Color and Texture Features for Content Based Image Retrieval

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Abstract

Content based image retrieval (CBIR) has been one of the most important research areas in computer science for the last decade. A retrieval method which combines color and texture feature is proposed in this paper. According to the characteristic of the image texture, we can represent the information of texture by Multi Wavelet transform. We choose the color correlogram in RGB color space as the color feature. The experimental results show that this method is more efficient than the traditional CBIR method based on the single visual feature and other methods combining color and texture.

1. Introduction

Application of World Wide Web (www) and the internet is increasing exponentially, and with it the amount of digital image data accessible to the users. A huge amount of Image databases are added every minute and so is the need for effective and efficient image retrieval systems. There are many features of content-based image retrieval but four of them are considered to be the main features. They are color, texture, shape, and spatial properties. Spatial properties, however, are implicitly taken into account so the main features to investigate are color, texture and shape. Though there are many techniques of search this paper will focus on color and texture features for CBIR. The main motivation of the present work is to use the Multi Wavelet decomposition scheme and color correlogram, which yield improved retrieval performance. Through combination of Multi wavelet decomposition and color correlogram we can increase the number of features, which in turn improves the retrieval accuracy. To support the efficient and fast retrieval of similar images from image databases feature extraction plays an important role in content-based image retrieval. A fundamental ingredient for content based image retrieval is the technique used for comparing images.

2. Color

Color feature is one of the most widely used features in low level feature [6]. Compared with shape feature and texture feature, color feature shows better stability and is more insensitive to the rotation and zoom of image. Color not only adds beauty to objects but also more information [1], which is used as powerful tool in content-based image retrieval. In color indexing, given a query image, the goal is to retrieve all the images whose color and texture compositions are similar to those of query image. In color image retrieval there are various methods, but here we will discuss some prominent methods.

Typical characterization of color composition is done by color histograms [7]. In 1991 Swain and Ballard [2] proposed the method, called color indexing, which identifies the object using color histogram indexing. Color histograms are way to represent the distribution of colors in images where each histogram bin represents a color in a suitable color space (RGB etc) [3]. A distance between query image histogram and a data image histogram can be used to define similarity match between the two distributions. To overcome problem with histogram in 1995 Mehtre et al [4] proposed two new color- matching methods as “Distance Method” and “Reference Color Table Method”, for image retrieval. They used a coarse comparison of the color histograms of the query and model images in the Distance method they proposed.

Most color histograms are very sparse and thus sensitive to noise. In 1995 Stricker and Orengo [5] proposed cumulated color histogram. Their results are better than color histogram approach. Observing the fact that the color histograms lack information about how color is spatially distributed, in 1997 Rui and Huang [6], introduced a new color feature for image retrieval.
retrieval called color correlogram. This feature characterized how the spatial correlation of pairs of color changes with distance in an image. Usually, because the size of color correlogram is quite large, the color auto correlogram is often used instead. This feature only captures spatial correlation between identical colors. The main contributions of this paper are as follows. Here we have proposed a Multiwavelet-based approach used for texture feature extraction and color correlograms are used for color feature extraction for CBIR. These color and texture features are combined to improve the retrieval efficiency.

3. Multi Wavelet Transform

Multiwavelets were defined using several wavelets with several scaling functions [10]. Multiwavelets have several advantages in comparison with scalar wavelet [8]. The features such as compact support, Orthogonality, symmetry, and high order approximation are the base features for this transform. A scalar wavelet cannot possess all these properties at the same time. On the other hand, a Multiwavelet system can simultaneously provide perfect representation while preserving length (Orthogonality), good performance at the boundaries (via linear-phase symmetry), and a high order of approximation (vanishing moments) [9]. Thus Multiwavelets offer the possibility of superior performance and high degree of freedom for image processing applications, compared with scalar wavelets. The study of Multiwavelets was initiated by Goodman, Lee and Tang. The special case of Multiwavelets with multiplicity 2 and support (0, 2), was studied by Chui and Lian. When a multi resolution analysis is generated using multiple scaling functions and wavelet functions, it gives rise to the notion of Multiwavelets [10]. A Multiwavelet with ‘r’ scaling functions and ‘r’ wavelet functions is said to have multiplicity ‘r’. When r = 1, with one scaling function and one wavelet function, the Multiwavelet system reduces to scalar wavelet system. In Multiwavelet transforms they have two or more scaling functions and wavelet functions. The set of scaling functions are represented using the vector notation

\[ \phi(t) = [\phi_1(t) \phi_2(t) \ldots \phi_r(t)]^T \]  

Where \( \Omega(t) \) is called the multi-scaling function. The Multiwavelet function is defined from the set of wavelet function

\[ \psi(t) = [\psi_1(t) \psi_2(t) \ldots \psi_r(t)]^T \]  

When \( r = 1 \), \( \psi(t) \) is called a scalar wavelet or simply wavelets. Multiwavelets differ from scalar wavelet systems in requiring two or more input streams to the Multiwavelet filter bank. Multiwavelets are an extension of the scalar wavelet to the vector case. As in the scalar wavelet case, the theory of Multiwavelets is based on the idea of multi resolution analysis (MRA). The difference is that Multiwavelets have several scaling functions. The multi scaling function and the Multiwavelet function will satisfy matrix dilation equations,

\[ \phi(t) = \sqrt{2} \sum_{k=-\infty}^{\infty} H_k \phi(2t - k) \]  

\[ \psi(t) = \sqrt{2} \sum_{k=-\infty}^{\infty} G_k \phi(2t - k) \]  

The filter coefficients \( H_k \) and \( G_k \) are N by N matrices instead of scalar. Corresponding to each Multiwavelet system, there is a matrix-valued with multi-rate filter bank. A Multiwavelet filter bank has “taps” that are N × N matrices. One desirable feature of any transform used in image retrieval is the amount of energy compaction achieved. A filter with good energy compaction Properties can decorrelate a fairly uniform input signal into a small number of scaling coefficients containing most of the energy and a large number of sparse wavelet coefficients. Therefore better performance is obtained when the wavelet coefficients have values clustered about zero with little variance. Thus Multiwavelets have the potential to offer better representative quality than the conventional scalar transforms. Finally, Multiwavelets can achieve better level of performance than scalar wavelets with similar computational complexity. Wavelets are useful tools for image processing applications such as image retrieval and denoising.

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| H1L1 | H1L2 | H1H1 | H1H2 |
| H2L1 | H2L2 | H2H1 | H2H2 |

Figure1. Image decomposition after a single level decomposing for (a) Scalar wavelets and (b) Multi-wavelets.
Figure 2. Conventional iteration of Multiwavelet decomposition.

During a single level of decomposition using a scalar wavelet transform, the 2-D image data is replaced by four blocks corresponding to the sub bands representing either low pass or high pass in both dimensions. These sub bands are illustrated in Figure 1. The Multi-wavelets used here have two channels, so there will be two sets of scaling coefficients and two sets of wavelet coefficients. Since multiple iteration over the low pass data is desired, the scaling coefficients for the two channels are stored together. Likewise, the wavelet coefficients for the two channels are also stored together. The Multi-wavelet decomposition sub bands are shown in Figure 2. For Multi-wavelets the L and H have subscripts denoting the channel to which the data corresponds. For example, the sub band labeled L1H2 corresponds to data from the second channel high pass filter in the horizontal direction and the first channel low pass filter in the vertical direction. This shows how a single level of decomposition is done. In practice, there is more than one decomposition performed on the image. Successive iterations are performed on the low pass coefficients from the previous stage to further reduce the number of low pass coefficients. Since the low pass coefficients contain most of the original image energy, this iteration process yields better energy compaction. After a certain number of iterations, the benefits gained in energy compaction becomes rather negligible compared to the extra computational effort. Usually five levels of decomposition are used.

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4. Proposed Algorithm

The basic steps involved in the proposed CBIR system includes database processing and resizing, creation and normalization of feature database, comparison and image retrieval. Steps of the proposed algorithm are as follows.

A. Texture feature extraction:

1. Convert all data base images into gray images.
2. Decompose each image in the Multi wavelet domain.
3. Compute the standard deviation $\sigma_k$ on each sub band of the Multi Wavelet decomposed image.
4. The resulting SD vector is $\vec{f} = [\sigma_1, \sigma_2, \sigma_3, \ldots, \sigma_n]$

B. Color feature extraction:

1. Load the image.
2. Separate the R, G, and B spaces from the image.
3. Quantize the each color space into 32 levels.
4. Apply the correlogram in 0°, 45°, 90°, and 135° on each color space.
5. Construct the feature vector by using correlogram.

C. Combined feature

Form the combined feature vector by concatenating the color feature and texture feature.

D. Apply query image and calculate the combined feature vector as given in steps A to B.

E. Calculate the similarity using Euclidean distance.

$$D_{q_i} = \sqrt{(f_q - f_i)^2}$$

F. Retrieve all relevant images to query image based on minimum “Euclidean distance”.

5. Experimental Results

Comparison of average retrieval accuracy for 640 different colored textures using correlogram and Multi Wavelet transform is provided. When Tile 10.bmp is given as query and retrieved using three different methods of retrieval used, in this paper following results were obtained. The results obtained by both the
texture features and color features consideration the retrieval efficiency is 82% that is fourteen images retrieved from the database are of same texture and color contents. Red, Green and blue curves in figure 1 indicates the average retrieval efficiency using only color, only texture and color and texture combined respectively.

The MIT VisTex database used in our experiment consists of 40 different textures [11]. The size of each texture is 512x512. Each 512x512 image is divided into sixteen 128x128 non-overlapping sub-images, thus creating a database of 640 (40x16) images. The performance of the proposed method is measured in terms of average retrieval rate (ARR) is given by Eq. (5).

\[ ARR = \frac{1}{|DB|} \sum_{i=1}^{16} R(I_i, n) \]  

6. Conclusions
After the absolute analysis of the results obtained by each method following conclusions can be drawn. When only color is considered as retrieval parameter in CBIR gives only 62.5% of average retrieval efficiency. Similarly when only texture features are considered as retrieval parameter there is not much improvement in the retrieval efficiency. The average retrieval efficiency obtained by this method is only 68.75%. This shows that only texture features or only color features are not sufficient to describe an image. But there is considerable increase in retrieval efficiency when both color and texture features are combined for CBIR. The average percent retrieval efficiency has increased up to 75%. Thus it is rightly said in [1] that only color or only texture cannot differentiate a cheetah and a tiger.

7. References

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