Abstract: Digital images have extended its prospect in numerous directions, resulting in an explosion in the volume of image data required to be organized. While most traditional image retrieval systems perform searches using comparisons of text based strings, content based systems extract features from the content of an image to judge its similarity with another. The image retrieval problem is motivated by the need to search the exponentially escalating space of image and video databases resourcefully and effectively[3]. Low level features like as color, Texture, shape etc. are used to calculate similarity or dissimilarity between archive of images. This Paper Provides Comparative Study of Different Low Level Feature Extraction Techniques for Content Based Image Retrieval.

Keywords- CBIR, Color, Texture, Shape Feature Extraction, Similarity Measurement.

I. INTRODUCTION

The Recent Development of computing Hardware has resulted in a rapid increase of visual information such as a database of images. Modern databases now a days having the contents in the form of images and so there is a need for such a system which can retrieve similar image on the basis of content-based search capabilities. These phenomena led to the implementation of many content-based image retrieval systems [3], [4], [5]. To successfully utilize this database now a day’s having the contents in the form of images and so there is a need for such a system which can retrieve similar image on the basis of content-based search capabilities. These phenomena led to the implementation of many content-based image retrieval systems [1], [2], [3]. However, there are many problems faced in designing such a retrieval system. The most basic issue is how to measure the similarity in terms of content? Content based image retrieval can be classified as one of these three types [5]:

- Manual annotation,
- Automatic feature extraction and retrieval, and
- Combinations of both.

Conventional information retrieval is based solely on text, and these approaches to textual information retrieval have been transplanted into image retrieval in a variety of ways, including the representation of an image as a vector of feature values. However, “a picture is worth a thousand words.” Text based image retrieval is non standardized because different users use different keywords for annotation. As mentioned before, manual systems require too much manpower taking into account the amount of image data available nowadays.

Fig 1: General Image Retrieval System [3]
Text descriptions are Subjective and incomplete because it cannot depict Complicated image feature very well. Another method is content based. Image contents are much more versatile compared with text, and the amount of visual data is already enormous and still expanding very rapidly. However, this requires linear time with respect to the size of the database and quickly becomes impractical for large databases. Semi-automatic systems provide tools to accelerate the annotation process. The General CBIR system as follows [3].

II. RELATED WORK

A. Low-Level Features

Low level image feature extraction and its usage in image retrieval is a well-established approach. The most common image features used in the literature are: color, texture, and object shape (spatial layout) [11]. These content features are discussed with Indexing and retrieval is carried out automatically in this approach. This is an important issue, specifically when we are dealing with large-scale image databases. Moreover, implementation can be easily managed using feature vectors and a similarity/distance measure.

1). Color Feature

Color is the most popularly used features in image retrieval and indexing. On the other hand, due to its inherent nature of inaccuracy in description of the same semantic content by different color quantization and /or by the uncertainty of human perception, it is important to capture this inaccuracy when defining the features. We apply fuzzy logic to the traditional color histogram to help capture this uncertainty in color indexing [3] [5]. In image retrieval systems color histogram is the most commonly used feature. The main reason is that it is independent of image size and orientation. Also it is one of the most straight-forward features utilized by humans for visual recognition and discrimination. Statistically, it denotes the joint probability of the intensities of the three color channels. Once the image is segmented, from each region the color histogram is extracted. The major statistical data that are extracted are histogram mean, standard deviation, and median for each color channel i.e. Red, Green, and Blue. So totally $3 \times 3 = 9$ features per segment are obtained. All the segments need not be considered, but only segments that are dominant may be considered. because this would speed up the Calculation and may not significantly affect the end result.

2). Color Feature Extraction Models

The extraction of the color features for each of the methods is performed in the HSV (hue, saturation and value) perceptual color space, where Euclidean distance corresponds to the human visual system’s notion of distance or similarity between colors [3].

1) The Conventional Color Histogram

The conventional color histogram (CCH) of an image indicates the frequency of occurrence of every color in the image. From a probabilistic perspective, it refers to the probability mass function of the image intensities [3].

2) The Color Correlogram

The color correlogram (CC) expresses how the spatial co-relation of pairs of colors changes with distance. A CC for an image is defined as a table indexed by color pairs, where the $d^{th}$ entry at location $(i,j)$ is computed by counting number of pixels of color $j$ at a distance $d$ from a pixel of color $i$ in the image, divided by the total number of pixels in the image [5].

3) Texture Feature:

Texture is another important property of images. Various texture representations have been investigated in pattern recognition and computer vision. Basically, texture representation methods can be classified into two categories: structural and statistical. Structural methods, including morphological operator and adjacency graph, describe texture by identifying structural primitives and their placement rules. They tend to be most effective when applied to textures that are very regular. There is no precise definition for texture. However, one can define texture as the visual patterns that have properties of homogeneity that do not result from the presence of only a single color or intensity. Texture determination is ideally suited for medical image retrievals [4] [5].

4). Texture Feature Extraction Models

1) The Steerable pyramid

This pyramid recursively splits an image into a set of oriented sub -bands and a low pass residual. The image is decomposed into on decimated low pass sub bands and a set of un-decimated directional sub bands. Analytically the band pass filter in polar co ordinates [4], [5].

2) The Contourlet Transform

This is combination of a Laplacian pyramid (LP) and a Directional Filter Bank (DFB). LP provides the multiscale decompositions and DFB provides multidirectional decompositions. The LP is decompositions of original image into a hierarchy of images such that each level corresponds to a different band of image frequencies [1], [3].

3) The Gabor Wavlet Transform

This Transform dilates and rotates the Two dimensional Gabor function. The image is then convolved with each of the obtained Gabor functions [3] [12].

5) Shape Feature

Shape is used as another feature in image retrieval. However, it is evident that Retrieval by shape is useful only in very restricted environments, which provide a good basis for segmentation (e.g. art items in front of a homogeneous background). Shape descriptors are diverse, e.g. turning angle functions, deformable templates, algebraic moments, and Fourier coefficients[5].

6) Combinations of color, texture, and shape

Features Similarity is based on visual characteristics such as dominant colors, shapes and textures. Many systems provide the possibility to Combine or select between one or more models. In a combination of color, texture and contour features is used. Extends the color histogram with textural information by weighting each
Pixel’s contribution with its Laplacian. Also provides several different techniques for image retrieval [5] [6].

7) Comparison of the Color and Texture Features

Color and Texture feature models can be compared on the basis of the parameters like computational speed, Dimensionality, Similarity, Number of orientation, Sub bands, retrieval results etc. To understand these tables are prepared which will exhibits the difference between these two feature models more specifically. Table 1 lists the pros and cons of the color features described in section and The Table 2 lists the pros and cons of the texture features described in section

Table1. Pros and Cons of the Two Color Feature Model [5]

<table>
<thead>
<tr>
<th>Color Feature</th>
<th>Pros</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conventional</td>
<td>-Simple</td>
<td>-High dimensionality</td>
</tr>
<tr>
<td>Color Histogram</td>
<td>-Fast</td>
<td>-No color similarity</td>
</tr>
<tr>
<td>Correlogram</td>
<td>-Encodes</td>
<td>-No spatial info</td>
</tr>
</tbody>
</table>

Table 2 Pros and Cons of the Three Texture Feature Model [5]

<table>
<thead>
<tr>
<th>Texture Feature</th>
<th>Pros</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Steerable Pyramid</td>
<td>-Supports any number of orientation</td>
<td>-Sub-bands undecimated, hence more computation and storage</td>
</tr>
<tr>
<td>Contourlet Transform</td>
<td>-Lower sub-bands decimated</td>
<td>-Number of orientations supported needs to be power of 2</td>
</tr>
<tr>
<td>Gabor Wavelet Transform</td>
<td>-Achieves highest retrieval results</td>
<td>-Results in over-complete representation of image</td>
</tr>
</tbody>
</table>

III. FEATURE EXTRACTION

The goal of feature extraction is to obtain compact, perceptually relevant representation of the color image content [5, 11]. So far, features based on the image histogram have been widely used in image retrieval. Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification algorithm which over fits the training sample and generalizes poorly to new samples. In this Dissertation global feature representation technique to extract the features of an image because this technique is very efficient in computation and storage. Here four kinds of global features are discussed:

A. Grid Color Moment

Color feature is one of the most widely used features in low level feature. 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, 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. In 1991 Swain and Ballard proposed the method, called color indexing, which identifies the object using color histogram indexing [7].

Most color histograms are very sparse and thus sensitive to noise. In 1995 Stricker and Orengo 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 Huan, introduced a new color feature for image 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 [8].

B. Local Binary Pattern

The LBP code of the centre pixel in the neighbourhood is obtained by converting the binary code into a decimal one. Based on the operator, each pixel of an image is labelled with an LBP code. The 256-bin histogram of the labels contains the density of each label and can be used as a texture descriptor of the considered region. Feature extraction is implemented as follows: First, the face image is divided into several non-overlapping blocks [7]. Then, LBP histograms are calculated for each block. Finally, the block LBP histograms are concatenated into a single vector [8].

C. Gabor Wavelet Texture

In the one-dimensional case, the Gabor function consists of a complex exponential (a cosine or sine function, in real case) localized around $x = 0$ by the envelope with a Gaussian window shape [6].

$$g_{\alpha, \xi}(x) = \sqrt{\alpha / \pi} e^{-\alpha x^2} e^{-i\xi x}$$

For $\alpha \in \mathbb{R}$ and $\xi \in \mathbb{R}$, where $\alpha = (2\sigma^2)^{-1}$, $\sigma^2$ is a variance and $\xi$ is a frequency. Dilation of the complex exponential
function and shift of the Gaussian window when the dilation is fixed form kernel of a Gabor transform. The Gabor transform (a special case of the short-time Fourier transform) employs such kernel for time-frequency signal analysis [64]. The mentioned Gaussian window is the best time frequency localization window in a sense of the Heisenberg uncertainty principle [8].

\[
g_\alpha,\xi(x) = g_{\alpha,\xi_0}(x_0) g_{\alpha,\xi_1}(x_1)
\]

For \(\xi = (\xi_x, \xi_y)\) and \(x = (x_0, x_1)\). Here, the actual frequency of the two-dimensional function is determined by \(\xi = (\xi_x^2 + \xi_y^2)^{1/2}\). Furthermore, \(\theta = \arctan(\xi_y/\xi_x)\) is an angle between \(x\)-axis and a line perpendicular to the ridges of a wave (wave fronts). Elements of a family of mutually similar Gabor functions are called wavelets when they are created by dilation and shift from one elementary Gabor function (mother wavelet), i.e.

\[
g_{\alpha,\xi,a,b}(x) = |a|^{-1/2} g_{\alpha,\xi} \left( \frac{x - b}{a} \right)
\]

For \(a \in R^2\) (scale) and \(b \in R\) (shift). By convention, the mother wavelet has the energy localized around \(x = 0\) as well as all of the wavelets are normalized \(||g|| = 1\). Although the Gabor wavelets do not for mthornormal bases, the discrete set of them form a frame [6, 7].

**D. Edge-Orientation Histograms**

Color histogram is the most traditional and the most widely used way to represent color patterns in an image. It is a relatively efficient representation of color content and it is fairly insensitive to variations originated by camera rotation or zooming (Del Bimbo, 1999; Smeulders, et al., 2000). Also, it is fairly insensitive to changes in image resolution when images have quite large homogeneous regions and insensitive to partial occlusions as well [3] [5].

In our study, the HSV color histogram is generated for each image on either the whole image level or the sub image level. On whole image level, a two-dimensional global histogram of both the hue component and saturation component is computed. Then, the two histograms \(h\) and \(s\) are combined into one \(h \approx s\) histogram with 100 bins, which is taken to be the representing feature vector of each image.

**E. Similarity Measurement**

Similarity measurement is a key to CBIR algorithms. These algorithms search image database to find images similar to a given query, so, they should be able to evaluate the amount of similarities between images. To measure the similarity the general approach is to represent the data features as multi-dimensional points and then to calculate the distances between the corresponding multi-dimensional points. Selection of metrics has a direct impact on the performance of a retrieval system [8] [12].

**IV. CONCLUSION AND FUTURE WORK**

The key part of this Paper is a broad comparison of state-of-the-art color and texture feature extraction techniques for CBIR. The Grid Color Moment and the Gabor wavelet transform were found to give up the highest color and texture retrieval marks, respectively, at the cost of superior Computational convolution. In future work, we will explore methods for combining color and texture features, In Future Work we perform clustering on images, these are clustered into different groups and Build a system in which Image Retrieval uses Random walk Method and similarity matching are performed by Hybrid representation[9][10].

**REFERENCES**


