

Content Based Image Retrieval Using Visual Content

Shital A Patil¹, Manoj E Patil²

¹ME Scholar, TCT, RGTU, shital_a_patil2004@yahoo.co.in ,Bhopal (M.P) India;

²Department of CSE, TCT, RGTU, mepatij@gmail.com, Bhopal (M.P) India;

Abstract – Content based image retrieval (CBIR) is a technique, which uses the visual content to search the images from large-scale image database as per user's interest. The visual contents are color, shape, texture and spatial location. A image retrieval algorithm based on texture and color features was proposed. Color extraction and comparison are performed using Conventional color histograms (CCH) and the Quadratic Distance and texture extraction and comparison are performed using the concept of Wavelet Transform Model and the Euclidean distance. Experimental results show that the proposed algorithm has reasonable and robust performance and is more effective.

Keywords: Content based image retrieval (CBIR), Feature extraction

I. Introduction

Content based image retrieval (CBIR) [1][2], is a technique, which uses the visual content to search the images from large-scale image database as per user's interest. The visual contents are color, shape, texture and spatial location.

Mainly the CBIR system is required to effectively and efficiently use information from repositories [1][3] Such a system helps users (even those unfamiliar with the database) to retrieve relevant images on their contents.

In CBIR each image that is stored in the database and its features are extracted and compared to the features of the query image. It involves two steps.

I.1. Feature Extraction

The first step in this process is to extract the image features to a distinguishable extent.

I.2. Matching

The second step involves matching these features to obtain result.

II. CBIR System

II.1. Block Diagram

Basic idea behind CBIR is that, when building an image database, feature vectors from images (the features can be color, shape, texture, region or spatial features, features in some compressed domain, etc.) are to be extracted and then store the vectors in another database for future use. When given a query image its feature vectors are computed. If the distance between feature vectors of the query image and image in the database is small enough, the corresponding image in the database is to be considered as a match to the query. The search is usually based on similarity rather than on

exact match and the retrieval results are then ranked accordingly to a similarity index.[4]

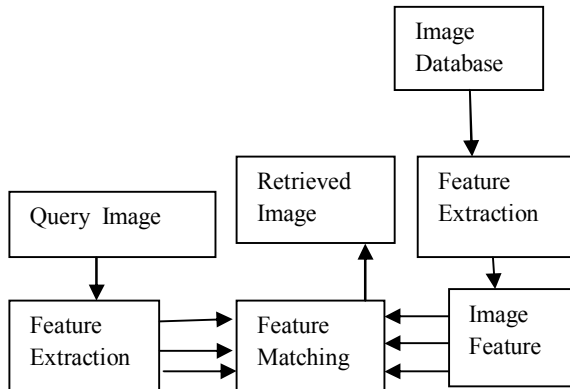


Fig.1. Block Diagram of CBIR

II.2. Visual Content of Image (Features of Images)

There are three types of primitive features:

- Color
- Texture
- Shape

II.2.1 Colour

Colour is a property that depends on the reflection of light to the eye and the processing of that information in the brain. Usually colours are defined in three dimensional colour spaces. These could either be **RGB** (Red, Green, and Blue), **HSV** (Hue, Saturation, and Value) or **HSB** (Hue, Saturation, and Brightness). The last two are dependent on the human perception of hue, saturation, and brightness.

Most image formats such as **JPEG**, **BMP**, **GIF**, use the RGB colour space to store information. The RGB colour space is defined as a unit cube with red, green, and blue axes. Thus, a vector with three co-ordinates represents the colour in this space. When all three coordinates are set to zero the colour perceived is black. When all three coordinates are set to 1 the colour perceived is white..

The main method of representing colour information of images in CBIR systems is through colour histograms. A colour histogram is a type of bar graph, where each bar represents a particular colour of the colour space being used. The bars in a colour histogram are referred to as bins and they represent the x-axis. The number of bins depends on the number of colours there are in an image. The y-axis denotes the number of pixels there are in each bin. In other words how many pixels in an image are of a particular colour.

The colour map of each row represents the colour of a bin. The row is composed of the three coordinates of the colour space. The first coordinate represents hue, the second saturation, and the third, value, thereby giving HSV. The percentages of each of these coordinates are what make up the colour of a bin. Also one can see the corresponding pixel numbers for each bin, which are denoted by the blue lines in the histogram. Quantization in terms of colour histograms refers to the process of reducing the number of bins by taking colours that are very similar to each other and putting them in the same bin.

There are two types of colour histograms,

- Global colour histograms (**GCHs**)
- Local colour histograms (**LCHs**)
-

A GCH represents one whole image with a single colour histogram. An LCH divides an image into fixed blocks and takes the colour histogram of each of those blocks . LCHs contain more information about an image but are computationally expensive when comparing images.[5]

II.2.2 Texture

Texture is that property of all surfaces that describes visual patterns, each having properties of homogeneity. It contains important information about the structural arrangement of the surface, such as; clouds, leaves, bricks, fabric, etc. It also describes the relationship of the surface to the surrounding environment. In short, it is a feature that describes the distinctive physical composition of a surface.

There are three principal approaches used to describe texture; statistical, structural and spectral.

- Statistical techniques characterize textures using the statistical properties of the grey levels of the points/pixels comprising a surface image. Typically, these properties are

computed using: the grey level co-occurrence matrix of the surface, or the wavelet transformation of the surface.

- Structural techniques characterize textures as being composed of simple primitive structures called “texels” (or texture elements).
- Spectral techniques are based on properties of the Fourier spectrum and describe global periodicity of the grey levels of a surface by identifying high-energy peaks in the Fourier spectrum

Textures can be modeled as quasi-periodic patterns with spatial/frequency representation. The wavelet transform transforms the image into a multi-scale representation with both spatial and frequency characteristics.

In a sense, a wavelet is a waveform that is bounded in both frequency and duration. While the Fourier transform converts a signal into a continuous series of sine waves, each of which is of constant frequency and amplitude and of infinite duration, most real-world signals (such as music or images) have a finite duration and abrupt changes in frequency. This accounts for the efficiency of wavelet transforms. This is because wavelet transforms convert a signal into a series of wavelets, which can be stored more efficiently due to finite time, and can be constructed with rough edges, thereby better approximating real-world signals.

II.2.3 Shape

Shape may be defined as the characteristic surface configuration of an object; an outline or contour. It permits an object to be distinguished from its surroundings by its outline. Shape representations can be generally divided into two categories:

- Boundary-based, and
- Region-based.

III. Proposed CBIR System

We are developing a project in matlab for implementing CBIR using color and texture feature

III.1 Colour

III.1.1 Quadratic Distance Metric

The equation we used in deriving the distance between two colour histograms is the quadratic distance metric:

$$d^2(Q, I) = (H_Q - H_I)^t A (H_Q - H_I) \quad (1)$$

The equation consists of three terms. The derivation of each of these terms will be explained in the following sections. The first term consists of the difference between two colour histograms; or more precisely the difference in the number of pixels in each bin. This term is obviously a vector since it consists of one row. The number of columns in this vector is the number of bins in a histogram. The third term is the transpose of that vector. The middle term is the similarity matrix. The final result **d** represents the colour distance between two images. The closer the distance is to zero the closer the images are in colour similarity.

III.1.2. Histograms

We used Global colour histograms in extracting the colour features of images. By default the number of bins represented in an image's colour histogram using the **imhist()** function in MatLab is 256. Meaning that in our calculations of similarity matrix and histogram difference, the processing would be computationally expensive. Initially we decided to quantize the number of bins to 20.

QBIC's similarity matrix equation was using the **HSV** colour space in its calculation.

III.1.3. Similarity Matrix

Consider the colour histograms of two images **Q** and **I**, the.

A simple distance metric involving the subtraction of the number of pixels in the 1st bin of one histogram from the 1st bin of another histogram and so on is not adequate. This metric is referred to as a *Minkowski-Form Distance Metric*, shown below, which only compares the “same bins between colour histograms.

III.2. Texture

III.2.1. Pyramid-Structured Wavelet Transform

It is mostly significant for textures with dominant frequency channels. Using the pyramid-structured wavelet transform, the texture image is decomposed into four sub images, in low-low, low-high, high-low and high-high sub-bands. At this point, the energy level of each sub-band is calculated. This is first level decomposition. Using the low-low sub-band for further decomposition, we reached fifth level decomposition, for our project.

III.2.2. Energy Level

Energy Level Algorithm:

- Decompose the image into *four* sub-images
- Calculate the energy of all decomposed images at the same scale, using:

$$E = \frac{1}{MN} \sum_{i=1}^m \sum_{j=1}^n |X(i, j)|$$

where M and N are the dimensions of the image, and X is the intensity of the pixel located at row i and column j in the image map.

- Repeat from step 1 for the low-low sub-band image, until index *ind* is equal to 5. Increment *ind*.

Using the above algorithm, the energy levels of the sub-bands were calculated, and further decomposition of the low-low sub-band image. These energy level values are stored to be used in the Euclidean distance algorithm.

III.2.3. Euclidean Distance

Euclidean Distance Algorithm:

- Decompose query image.
- Get the energies of the first dominant k channels.
- For image i in the database obtain the k energies.
- Calculate the Euclidean distance between the two sets of energies, using:

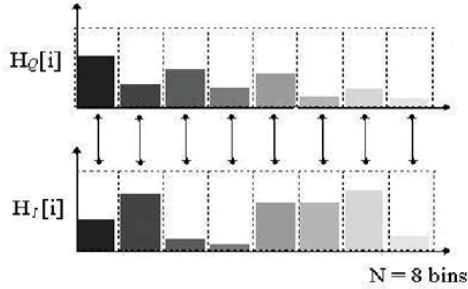


Fig.2. Minkowski Distance Approach

$$a_{q,i} = 1 - \frac{\left[\left(v_q - v_i \right)^2 + \left(s_q \cos(h_q) - s_i \cos(h_i) \right)^2 + \left(s_q \sin(h_q) - s_i \sin(h_i) \right)^2 \right]^{\frac{1}{2}}}{\sqrt{5}} \quad (2)$$

which basically compares one colour bin of H_Q with all those of H_I to try and find out which colour bin is the most similar, as shown below:

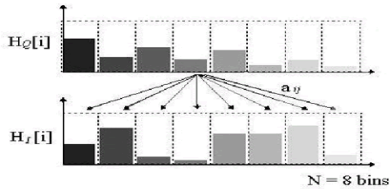


Fig.3. Quadratic Distance Approach

This is continued until we have compared all the colour bins of H_Q . In doing so we get an $N \times N$ matrix, N representing the number of bins. What indicates whether the colour patterns of two histograms are similar is the diagonal of the matrix, shown below. If the diagonal entirely consists of ones then the colour patterns are identical. The further the numbers in the diagonal are from one, the less similar the colour patterns are. Thus the problem of comparing totally unrelated bins is solved.

After obtaining all the necessary terms, similarity matrix, and colour histogram differences, for a number of images in our database, we implemented the results in the final equation, **Quadratic Distance Metric**. Images that where totally unrelated had colour distances smaller than those that where very similar[5].

$$D_i = \sum_{k=1}^k (x_k - y_{i,k})^2$$

- Increment i . Repeat from step 3.

The Euclidean distance is calculated between the query image and every image in the database. This process is repeated until all the images in the database have been compared with the query image.

IV. Result

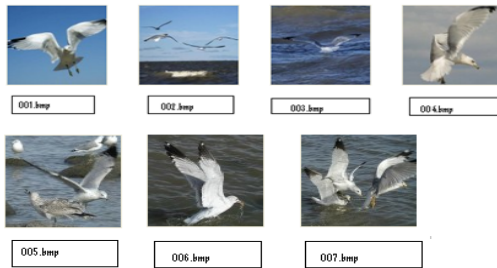


Fig.4.Image database



Fig. 5. The query image: 001.bmp

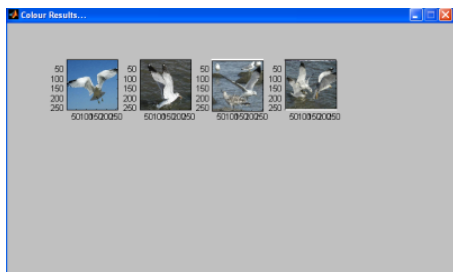


Fig. 6. Colour Results for the searching for 001.bmp

TABLE I

File Name	Colour Distance
001.bmp	0
006.bmp	16.32
005.bmp	17.01
007.bmp	17.09

Colour distance between query and results

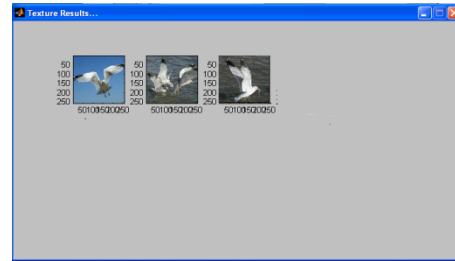


Fig.7. Texture Results for the searching for 001.bmp

The above results are sorted according to the Euclidean distance. These are shown below:

TABLE II

File Name	Euclidean Distance
001.bmp	0
007.bmp	1.71
006.bmp	2.17

Euclidean distance between query and results

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Author’s Profile

Shital A Patil is Pursuing M.Tech in Computer Science & Engineering at TCT,Bhopal affiliated to Rajiv Gandhi Technical University University, Bhopal, MP, India.

Manoj E Patil is Pursuing M.Tech in Computer Science & Engineering at TCT,Bhopal affiliated to Rajiv Gandhi Technical University University, Bhopal, MP, India.