Swain, the histogram intersection is at the core of whole retrieval. A normalized intersection of two histograms used as similarity measure in color indexing is defined as

$$S(I,J)=\frac{\sum_{k=1}^{n}\min(I_k,J_k)}{\sum_{k=1}^{n}J_k} \tag{5}$$

where I and J are a pair of histograms each containing n bins. I_k and J_k are the $k'th$ histogram bins of image I and J respectively. The result of the intersection of model histograms with database histograms is the number of pixels from the model image that have corresponding pixels of the same color in the database image.

At the graph representation, intersection of two graphs such as modified color adjacency graph (MCAG) is defined as follows.

$$S(I,J)=\frac{\|\overline{M_I}\cap\overline{M_J}\|}{\|\overline{M_I}\cup\overline{M_J}\|} \tag{6}$$

where $\overline{M_I}$ and $\overline{M_J}$ are MCAG of images I and J, and $\overline{M_I}\cap\overline{M_J}$ is the matrix in which the element is the smaller one of two corresponding labels. $\|\overline{M}\|$ is the sum of all elements in the matrix and $\|\overline{M_I}\cup\overline{M_J}\|=\|\overline{M_I}\|+\|\overline{M_J}\|-\|\overline{M_I}\cap\overline{M_J}\|$ is reduced matrix with common nodes and edges.

We use the similar intersection method to measure the similarity of the binary codes of the same colors of two images.

Let $B_{C_k}(I)=(\ b_1^{\,k}\ \ b_2^{\,k}\cdots\ b_n^{\,k}\ )$ denotes binary code of adjacent colors of k'th color C_k in image I, then the intersection result of two images I and J about color C_k is formulated as:

$$S_k(I,J)=\frac{NC_k^{\,1}(I,J)}{N_k^{\,1}(I)+\ N_k^{\,1}(J)-\ NC_k^{\,1}(I,J)}, \tag{7}$$

where $N_k^{\,1}$ is the number of code 1 at a binary string whose elements are 1 or 0 and $NC_k^{\,1}$ is the number of common 1 at same labels of two matrix, n is the number of colors.

For example, if $B_{C_k}(I)=[\ 0\ 0\ 1\ 0\ 1\ ]$ and $B_{C_k}(J)=[\ 0\ 0\ 1\ 1\ 0\ ]$ indicate binary codes of k 'th color in image I and M respectively, then $NC_k^{\,1}\ (I,J)=1$, $N_k^{\,1}\ (I)=2$ and $N_k^{\,1}\ (J)=2$. So the intersection result is $S_k(I,J)=\frac{1}{2+2-1}\approx 0.33$.

Concerning all the colors in the images, the total intersection is computed as:

$$S(I,J)=\frac{1}{n}\sum_{k=1}^{n}S_k(I,J) \tag{8}$$

For example, if the binary matrix of image I and J are arrayed as:

$$\mathrm{C_I}=\begin{bmatrix}0&0&0&0&1\\0&0&1&0&1\\0&0&0&0&1\\0&0&0&0&0\\0&0&0&0&0\end{bmatrix},\quad \mathrm{C_J}=\begin{bmatrix}0&0&0&0&1\\0&0&1&1&0\\0&1&0&0&1\\0&0&1&0&0\\0&1&0&0&0\end{bmatrix}, \tag{9}$$

then according to the equation (7), the intersection result, S(I,J), is 0.375.

In the other hand, we use the same method as the histogram intersection for the matching of the gradient feature after the gradient distribution is divided to several groups, the similarity measure is formed as follows.

$$S(I,J)=\frac{\sum_{k=1}^{n}\min(I_k,J_k)}{\sum_{k=1}^{n}J_k} \tag{10}$$

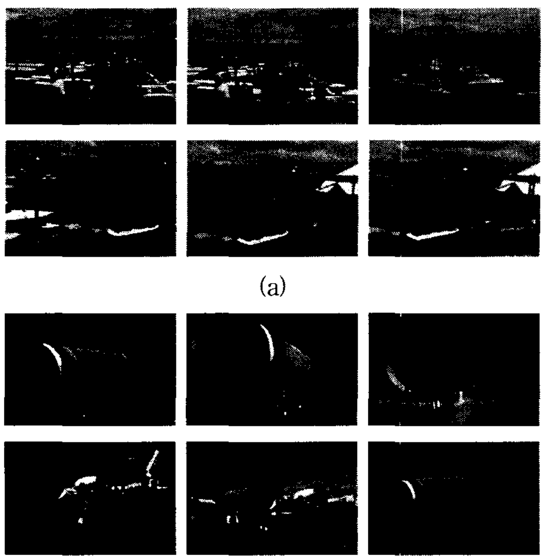
where I and J are the gradients of two images each containing n bins. I_k and J_k are the k'th element of I and J respectively.

Ⅳ. EXPERIMENTS AND DISCUSSIONS

1. Image Database and Query

In this work, experiments have been carried out on a database including 5466 images with various sizes taken from multicolored objects in real world scenes. The database includes natural scenes, indoor images, plants, animals, landscapes, people, news cuts and paints etc. Large variety of our image database prevent the bias on a particular type of images. Independent 50 query images and the corresponding relevant image sets were chosen from the database.

Each query image has various number of relevant images. Some of the relevant images in a query set are lightly or significantly transformed, rotated, zoomed or occluded from the query image. Several example queries and corresponding relevant images for each query image are listed bellow.



(a)

(b)

Fig. 7. (a) Query image and the relevant images in query 36;
(b) Query image and the relevant images in query 47.

그림 7. (a) 질의 36에서의 질의 영상과 관련 영상들
(b) 질의 47에서의 질의 영상과 관련 영상들

2. Retrieval Accuracy Measure

Before presenting the results, we introduce some popular retrieval accuracy measures Recall and Precision.

Recall and Precision are the most commonly used statistical measures measuring how many relevant images are retrieved successfully. The definition of Recall and Precision is given below.

	Relevant	Not Relevant
Retrieved	A (correctly retrieved)	B (incorrectly retrieved)
Not Retrieved	C (missed)	D (correctly rejected)

$$Recall = \frac{relevant\ \ retrieved}{all\ relevant} = \frac{A}{A+C} \tag{11}$$

$$Precision = \frac{relevant\ retrieved}{all\ retrieved} = \frac{A}{A+B} \tag{12}$$

Recall is the proportion of relevant images in the database that are retrieved in response to a query. Precision is the proportion of retried images that are relevant to the query.

3. Performance and Discussion

Several experiments are carried out to compare the proposed method with histogram intersection and graph intersection strategies. Each method is performed by retrieving 50 query images successively and the corresponding K images with highest similarities are ranked for each query, and then three retrieval accuracies introduced above are calculated consequently.

For the proposed method, the proper number of representative colors is determined as 64 relating to the selection of the threshold which is used to compute the gradient of each pixel in the first step. Therefore the number of quantization levels in the two intersection methods is also chosen to be 64 to meet the convenience of the comparison. So the number of features used in histogram intersection method is 64, and the amount of the features in graph intersection is much larger than 64 relating to the occurrence of colors in the images. The number of features used in the proposed method equals to 72-the sum of the number of adjacency features 64 and the number of gradient histogram bins which is 8 in this work. Using proposed binary representation, in this work, the average number of elements indexed to digit 1 in the adjacency feature matrix is about 30. It facilitates the feature matching and therefore accelerates the retrieval while achieving good retrieval performances.

Table 1 shows the average recall and precision measures of three methods.

Table 1. Comparison of retrieval accuracy for three methods.
표 1. 세 가지 방법의 검색 효율 비교

	Recall	Precision
Histogram intersection	0.82	0.21
Graph intersection	0.89	0.22
Proposed method	0.92	0.24

From the definition of each accuracy measure, we know that the larger recall and precision, the more efficient the retrieval. From the above results, we can see that the proposed approach yields more successful performance than the other two existing methods.

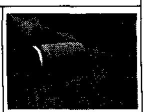
In particular, we choose query 36 and query 47 to compare the retrieval results. The query images and the corresponding relevant images are shown in Fig. 7. The first images are the query images. As shown in the figure, the relevant images in query 36 are taken at the same scene but four of them do not contain the people appearing in the query image. The relevant images in query 47 contain both the same scene and the same object, however, they have different appearances because of the change on viewing direction. The retrieval ranks of each relevant images of the two queries are listed in Table. 2 and Table. 3.

Higher rank means lower efficiency. The figures show that the two existing methods failed at retrieving all the relevant images within the rank limit of 24, but the proposed method not only

Table 2. The ranks of relevant images with object elimination.
표 2. 객체의 제거에 의한 관련 영상들의 랭크

Method	Retrieval Rank					
						
Histogram intersection	1	2	36	32	85	140
Graph intersection	1	2	3	10	15	99
Proposed method	1	2	5	5	11	12

Table 3. The ranks of relevant images with zooming effect.
표 3. 확대/축소에 의한 관련 영상들의 랭크

Method	Retrieval Rank					
						
Histogram intersection	1	11	8	76	64	49
Graph intersection	1	2	27	10	3	17
Proposed method	1	3	5	7	8	10

retrieved all the relevant images but also achieved much higher ranks. All these results confirm the robustness of the proposed method to various changes of external conditions with less feature storage.

V. CONCLUSION

In this paper we present a robust content-based color image retrieval method integrating the features of the color adjacency and the gradient distribution. This method is based on the difference of neighboring colors to prevent the drawbacks caused by the uniform quantization which is commonly used at most histogram-based methods. Furthermore, the proposed method uses binary representation method for the feature to emphasize only a small number of dominant elements which are carrying the major color organization information of an image and reduce the amount of feature storage.

It is commonly known that the uniform quantization causes some similar colors indexed differently and therefore degrades the efficiency of retrieval results. To cope with this problem, the color gradient is first computed in this work for each pixel instead of color quantization to observe the exact color differences. Then, we classify the neighboring colors into either similar ones or different ones according to the color differences, and assign different kind of indices to them. For those similar colors, we consider them as components of a relatively homogeneous region, and count them to the gradient distribution. On the other hand, those remarkably different colors are marked as color edges and contribute the adjacency information to the adjacency feature. The computation of the gradients is carried on the original values rather than quentized values of image pixels, therefore more precise color differences are taken into account and the problem caused by uniform quantization can be avoided.

A new method we call binary representation is proposed as well to reduce the size of features in this paper. By this method only a coarse comparison is performed for two images. Among the vast numbers of elements of a constructed 2D feature matrix, only a few dominant ones capture the main edge components and the rest remained with less or no information. Therefore we label several peak elements with binary digit 1 indicating edges in the image while the rest with 0 so that the matrix is represented as a set of binary codes. Also a specific feature matching function is proposed. The binary representation and matching strategy reduces the storage amount and improves the retrieval rate significantly.

From the experiments that have been carried out by 50 queries applied on a database consisting of 5466 images, the result of the proposed method shows that it is more robust to various condition and attains higher retrieval accuracy than the other conventional intersection methods.

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