Image Retrieval System Based on Color Layout Descriptor and Gabor Filters

Hamid A. Jalab
Department of Computer System and Technology .University Malaya
Kuala Lumpur, Malaysia
hamidjalab@um.edu.my

Abstract— **The current paper presents a content-based image retrieval (CBIR) system using the image features extracted by a color layout descriptor (CLD) and Gabor texture descriptor. CLD represents the spatial distribution of colors with a few nonlinear quantized DCT coefficients of grid-based average colors, whereas the Gabor filter works as a bandpass filter for the local spatial frequency distribution. These two descriptors are very powerful for CBIR systems. Furthermore, combining the color and texture features in CBIR systems leads to more accurate results for image retrieval. To compare the performance of image retrieval method, average precision and recall are computed for all queries. The results showed an improved performance (higher precision and recall values) compared with the performance using other CBIR methods.**

Keywords- Image retrieval; Color Layout Descriptor; Gabor filter; Color-texture; Image database

I. INTRODUCTION

The term content-based image retrieval (CBIR) appears to have been first used in the literature by Kato [1992] to describe his experiments in the automatic retrieval of images from a database by color and shape [1].

The typical CBIR system performs two major tasks. The first one is feature extraction, where a set of features is extracted to describe the content of each image in the database. The second task is the similarity measurement between the query image and each image in the database, using the feature extraction. The feature extraction values for a given image are stored in a descriptor that can be used for retrieving similar images. Image descriptors are descriptions of the visual features of the contents in images that produce such descriptions. They describe elementary characteristics, such as color, texture, shape or motion, among others. The key to a successful retrieval system is choosing the right features to accurately represent the images and the size of the feature vector. The features are either global, for the entire image, or local, for a small group of pixels. According to the methods used in CBIR, features can be classified into low-level and high-level features [2]. Color features are the most widely used low-level features for image retrieval because it is one of the most straightforward features utilized by humans for visual recognition. However, image retrieval using color features often gives disappointing results because, in many cases, images with similar colors do not have similar content. This is because the computed global color features often fail to capture color distributions or textures within the image [3]. Texture is an important feature of natural images. Texture models can be divided into the following classes[4]:

- Statistical methods. This approach explored the gray level spatial dependence of texture;
- Geometric methods;
- Model-based methods (e.g., random field models and fractals);
- Filtering methods. Spatial and Fourier domain filtering, Gabor filtering, and wavelet filtering.

A wide variety of techniques for color and texture combination have been proposed. Few of the techniques used global color and texture features [2, 5, 6], whereas few others used local color and texture features [7, 8, 9]. The latter approach segments the image into regions based on color and texture features. MPEG-7 or, formally, the "Moving Pictures Expert Group Multimedia Content Description Interface," is the first thorough attempt in this direction and will become an international standard of ISO/IEC [8].

CLD is commonly deployed in image retrieval systems. Reference[10] addressed the issue using the MPEG-7 color layout descriptor as a compact image feature description for high-speed image/video segment retrieval. The image retrieval system introduced by [11] is based on a query by layout method using such visual descriptors as edge histogram descriptor and the color layout descriptor in MPEG-7. Reference [12] proposed the efficient use of MPEG-7 color layout and edge histogram descriptors in CBIR Systems.

A variety of techniques have been developed for measuring texture similarity. The Gabor filter (or Gabor wavelet), widely adopted to extract texture features from images for image retrieval, has shown to be very efficient [11]. To date, many proposed retrieval techniques adopt the Gabor wavelet as a useful texture descriptor. The image retrieval system introduced by [13] is based on two texture features, namely, the composite sub-band gradient (CSG) vector and the energy distribution pattern (EDP)-string. Both features are generated from the sub-images of a wavelet decomposition of the original image. Reference[14] proposed a CBIR system using the Gabor texture features to achieve rotation invariance by a circular shift of the feature elements. Reference[15] proposed a query by the example technique and relevance feedback, where a Gabor filter-based image feature extraction is first proposed.

The current paper proposes a method combining both color and texture features to improve retrieval performance. Both the CLD and Gabor texture descriptors are computed from the images, and the images in the database are indexed using both types of features. The retrieval, based on a combination of the CLD and Gabor texture descriptors, will help significantly improve the retrieval performance. The rest of the current paper is organized as follows. Section II discusses the features for image retrieval. Section III provides a quick preliminary overview of both the CLD and Gabor filters. Section IV gives the retrieval results and evaluation. Section V provides the conclusions.

II. FEATURES FOR IMAGE RETRIEVAL

A. Color layout descriptor

A color descriptor is a numeric quantity that describes a color feature of an image. In the current paper, the CLD descriptor was extracted to represent the color content of an entire image. The CLD is a very compact and resolution-invariant representation of color for high-speed image retrieval and was designed to efficiently represent the spatial distribution of colors. This feature can be used in a wide variety of similarity-based retrieval, content filtering, and visualization. The CLD is especially useful for spatial structure-based retrieval applications. The function of the CLD basically is in the image-to-image matching and video clip-to-clip matching. The extraction of the descriptor consists of four stages [8]: image partitioning, dominant color selection, DCT transform, and non-linear quantization of the zigzag scanned DCT coefficients, as illustrated in Figure 1.

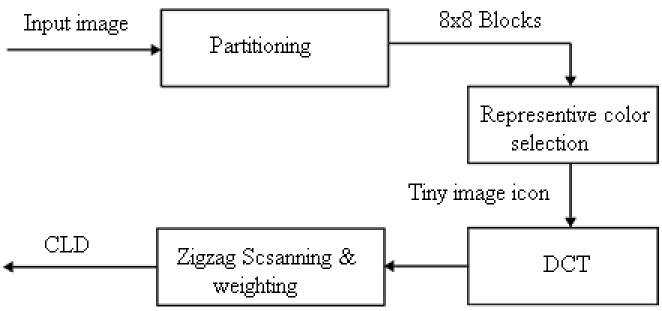

Figure 1. A block diagram of the CLD extraction

The similarity between two CLD measurements of a query image Q and a target image T in the database is calculated as follows [8]:

$$\boldsymbol{D} = \sqrt{\sum_{i\in(Y)}^{m} \boldsymbol{w1}_i(\boldsymbol{Y}_i - \boldsymbol{Y}'_i)^2} + \sqrt{\sum_{i\in(Cb)}^{m} \boldsymbol{w2}_i(\boldsymbol{Cb}_i - \boldsymbol{Cb}'_i)^2} + \sqrt{\sum_{i\in(Cr)}^{m} \boldsymbol{w3}_i(\boldsymbol{Cr}_i - \boldsymbol{Cr}'_i)^2} \quad (1)$$

where Yb, Cb_i, and Cr_i denote the *ith* coefficients of Y, Cb, Cr color component, and $w1_i$, $w2_i$, and $w3_i$ are the weighting values for the *ith* coefficient, respectively. The lower value of D represents the higher similarity among the query image and database images.

B. Gabor filter (wavelet) descriptors

Texture classification is a highly interesting scientific topic. Among the various techniques published for texture classification, Gabor filtering has emerged as one of the leading approaches. Gabor filters are a group of wavelets, with each wavelet capturing energy at a specific frequency and a specific direction. Literature survey, in fact, shows that Gabor filters are implemented in various ways, with different values of filter parameters, resulting in different filter banks. Expanding a signal using this basis provides a localized frequency description, therefore capturing the local-features energy of the signal. Texture features can then be extracted from this group of energy distributions. The scale (frequency) and orientation tunable property of a Gabor filter makes it especially useful for texture analysis. Experimental evidence on human and mammalian vision supports the notion of spatial–frequency (multi-scale) analysis that maximizes the simultaneous localization of energy in both spatial and frequency domains.

After applying the discrete Gabor wavelet to transform G_{mn} the image $I(x, y)$ with the size $P \times Q$, with a different orientation at a different scale, we obtain an array of magnitudes:

$$E(m,n) = \sum_x \sum_y |G_{mn}(x,y)| \quad (2)$$

$$m = 0, 1, \ldots, M-1;\ n = 0, 1, \ldots, N-1$$

These magnitudes represent the energy content at a different scale and orientation of the image. The main purpose of texture-based retrieval is to find images or regions with similar textures. Therefore, the following mean μ_{mn} and standard deviation σ_{mn} of the magnitude of the transformed coefficients are used to represent the similar texture feature of the region:

$$\mu_{mn} = \frac{E(m,n)}{PxQ} \quad (3)$$

$$\sigma_{mn} = \frac{\sqrt{\sum_x \sum_y (|G_{mn}(x,y)| - \mu_{mn})^2}}{PxQ} \quad (4)$$

A feature vector f (texture representation) is created using μ_{mn} and σ_{mn} as the feature components. The choice of filter parameters is an important issue. The outputs organize 15 Gabor channels (3 scales and 5 orientations), which record the magnitudes of the Gabor filter responses. The feature vector is given by:

$$f = (\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01}, \ldots, \mu_{24}, \sigma_{24})$$

The texture similarity measurement of a query image Q and a target image T in the database is defined by [11]:

$$D(Q,T) = \sum_m \sum_n d_{mn}(Q,T) \quad (5)$$

where,

$$d_{mn} = \sqrt{\left(\mu_{mn}^{Q} - \mu_{mn}^{T}\right)^2 + \left(\sigma_{mn}^{Q} - \sigma_{mn}^{T}\right)^2} \quad (6)$$

III. Image Retrieval Using Both Color and Texture Features

This section discusses the image indexing and retrieval using combined CLD and Gabor descriptors, as explained in the previous section. The CLD and Gabor texture descriptors are useful in describing the relationship between colors and textures in an image. The two descriptors can be integrated to establish a color texture-based image retrieval system. Each image in the database is indexed using both CLD and Gabor texture descriptors. This process consists of uploading of the images into the memory and computing both descriptors. The final result is a database of CLDs and Gabor features linked to the images they represent. In the retrieval, images in the database, called target images, are ranked in descending order of similarity to the query image. The ranking of similarity is determined by the distance between the feature vector of the query image and the feature vector of the target image.

IV. Retrieval Results and System Evaluation

Performance tests for the system proposed by this study were implemented in Matlab 2009b on Intel(R)Core (TM)2 Duo CPU E6550 at 2.33GHz, 3GB RAM, system type 32-bit, Windows 7 Operating System. The proposed CBIR method is tested using an image database [16] with 1,000 images spread across 10 classes containing 100 images each; images in the same class are considered similar images. Figure 2 illustrates some of these images. Images in the same row belong to the same class. The class name is shown in Table 1.

TABLE I. THE CLASSES OF IMAGE DATABASE

Class number	Class Name
1	Tribe
2	Beach
3	Buildings
4	Buses
5	Dinosaurs
6	Elephants
7	Roses
8	Horses
9	Mountains
10	Food

We used 80 out of 1,000 images to test the performance of the proposed method. Eight images were chosen randomly from each class as the query image. Hence, a total of 80 query images were used. The images were resized to 256 × 256 × 3 before the feature extraction. To evaluate the retrieval performance, the common evaluation method, that is, a precision–recall pair, was used. Precision, P, is defined as the ratio of the number of relevant images retrieved A to the total number of images retrieved B. Precision P measures the accuracy of the retrieval. Recall R is defined as the ratio of the number of relevant images retrieved, A, to the total number of relevant images, C, in the database. Thus, Recall, R, measures the ability of the system to retrieve relevant information from all collected images. They may be computed according to the following equation,

$$\text{Precision}=A/B, \text{Recall}=A/C \quad (7)$$

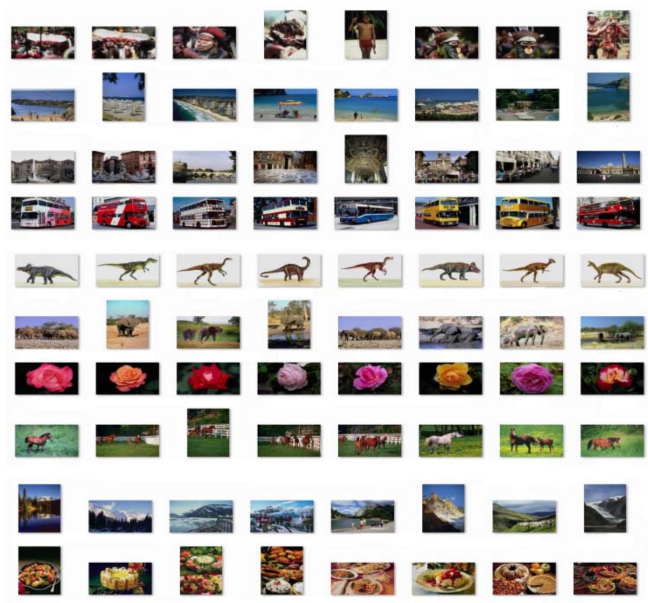

Figure 2. Images from the database

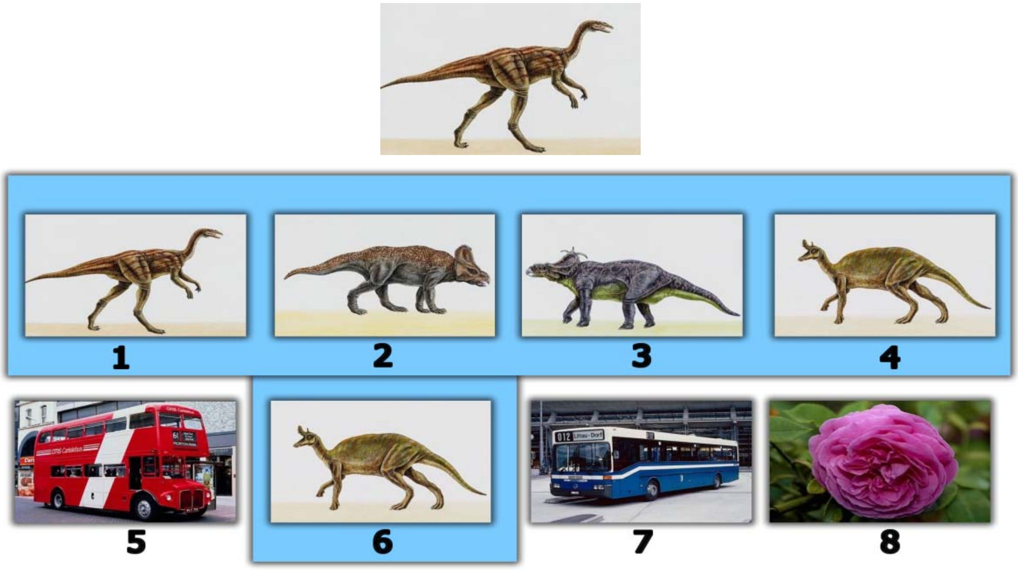

Figure 3. First eight retrieved images for the given Query Image

TABLE II. COMPARISON OF AVERAGE PRECISION

Class Name	J. Pujari and P. Hiremath [7] (%)	A. Hafiane and B. Zavidovique [17] (%)	Proposed Method (%)
Tribe	54	44.1	32.3
Beach	38	30.6	61.2
Buildings	40	38.2	39.2
Buses	64	67.6	39.5
Dinosaurs	96	97.2	99.6
Elephants	62	33.8	55.7
Roses	68	88.8	89.3
Horses	75	63.2	65.2
Mountains	45	31.3	56.8
Food	53	34.9	44.1

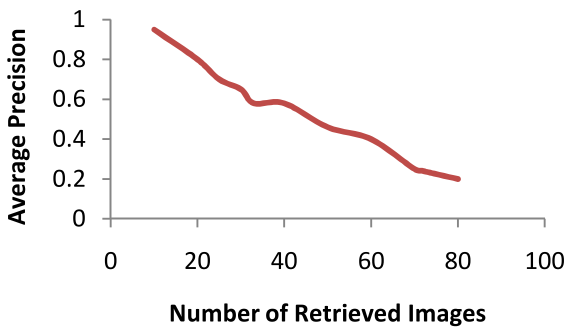

Figure 4. Average Final Precision Chart

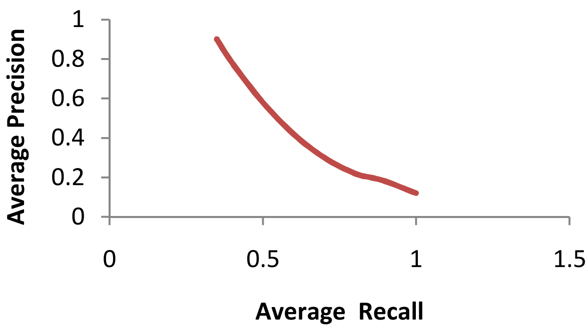

Figure 5. Average Precision vs. Average Recall

where, A is a set of relevant images retrieved by the system, B is a set of relevant and irrelevant images retrieved by the system for a particular query, and C is a set of all relevant images in collection for a particular query, taking into account that $A - |B \cap C|$. For each query, every image in the database set may be used as an example to retrieve a similar image (images in the same class are considered similar). The precision of the retrieval at each level of the recall is obtained. Figure 3 shows the results of the first 8 retrieved images for a sample query image in the proposed method, where the retrieved images are ranked by their Euclidean distances to their respective query image from left to right. The best, in terms of our goal, are the images in the blue boundary. The CBIR system provides satisfactory results, extracting quite relevant images from the same class. The average final precision chart of the CBIR method acts as one of the important parameters to judge its performance. Average precision is plotted against a number of retrieved images for each query, as shown in Figure 4. The y-axis represents the average precision; the x-axis shows the number of retrieved images for each query image. For all 80 query images, the average precision and recall are computed. The average of all precision is taken and plotted against the number of retrieved images, as shown in Figure 5. The average precision–recall values for this experiment are 56.15%–56.25%, respectively. A comparison of the experimental results with that of other standard retrieval systems [7, 17] is presented in Table II. The proposed method clearly gives a higher average precision in various images than the other two methods did.

V. CONCLUSIONS

In the current paper, a CBIR system based on CLD and Gabor texture descriptors was used to retrieve desired images from their databases. The images showed different visual contents, including color, shape, and texture. Among them, the color–texture characterization of an image is probably the most useful features to be approximated. Two image descriptors, namely, CLD and the Gabor texture, were presented to characterize both color and image texture for the image retrieval. CLD can describe the color features of the pixels, whereas the Gabor texture can effectively describe the texture distribution of similar colors in an image. These two descriptors can describe the different properties of an image; hence, they are further integrated to develop the CBIR system.
In our experiments, the proposed system exhibited better retrieval precision than the two previously conceived methods, regardless of whether they were gray texture images, color texture images or color natural images. Through a combination of these colors, texture descriptors provide a robust feature set for image retrieval. The experiments using the “wang.ist.psu” dataset demonstrate the efficacy of this method in comparison with the existing methods.

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