Content Based Image Retrieval using Spectral Feature Extraction Methods

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Abstract

Content-based image retrieval (CBIR) is a technique which uses visual content to search and compare images from large scale image databases according to the interests of users. Visual content of the image like color, shape, texture and spatial layout are widely used in CBIR. Texture features has been successfully used to provide a meaningful tool for searching image databases, as texture images generally contain unique visual patterns or spatial arrangements of pixels, so that describing textures, gray- level or color alone, may not yield to classify similar ones. In this paper we mainly concentrate on Spectral methods which extract texture features from the energy distribution in the frequency domain. The most popular spectral feature extraction methods are Fourier, wavelet, and Gabor filtering. In the first process it will extract the features from query and database images to a distinguishable extent using Gabor and wavelet Transforms. In the second process it involves matching these features to yield a result that is visually similar by feature matching process.

Keywords: *CBIR, Texture, Feature extraction, Gabor transform, Wavelet transform*

I. INTRODUCTION

Every day, many computer-based applications and equipment generate Terabytes of digital images. A huge amount of information exists in arts, medicine, military and many other fields. This huge amount of image data must be well organized to allow rapid and efficient browsing, searching and retrieval. Researchers are studying image retrieval from two different angles, one being text-based and the other visual based. Text-based methods use keywords and annotations, while visual-based methods use the visual contents of the image like color, shape, texture and spatial layout. This work is primarily focused on texture descriptors for CBIR systems.

Most of the real life images contain various types of textures, which are very complex due to the changes in scale, orientation, shape, contrast, etc. Due to such complexities, a clear-cut, widely accepted definition of texture does not exist. However, texture is one of the most important visual properties of an image.

In recent years, textural information has been widely used as a visual primitive in many CBIR systems [3]. The potential areas include industrial and biomedical surface inspection, ground classification and segmentation of satellite or aerial imagery, document analysis, scene analysis, texture synthesis for computer graphics and animation, biometric person authentication, content-based image retrieval and image coding [4].

The basic idea behind CBIR is when building an image database, feature vectors from images are extracted and storing the vectors in another database for future use. For the given a query image its feature vectors are computed. If the distance between feature vectors of the query image and images in the database is small enough, the corresponding image in the database is to be considered as a match to the query.

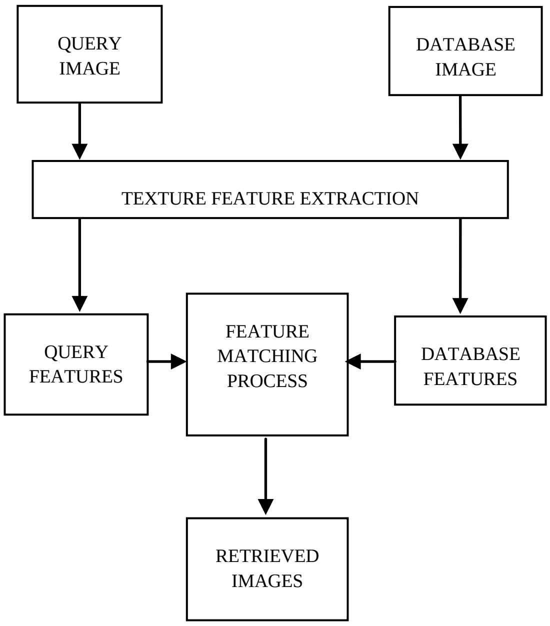

Figure1: Block Diagram of CBIR System

The search is usually based on similarity rather than on exact match and the retrieval results are then ranked accordingly to a similarity index. The block diagram of basic CBIR system is shown inFigure1.

II. LETRETURE REVIEW

In the first generation, text annotations are used to retrieve the image accordingly [2], to overcome the difficulties encountered by a text-based image retrieval system, content-based image retrieval was proposed in the early 1990s

The following systems are all leaders in the field of CBIR: QBIC from IBM (1993) has been cited as a primary reference by most of CBIR systems [1], visualSEEK (1996) and Netra (1997). Comprehensive surveys of these systems and their adopted techniques can be found in [1]. All the works mentioned above provide the main concepts upon which we built our system, especially the color and texture descriptors.

A number of previous works have been done addressing different feature extraction techniques of the image elements for image retrieval. In 2008, Wan Siti Halimatul MunirahWan Ahmad and Mohammad Faizal Ahmad Fauzi [5] have proposed feature extraction techniques in CBIR using CT Brain image (gray scale image). Weszka et. Al. in [6] compares the texture classification performance of first-order statistical features, second-order statistical features and Fourier power spectrum features. They reported that Fourier features have the worst performance, whereas the others are comparable. Ma and Manjunath in [7] compare various wavelet transform features.

III. PROPOSED DESIGN

A. *Texture Feature Extraction Methods*

The purpose of feature extraction is to represent any image using a sufficient number of values containing as much information as possible. Local descriptors of texture visual features were proposed to constitute the image signature. In order to build the signatures database, feature extraction is applied once in an initial phase to the images stored in the system database. Feature extraction is also applied to the query image for similarity retrieval.

1) Gabor Transform

The 2D Gabor filter acts as a local bandpass filter ,an image is filtered with set of Gabor filters preferred orientations and spatial frequencies that covers appropriately the spatial frequency domain and the feature obtained by feature vector field that is further used by feature matching process. Gabor is a technique that extracts information from an image. It’s a multi-scale, multi-resolution filter. The two-dimensional Gabor filter has following general form in the spatial domain.

$$G(x, y, f, \theta)\exp\left\{\frac{-1}{2}\left[\frac{x'^2}{\delta_{x'}^2}+\frac{y'^2}{\delta_{x'}^2}\right]\right\}\cos(2\pi f x^2) \quad (1)$$

$$x' = x\sin\theta + y\cos\theta \quad (2)$$

$$y' = x\sin\theta - y\cos\theta \quad (3)$$

Where f is the frequency of the sine plane wave along the direction θ (0, 45, 90 and 135 degrees) from the x-axis, δx' and δy' are the space constants of the Gaussian envelope along X’ and Y’ axes, respectively.

The Gabor function for the specified values of the parameters "wavelength", "orientation", "phase offset", "aspect ratio", and "bandwidth" are λ,θ,φ,ϒ,b respectively

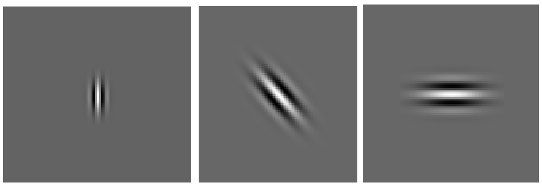

Figure2.Gabor Filter with angle 0, 45, 90 Degree

The fig2 shows images of Gabor filter kernels with values of the orientation parameter of 0, 45 and 90, from left to right, respectively. The values of the other parameters are as follows: wavelength 10, phase offset 0, aspect ratio 0.5, and bandwidth 1.

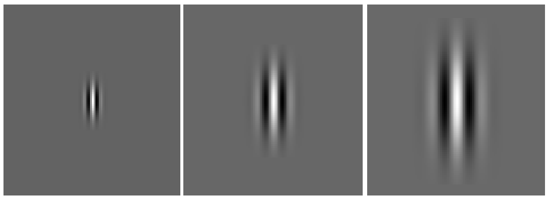

Figure3.Gabor Filter with Wavelength 5, 10, 15 resp.

The fig3 shows images of Gabor filter kernels with values of the wavelength parameter of 5, 10 and 15, from left to right, respectively. The values of the other parameters are as follows: orientation 0, phase offset 0, aspect ratio 0.5, and bandwidth 1.

The λ is wavelength of the cosine factor of the Gabor filter kernel and herewith the preferred wavelength of this filter. Its value is specified in pixels. Valid values are real numbers equal to or greater than 2. The value λ=2 should not be used in combination with phase offset φ=-90 or φ=90 because in these cases the Gabor function is sampled in its zero crossings. In order to prevent the occurence of undesired effects at the image borders, the wavelength value should be smaller than one fifth of the input image size.

2) Wavelet Transform

Wavelet is the multi-resolution analysis of an image and also it is proved that having the signal of both space and frequency domain [7]. An image can be taken as a kind of two dimension signal; the wavelet coefficient can describe the image high frequency information and then can be taken as the image texture feature. Textures can be modeled as quasiperiodic patterns with spatial/frequency representation. For texture extraction, Wavelet decomposition of image regions is used. By applying Wavelet on the color image four sub images will be produced which is: A low resolution copy of original image, and three-band passed filters in specific directions: horizontal, vertical and diagonal respectively. These sub images contain information about texture characteristics. To have a numerical measure of texture, mean and variations of these images will be calculated.

The simplest orthogonal filter bank is Haar filter bank [7]. It applies two channel filter banks namely, from (4) low pass filter and from (5) high pass filter. The low pass filter identifies the structure of the image (i.e.) edges, curves etc.

$$h_0[n] = \begin{cases} \frac{1}{\sqrt{2}}, & n = 0, -1 \\ 0, & otherwise \end{cases} \quad (4)$$

The high pass filter identifies the texture of the image.

$$h_1[n] = \begin{cases} \frac{1}{\sqrt{2}}, n = 0 \\ \frac{-1}{\sqrt{2}}, n = -1 \\ 0 \; otherwise \end{cases} \quad (5)$$

2 X 2 Haar transformation matrix is defined by

$$H_2 = \frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \quad (6)$$

The discrete wavelet transform is a hierarchical subband. The subbands are created by applying decomposition on original image. To start the decomposition, the image is filtered in both the horizontal and vertical directions using separable filters [7]. This creates four subbands as follows: Subband LL1 represents the horizontal and vertical low frequency components of the image. Subband HH1 represents the horizontal and vertical high frequency components of the image. Subband LH1 represents the horizontal low and vertical high frequency components. Subband HL1 represents the horizontal high and vertical low frequency components.

B. *Feature Matching Process*

The main goal of the similarity retrieval phase is to retrieve from the system image database the most similar images to the query image. The retrieved images will not necessarily be identical to the query image. In our system Euclidean distance is used because of its simplicity.

The smaller the distance, the more similar the image is. The Euclidean distance D between two points T=(t1, t2,…tn) and Q=(q1, q2,…qn) is given by (7).

$$D=\sqrt{\sum(T-Q)^2} \quad (7)$$

During the search the Euclidean distance [1] between the query image and the database images is computed.

IV. RESULTS AND DISCUTION

The experiments are conducted using Matlab 7.0 on an Intel Pentium-D 2.0GHz processor with 2GB memory. In this experiment 250 images, representing 5 different objects like group of animals, flowers, buildings etc taken in various views are used.

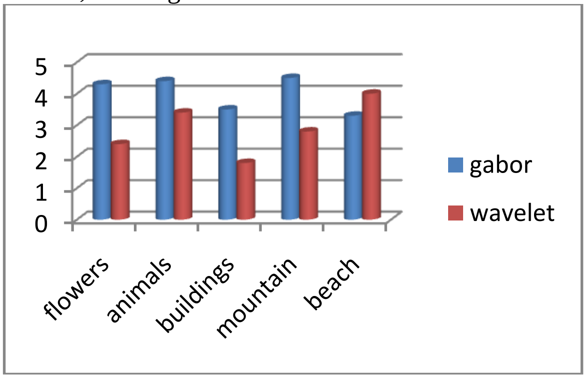

Figure4. Average Precision for each Category

From the quantitative measures the Gabor Transform gives the best result with more execution time, compared it with other technique. From the equation 10, the comparative chart of quantitative measure based upon sensitivity is shown in Figure3.

Wavelet transform retrieve the image at very fast compared it with other techniques; but gives the poor performance, Gabor transform takes much time but gives the best results.

Figure 5 shows an example of retrieval results obtained by Gabor Transform. Figure 6 shows an example of Retrieval of images using Wavelet Transform.

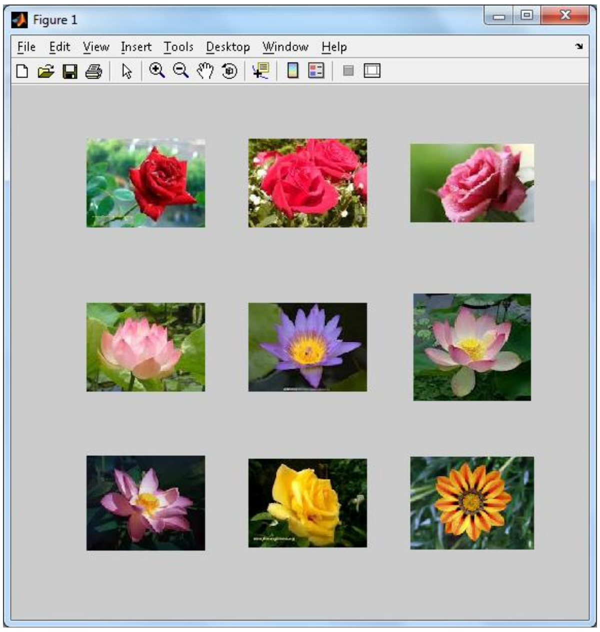

Figure5. Example of Retrieval of Image using Gabor Transforms

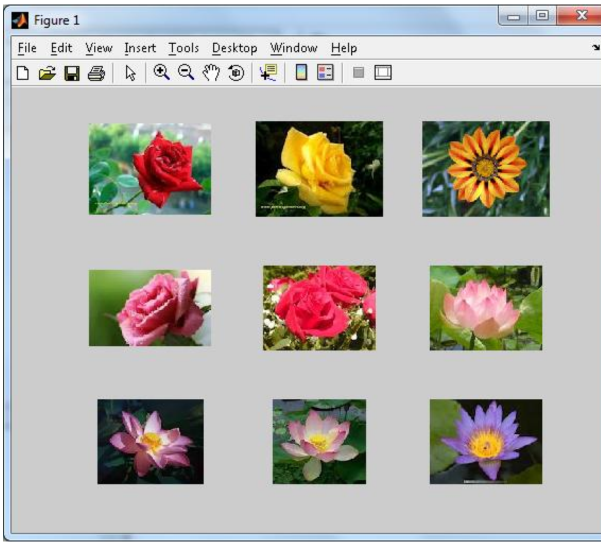

Figure6. Example of Retrieval of Image using Wavelet Transforms

V. CONCLUSION

A simple and efficient CBIR system is presented in this paper. A novel approach is introduced for feature extraction. This approach is based on local descriptors of the color and texture features. The use of Gabor filter is more effective than wavelet transform. The main advantage of this method is its simplicity.

For future work, applying the system in a general purpose image search engine will be considered different assignments of weights of color and texture features will be explored for different image categories/properties. Moreover, extra experiments will be conducted on larger databases for comparison with similar systems to identify and quantify the strengths and weakness of the proposed techniques.

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