An Image Retrieval System Based on the Feature of Color Differences among the Edges of Objects

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ABSTRACT

This paper focuses on color differences among the edges of objects in an image. The variations of colors among the objects in the image can depict the directions and simple geometric shapes of most objects in the image regardless of the influence from the shift variant of objects and scale variant in the image. Based on the feature of color differences among the edges of objects, this paper constructs an image retrieval system. Experimental results show that this system can effectively and quickly deliver the desired database images to the users.

Keywords: image retrieval, color-based image retrieval, color attribute, color histogram

1. INTRODUCTION

With the rapid advancement of multimedia and Internet technology, tremendous amounts of digital image data are generated every moment. Therefore, developing a speedy and accurate image retrieval system to effectively deal with the image data is necessary [1, 3-12]. The primary goal of this paper is to create an image retrieval system so as to assist the users instantly and effectively to retrieve their desired images from the database.

The distribution of pixel colors in an image generally contains interesting information. Recently, many researchers analyzed the color attributes of an image and used it as the feature of the image for querying [3-6, 8, 10, 12]. Color histogram [3, 6, 8, 10, 12] is one of the most frequently used image features in the field of color-based image retrieval. Kuo [8] provided an image retrieval system based on the statistical distribution of color histogram. This image retrieval system employs the mean, standard deviation, and skewness of each bin's pixel colors in color histogram as the features of an image.

The mean of the pixel colors in each bin can state the principal pixel colors of the image, and the standard deviation of the pixel colors can depict the variation of the pixel colors. The variation of the pixel colors in an image is called the color complexity of the image. The skewness of pixel colors can describe the direction and shift degree of the mean of the pixel colors in the bin.

The image retrieval system based on the statistical distribution of color histogram is insensitive to the rotation and shift variants of objects in images. However, it can state only the global properties of an image rather than the local properties. For example, it cannot describe the shapes and directions of the objects in an image. In order to solve these problems, this paper proposes the feature of color differences among the edges of objects (CDAEO feature). This feature can sketch not only the principle pixel colors and color complexity of an image, but also the directions and simple geometric shapes of most objects in the image. Moreover, this feature is indifferent to the scale variant and shift variant of objects in images.

Based on the CDAEO feature, this paper presents an image retrieval system. In this system, a user can input a query image into the system with a tool such as a scanner. Then the system compares the color features of database images, that were previously extracted and stored in a database, with those of the query image, and sends the user the most similar database images.

In the next section of this paper, Kuo's method [8] is briefly introduced. The third section gives all the details about the CDAEO feature, and constructs an image retrieval system based on this CDAEO feature. Section 4 shows the experimental results in this paper. The conclusions will be given in section five.

2. RELZATED WORKS

Kuo [8] adapted a statistical method to analyze the distribution of the pixel colors of each bin in the color histogram of an image. First, this method uses K-means algorithm [2, 6] to group the pixels of all the database images into k clusters according to their similarities in colors. It employs the mean of all the pixel colors in a cluster as the center of gravity in this cluster. Here, each cluster corresponds to one bin in a color histogram.

This method then assigns each pixel P in an image to the most similar one of these k bins based on the color distance between P and the center of gravity in each bin. Meanwhile the mean (μ), standard deviation (σ) and skewness (s) of the pixel colors in each bin are figured out. Suppose n is the number of pixels in the bin, and x_i is the color value of the i-th pixel in this bin. Then, μ, σ and s are defined as follows：

$$u = \frac{1}{n}\sum_{i=1}^{n} x_i ,$$

$$\sigma = \left[\frac{1}{n-1}\sum_{i=1}^{n}(x_i - u)^2\right]^{1/2} , \text{ and}$$

$$s = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{x_i - u}{\sigma}\right)^3 .$$

In this proposed technique, the image matching distance $dist$ between a database image and a query image is defined as follows:

$$dist = \sum_{i=1}^{k}\left[\left(\frac{\mu_i - \mu_i'}{max_{u_i}}\right)^2 + \left(\frac{\sigma_i - \sigma_i'}{max_{\sigma_i}}\right)^2 + \left(\frac{s_i - s_i'}{max_{s_i}}\right)^2\right]$$

,

where μ_i, σ_i, and s_i are the features of the database image on bin i; μ_i', σ_i', and s_i' are those of the query

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image on bin i. In addition, max_{u_i}, max_{σ_i}, and max_{s_i} are the respective maximal values among μ_i s, σ_i s, and s_i s of all the database images.

3. THE CDAEO FEATURE

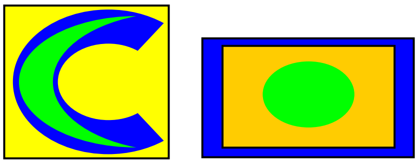
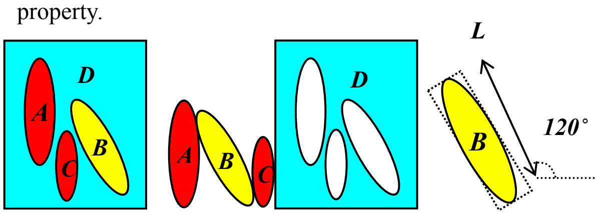


Figure 1: Three different shape objects with the same area and color

Kuo's method can explain the principal pixel colors of an image, and it is indifferent to the rotation and shift variants of objects in images. However, it cannot describe the shapes and directions of the objects in an image. The perimeters of objects and the objects around each other in an image can provide significant information for image retrieval. Therefore, this paper presents the feature of color differences among the edges of objects (CDAEO feature). This feature can characterize not only the principle pixel colors and color complexity of an image, but also the directions and simple geometric shapes of most objects in the image. In addition, this feature is insusceptible to the scale variant and shift variant of objects in images.

In a full color image, a pixel color is generally described by a 24-bits memory space, so there are a total of 2^{24} different possible pixel color values. In the natural world, there are a great many images, each of which contains a group of large regions with a uniform color when the pixel colors of the images are quantized down to a small subset of representative colors. Many synthesized images like trademarks, cartoons, and flags possess this property.



(a) (b) (c)

Figure 2: A color image and its objects

Segmentation of objects is very important for extracting the shape attributes of an image [1, 9]. However, extracting objects from an image is very difficult because of discretization, occlusions, poor contrasts, viewing conditions, and noises, etc. [1]. An image with a limited color palette is generally composed of a set of unicolor regions. This paper considers each unicolor region to be an object; in this case, segmentation of objects is less difficult and entirely possible.

Enclosing an object with a minimal rectangle and representing the longest side of this rectangle by a segment line L, one can define the angle between L and the horizontal axis as the direction of the object. Figure 1(b) shows the objects A, B, C, and D contained in Figure 1(a)'s image. The direction of Object B in Figure 1(c) is 120°. The CDAEO feature can state not only the variation of the colors among the objects in an image, but also the shapes and directions of most objects in the image. Here, the object shape only means whether an object is a prolate or geometric square.

Before extracting the CDAEO feature of an image, all the pixels of the database images are categorized into k clusters by using K-means algorithm according to the similarity of their colors. The mean of all the pixel colors in each cluster is considered to be one color value in a color palette. In order to make image matching easier, the color palette containing k different colors is used as the common color palette CP for all images.

To extract the CDAEO feature of an image I, each pixel color C in I is replaced by one color in CP that is most similar to C so as to create an image I', which is as large as I and uses the k colors in CP as all its possible pixel colors. This image I' is called the color-reducing image of I.

Then each color C_i in CP is given a corresponding variable f_i. Meanwhile, all the pixels in each row of I' are scanned from left to right in horizontal (0°) direction. When the color C'_j of the j-th pixel P'_j in I' is different from that of the pixel P'_{j-1} prior to P'_j, the f_i, the color C'_j corresponding to, is added the color difference $((r_j-r_{j-1})^2+(g_j-g_{j-1})^2+(b_j-b_{j-1})^2)^{1/2}$ of C_j and C_{j-1}. Here, $(r_{j-1}, g_{j-1}, b_{j-1})$ and (r_j, g_j, b_j) are the three color components RGB of C_{j-1} and C_i, respectively, and C_{j-1} and C_i are the colors of the $(j-1)$-th and j-th pixels in I. When this procedure is repeated, finally the values of these k variables $f_1, f_2, \ldots, f_k$ are the CDAEO feature of I in 0° direction. We call the variables $f_1, f_2, \ldots, f_k$ the 0°-CDAEO feature of I.

Similarly, the same approaches can be used to calculate the CDAEO features of I in 45°, 90°, and 135° directions. We respectively call them the 45°, 90° and 135°-CDAEO features of I. Therefore, the CDAEO feature of each image has $4\times k$ dimensions.

When using a tool like a scanner to input an image, the image may be enlarged or compressed, because of different scanner resolution setups. We call this phenomenon the scale variant of images. Let I be an image with $H\times W$ pixels. To solve the problem of scale variant, the paper divides each variable f_i in the 0°-CDAEO feature of I by H, in the 90°-CDAEO feature of I by W and in 90° and 135°-CDAEO features of I by $(W^2+H^2)^{1/2}$. Therefore, the system has great robustness for resisting scale variant.

Generally, an image with great color complexity owns much more objects and the color differences among the objects are large. For example, an image of bright blue sky owns less number of objects and the color variation among the pixels in the image is minor; however an image of colorful scenery holds much more objects and the variation of its pixel colors is greater.

From the steps listed above, to obtain the CDAEO feature of an image, the color difference between each pixel pair P and P' is calculated, where P and P' are the edge pixels of two different objects in the image. Then the color difference is added to a variable f_i, which corresponds to the color of P. The more objects an image has and the greater color differences among the objects, the larger the CDAEO feature values of the image are. Thus, the CDAEO feature can describe the color complexity of an image.

When the values of the CDAEO feature in θ° (for $\theta = 0$, 45, 90, or 135) of an image are greater than those in other directions, most objects in the image are prolate, and the directions of most objects are $(\theta + 90)^\circ$. When the values of the CDAEO features in 0°, 45°, 90°, and 135° directions are close to one another, the shapes of most objects in the image are likely close to circular or square. As a result, the CDAEO feature can state the directions and simple geometric shapes of most objects in an image.

Consider two images I and I'. I is completely the same as I' except for the positions of their objects. We call the variant between I and I' the shift variant of objects. Figure 4 shows the image pairs with the shift variant of objects. This CDAEO feature is highly tolerant to this variant; that is, the shift variant of objects in images will not affect their CDAEO feature. However, the CDAEO feature is sensitive to noise variant and rotation variant in images. In other words, if a particular image has a great amount of noise added, or is rotated in a certain degree, it may be regarded as a different image from the original one by the image retrieval system. As in Figure 5 and Figure 6, there are image pairs with the noise and rotation variants respectively.

This paper also uses the CDAEO feature to develop an image retrieval system. Let $(f_1, f_2, \cdots, f_{4\times k})$ and $(f'_1, f'_2, \cdots, f'_{4\times k})$ respectively represent the CDAEO features of a certain database image D and the query image Q. The image retrieval system defines the image matching distance $Dist$ between Q and D as follows:

$$Dist = \sqrt{\sum_{i=1}^{4\times k}(f_i - f'_i)^2}\ .$$

We name this method the CDAEO method.

4. Experiments

The purposes of the experiments in this section are to investigate the performance of the CDAEO method, and to compare the performance with that of the method proposed by Kou [8]. Suppose $SetD = \{I_1, I_2, \ldots, I_{500}\}$ and $SetQ = \{I'_1, I'_2, \cdots, I'_{500}\}$ are two image sets each of which holds 500 full color images. This paper uses them as the testing images; the images in $SetD$ are the database images, while those in $SetQ$ are the query images. Each image pair I_i and I'_i are two different images randomly chosen from one animation, which is mostly downloaded from the websites http://sco25.mi.com.tw and http://www.mcsh.kh.edu.tw. In addition, some testing images come from the website http://wang.ist.psu.edu/IMAGE.

In these experiments, whenever a certain I'_i is selected as a query image, the image retrieval system returns the user L database images whose matching distances to I'_i are shortest. If I_i is one of these L transmitted images, we say the system correctly finds out the desired image. Otherwise, the system fails to respond to the desired image. In the following experiments, the accuracy rate of querying for a system will be explained with **ACC**. **SPACE** is the memory space required to store the feature values of the 500 database images. **TIME** is the total time that the system needs for executing these 500 queries.

Kuo [8] proposed an image retrieval system that employs the mean, standard deviation, and skewness of the pixel colors in each bin of the color histogram of an image as identifying the features of the image. The first experiment in the section is to test the performance of this image retrieval system. First, the K-means algorithm is used to classify all the pixels of database images to become 27 clusters according to the similarity of their colors, that is, $k = 27$. The averages of the three individual color components R, G, and B of all the pixels in each cluster form the respective color of the cluster. These 27 respective colors are the colors of the common color palette CP for all images (including database images and query images).

Then, all the pixels in each image are classified into 27 clusters, according to the similarity with the colors of CP. Finally, the mean (μ), standard deviation (σ), and skewness (s) of the pixel colors in each cluster are computed and used as the features of the image. Table 1 lists the results of this experiment. In this experiment, the memory space storing the features of these 500 database images is 500 (images) × 27 (clusters) × 3 (RGB) × 3 (μ, σ, s) × 4 **bytes** (a floating point) = 486000 bytes.

Table 2: Results of the second experiment

	ACC (%)	SPACE (bytes)	TIME (sec)
L=1	*91.2*	*216000*	*12.08*
L=2	*93.8*	*216000*	*12.19*
L=3	*94.0*	*216000*	*12.24*
L=4	*94.4*	*216000*	*12.31*
L=5	*95.6*	*216000*	*12.35*
L=10	*97.0*	*216000*	*12.83*
L=20	*98.6*	*216000*	*13.16*
L=30	*98.8*	*216000*	*13.27*
L=40	*99.2*	*216000*	*13.32*

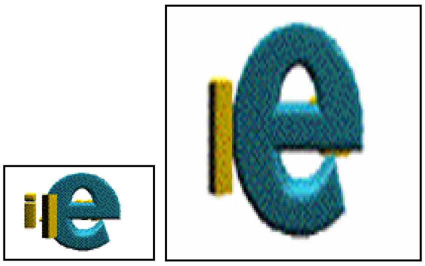
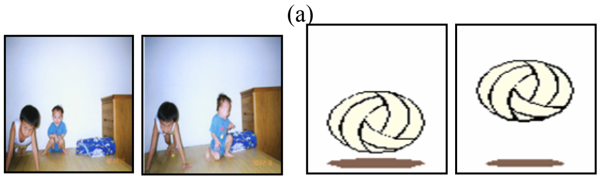


Figure 3: Two scale variant images

The second experiment is to explore the performance of the CDAEO method. This experiment also adapts the 27 colors of CP derived from the previous experiment as the common color palette of all images, and applies these 27 colors to substitute for all pixels' colors of the images. Because each image owns 4×27 CDAEO features, there are 108 feature values for each image. In the experiment, the memory space required to store the features of these 500 database images is 500 (images) × 108 (feature values) × 4 **bytes** (a floating point) = 216000 bytes. Table 2 states the results of the experiment.

(a)



(b) (c)

Figure 4: Three image pairs with shift variants of objects

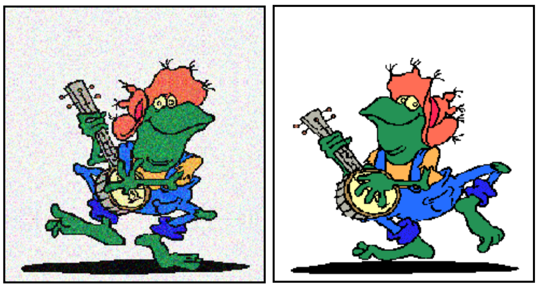
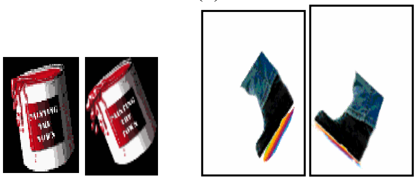


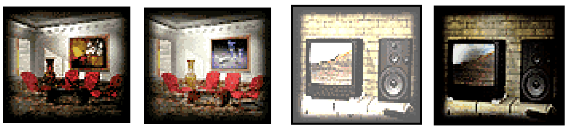
Figure 5: Two images with noise variant

(a)



(b) (c)

Figure 6: Three image pairs with rotation variants of objects

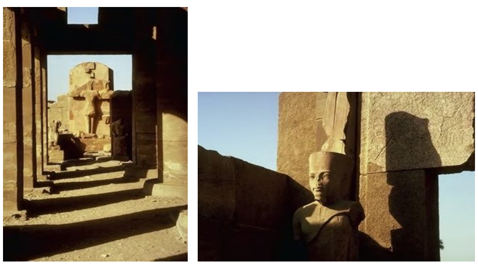


(a) (b)

Figure 7: Two image pairs with lightness variant images

Figure 8: Two images with hue variant

(a)

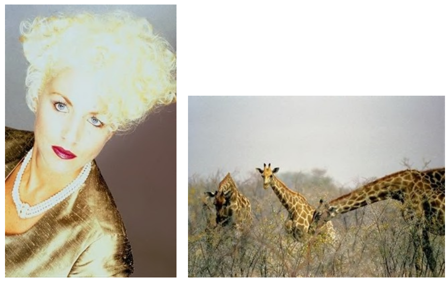


(b)

Figure 9: two image pairs with similar color histograms

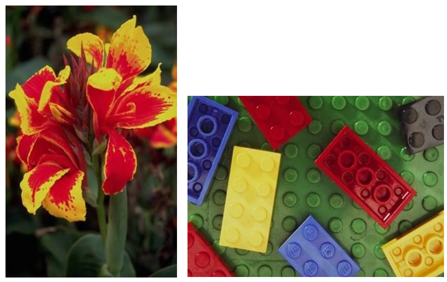
From the results of the experiments above, relative to Kuo's method, the CDAEO method can provide not only a better accuracy rate for querying, but also more effective executing time. The CDAEO method and Kuo's method can resist the scale variant of images and the shift variant of objects in images. Take the image pairs in Figures 3 and 4 for example; they are respectively regarded as the similar images in both methods. Moreover, both methods also consider the image pair with noise variant in Figure 5 to be the similar images.

Kuo's method is indifferent to the rotation variant of objects in images; however, the CDAEO method is only partially tolerant to the rotation variant of images. For example, all the image pairs in Figure 6 are separately viewed as the similar images in the first experiment; nevertheless, only those in Figure 6 (a) and (b) are looked upon as resembling images in the second experiment. Both methods are yet sensitive to the lightness and hue variants of images. They think of the image pairs in Figures 7 and 8 as dissimilar images.

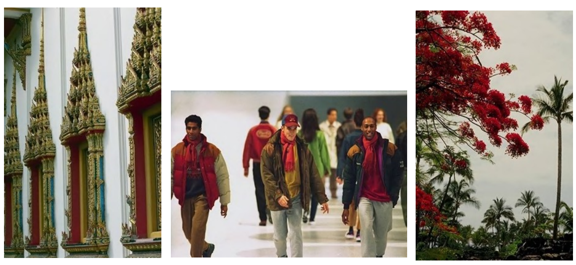


(a)

(b)



(c)



(d)

Figure 10: Some other image groups with similar color

Furthermore, both methods can depict the principal pixel colors of an image. For instance, they consider the image pairs with the same shapes of pixel colors in Figure 9 to be similar images. However, Kuo's method cannot state the distinction of the directions and simple geometric shapes among the objects in the images. The images of each group in Figure 10 have similar color histograms, but differ in shape and direction. These objects are regarded as similar images in the first experiment; however, in the second experiment, the CDAEO method can distinguish them.

5. Conclusions

This paper presents the CDAEO feature. Based on this feature, an image retrieval system is constructed. The feature can state not only the principal pixel colors and color complexity of an image, but also the geometric shapes and directions of most objects in the image. Additionally, this feature is robust in the shift variant of objects and scale variant of the image. It can still partially resist the rotation variant of objects and noise variant in images. However, it is susceptible to hue and lightness variants of images. The experimental results show that the CDAEO method provides a better performance rate in accuracy and executing time for querying than Kuo's method does.

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