

# A Review on Similarity Distance Measure, Color, Texture Features Available For Content Based Image Retrieval

*Meharban M S,  
M. Tech student,  
Department Of Computer Science,  
Model Engineering College ,Thrikkakara, Kerala  
Dr. Priya S, Dr. Ashok kumar T  
Associate Professors  
Department Of Computer Science, Department Of Electronics  
Model Engineering College ,Thrikkakara , Kerala*

**Abstract:** The explosive growth of digital libraries due to Web cameras, digital cameras, and mobile phones equipped with such devices is making the database management by human annotation an extremely tedious and clumsy task. Thus there exists a need for developing an efficient expert technique that can automatically search the desired image from the huge database. Content-based image retrieval (CBIR) is one of the commonly adopted solutions for such applications. So nowadays the content based image retrieval is becoming a source of exact and fast retrieval. Content Based Image Retrieval (CBIR) is a one of the image retrieval technique which uses visual features of an image such as color, shape, and texture features etc. It permits the end user to give a query image in order to retrieve the stored images in database according to their similarity to the query image. This survey covers approaches used for extracting low level features, various distance measures for measuring the similarity of image and performance measures.

**Keywords:** CBIR, Color, Shape, Texture.

## I. INTRODUCTION

In the last few years, the rapid growth of the Internet has enormously increased the number of image collections available. The accumulation of these image collections (including art works, satellite and medical imagery) is attracting more and more users in various professional fields for example geography, medicine, architecture, advertising, design, fashion and publishing. Image retrieval is concerned with techniques for storing and retrieving images both efficiently and effectively. Early image retrieval methods locate the desired images by matching keywords that are assigned to each image manually. However, as a result of the large number of images in collections, manual processing has become impractical.

Content Based Image retrieval uses the visual contents of an image such as color, shape, texture, and spatial layout to represent and index the image. In typical Content Based Image retrieval systems, the visual contents of the images in the database are extracted and described by multi-dimensional feature vectors. The feature vectors of the images in the database form a feature database. To retrieve images, users provide the retrieval system with example images or sketched figures. The system then changes these examples into its internal representation of feature vectors. The similarities or distances between the feature vectors of the query example or sketch and those of the images in the database are then calculated and retrieval is performed with the aid of an indexing scheme. The indexing scheme

provides an efficient way to search for the image database. Recent retrieval systems have incorporated users' relevance feedback to modify the retrieval process in order to generate perceptually and semantically more meaningful retrieval results.

A typical CBIR system involves two phases. The indexing phase extracts the image features from all of the images in the database which is later stored in database as feature vector. In the searching phase, the retrieval system derives the image features from an image submitted by a user (as query image), which are later utilized for performing similarity matching on the feature vectors stored in the database. The image retrieval system finally returns a set of images to the user with a specific similarity criterion, such as color similarity and texture similarity [1].

The need for Content Based image retrieval is to retrieve images that are more appropriate, along with multiple features for better retrieval accuracy. Usually in search process using any search engine, which is through text retrieval, which won't be so accurate. So, we go for Content Based image retrieval. Content Based Image Retrieval also known as query by image content (QBIC) and content-based visual information retrieval (CBVIR). The similarity measurements and the representation of the visual features are two important issues in Content-Based Image Retrieval (CBIR).

## II. EXISTING TECHNIQUE FOR FEATURE EXTRACTION

In CBIR systems, a feature is a characteristic that can capture a certain visual property of an image. In feature extraction, features such as color, texture or shape from image are extracted and creates a feature vector for each image.

### A. COLOR FEATURE

The color feature is one of the most widely used visual features in image retrieval. It is relatively robust to background complication and independent of image size and orientation. Mostly CBIR system use color space, histogram, moment, color coherence vector and color structure descriptor. Color space consists of three dimensional spaces and color is used as a vector in it. Color spaces are required for description of color based retrieval of image. Mostly RGB, HSV, HSI, YCrCb, LAB. The selection of color space is done from uniformity characteristics and uniformity means to have colors points having similar distance in color space as perceived by human eye [15].

- ❖ Color Histogram: In image retrieval, the color histogram [15] is the most commonly used color feature representation. Statistically, it denotes the joint probability of the intensities of the three color Channels. The predominant color representation used in Image retrieval is the RGB color space representation. In this representation, the values of the red, green, and blue color channels are stored separately.
- ❖ Color Correlogram: Is used to characterize not only the color distributions of pixels, but also the spatial correlation of pairs of colors. The first and the second dimension of the three-dimensional histogram are the colors of any pixel pair and the third dimension is their spatial distance. Color autocorrelogram provides the best retrieval results, but is also the most computational expensive due to its high dimensionality.
- ❖ Color Co-Occurrence Feature: It is derived from the color co-occurrence matrix. CCF is computed from the two HBTC color quantizer. The minimum and maximum color quantizer is firstly indexed using a specific color codebook. The color co-occurrence matrix is subsequently constructed from these indexed values [1].
- ❖ Color Moments: This feature have been successfully used in many retrieval systems (like QBIC), especially when the image contains just the object. The first order (mean), the second (variance) and the third order (skewness) color moments have been proved to be efficient and effective in representing color distributions of images [15].

<b>Color Feature</b>	<b>Pros</b>	<b>Cons</b>
Conventional color histogram	Simple, fast computation, invariant to any transformation	No spatial information
Color moment	Low complexity	Precision low
Fuzzy color histogram	Fast computation. Robust to quantization noise.	More computation
Color Correlogram	Encode spatial info	Very slow computation
Color Autocorrelogram	Encode spatial info, low complexity	Precision low
Color Structure Descriptor	Both color distribution and local structure of the color, Hmmd color space	No spatial information
Scalable Color Descriptor	Simple, fast, Hsv color space	No spatial information
Color Co-occurrence Feature	Include spatial info, low complexity, high speed, reduce the feature dimensionality	Codebook needed
Color Coherence Vector	Include spatial information	Complexity high

**Fig-1**  
**Color features for retrieval of image**

### **B. TEXTURE FEATURE**

Texture refers to the visual patterns that have properties of homogeneity that do not result from the presence of only a single color or intensity. It is an innate property of virtually all surfaces, including clouds, trees, bricks, hair, and fabric. It contains important information about the structural arrangement of surfaces and their relationship to the surrounding environment [12]. Texture features are extracted using GLCM, Gabor Transform and Tamura Features, Local Binary pattern.

- ❖ **Gray Level Co-occurrence matrix (GLCM):** This approach explored the gray level spatial dependence of texture. It first constructed a co-occurrence matrix based on the orientation and distance between image pixels and then extracted meaningful statistics from the matrix as the texture representation. It is used to calculate how often pixels with gray level value  $i$  occurs horizontally adjacent to a pixel with a value  $j$ . Finding co-occurrence matrix is to remove redundancy. The features extracted are Energy, Entropy, Contrast and Correlation. These values are obtained by using formula. Matching is done with query image and database images. Contrast measures local variations in gray level co-occurrence matrix. It returns a measure of

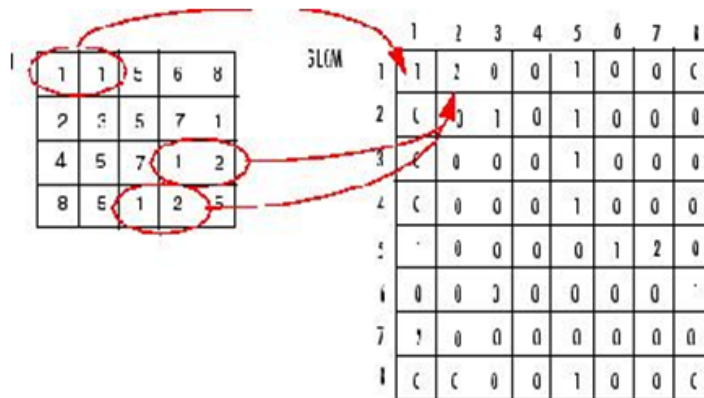
intensity contrast between a pixel and its neighbor over the whole image. Correlation measures joint probability occurrence of specified pixel pairs. It returns a measure of how correlated a pixel to its neighbor of over whole image. The range lies within [-1,1]. Correlation is 1 for positively image. It's -1 for negatively image. Energy provides the sum of squared elements in GLCM known as uniformity or angular second moments. Range lies within range [0 1]. Energy is 1 for constant image. Homogeneity: It measures closeness of distribution of elements in GLCM to GLCM diagonal. Homogeneity is 1 for diagonal matrix. The range lies within [0 1].

$$\text{Homogeneity} = \sum_{i,j} \frac{p(i,j)}{1 + |i - j|}$$

$$\text{Energy} = \sum_{i,j} p(i,j)^2$$

$$\text{Correlation} = \frac{\sum_{i,j} (i - \mu_i)(j - \mu_j)p(i,j)}{\sigma_i \sigma_j}$$

$$\text{Contrast} = \sum_{i,j} |i - j|^2 p(i,j)$$



**Fig 2: Gray level co-occurrence matrix computation**

- ❖ Tamura Features: The six visual texture properties were *coarseness*, *contrast*, *directionality*, *linelikeness*, *regularity*, and *roughness*. The first three components of Tamura features have been used in some early well-known image retrieval systems, such as *QBIC* and *Photobook*. One major distinction between the Tamura texture representation and the co-occurrence matrix representation is that all the texture properties in Tamura representation are visually meaningful, whereas some of the texture properties used in co-occurrence matrix representation may not be (for example, entropy). This characteristic makes the Tamura texture representation very attractive in image retrieval, as it can provide a more user-friendly [12].
- ❖ Bit Pattern Feature: Characrizes the edge, shape, visual pattern, and textural information in an image. BPF can be obtained by tabulating the occurrence of a specific bit pattern codebook in an image. Binary vector quantization produces a representative bit pattern codebook from a set of training bit map image.

❖ **Edge Histogram Descriptor (EHD):** Edge features are taken from the Edge Histogram Descriptor (EHD) that is the local edge distribution in the image. To localize edge distribution to a certain area of the image, we divide the image space into 4x4 sub-images. To define different edge types, the sub-image is further divided into small square blocks called image-blocks. EHD generate the semi-global and global histograms generated from the local histogram bins help to improve the retrieval performance [14].

❖ **Local Binary Pattern:** LBP method provides a robust way for describing pure local binary patterns in a texture. It gives Relationship between center pixel and its surrounding neighbors. The LBP operator was introduced by in for texture classification. Given a center pixel in the image. LBP is a two-valued code. The LBP value is computed by comparing gray value of center pixel with its neighbors, using the below equations (1) and (2) [2].

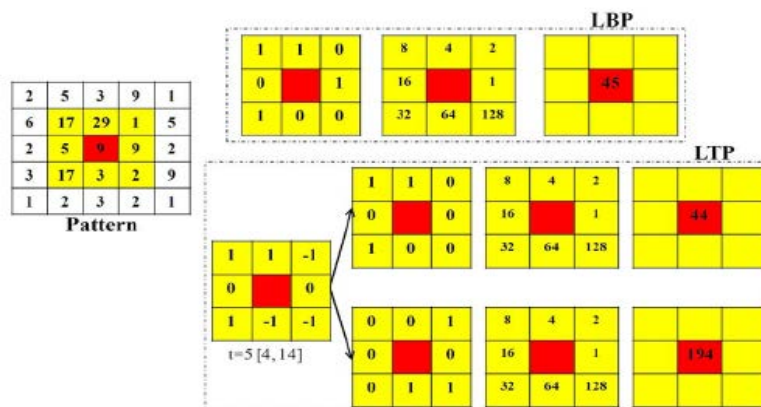
Where,  $G_c$  - Gray value of the center pixel  
 $G_p$  - Gray value of its neighbors  
 $P$  - Is the number of neighbors  
 $R$  - Is the radius of the neighborhood

$$\begin{cases} \text{LBP}_{P,R} = \sum_{p=1}^P 2^{(p-1)} \times X(G_p - G_c) & (1) \\ X(x) = \begin{cases} 1, & x \geq 0 \\ 0, & \text{else} \end{cases} & (2) \end{cases}$$

❖ **Local Ternary Pattern (LTP):** LTP [2] is a three-valued code, in which gray values in the zone of width  $\pm T$  around  $G_c$  are quantized to zero, those above  $(G_c+T)$  are quantized to +1, and those below  $(G_c-T)$  are quantized to -1. Local Ternary Patterns are an extension of Local Binary Pattern. Unlike LBP, it does not threshold the pixels into 0 and 1 rather it uses a threshold constant 'T' to threshold pixels into three values. Here specified 'T' is a threshold, LTP code more resistant to noise. LTP can be determined by equation (3).

$$Y(x, G_c, T) = \begin{cases} +1, & (G_c+T) \leq x \\ 0, & (x-G_c) < T \\ -1, & (G_c-T) \geq x \end{cases} \quad (3)$$

❖ **Local Tetra Pattern:** The LBP and the LTP are able to encode images with only two (either "0" or "1" and three ("0," "-1," or "1")) distinct values, respectively. However, the LTrP is able to encode images with four distinct values as it is able to extract more detailed information. The LBP and the LTP encode the relationship between the gray value of the center pixel and its neighbors, whereas the LTrP encodes the relationship between the center pixel and its neighbor. LTrP that is calculated based on the direction of pixels using horizontal and vertical derivatives [2].



**Fig 3: Example of obtaining LBP and LTP for the 3×3 pattern**

<b>Texture Feature</b>	<b>Pros</b>	<b>Cons</b>
Tamura feature	Effective retrieval	Highly complex
Wavelet filter	Detect different frequency and orientation	Precision low
Gray level co-occurrence matrix	Including position of pixels having similar gray level values.	High dimensionality
Gabor filter	High retrieval	Computation expensive
Steerable pyramid	Support any no of orientation	Storage space is high
Edge histogram descriptor	Computation easy	Retrieval result poor
Gabor moment	Low dimensionality	Computation expensive
Bit Pattern feature	Low complexity, high precision, capture edge visual pattern, texture information	Codebook needed
LBP,LTP,LTRP	Best feature for texture retrieval	Only suitable for gray scale image

**Fig 4: Texture feature for image retrieval**

### *C. SHAPE*

Another major image feature is the shape of the object contained in the image Shape feature of image may be defined as the characteristic surface configuration of an object; an outline or contour. Generally the shape feature is divided into two categories, region based and boundary-based. The mostly used representations for these two categories are Fourier descriptor and moment invariants. The Fourier descriptor is to use the Fourier transformed boundary as the shape feature. The Moment invariants are to use region-based moments, which are invariant to transformations as the shape feature [8].

### **III. SIMILARITY DISTANCE MEASURES**

The main step of the image retrieval task (as well as in image classification) is in the similarity distance

Computation for the nearest neighbor searching, in which the similarity degree between two images is measured. The similarity distance computation plays an important role in the image retrieval system. Image retrieval performance is very sensitive to the specific distance metric chosen by a user. Image matching between two images (the query image and target image in database) can be performed by calculating the similarity distance between their feature descriptor. After similarity distance computation, the system subsequently returns a set of retrieved image ordered in ascending manner based on their similarity distance score. Lower score on similarity distance indicates more degree similarity between two images and vice versa. The similarity distance between the two images (query and target image) can be formally defined under various distance metric as follows. Let the query feature vector represented by Q and the database feature vector by D [3].

Distance Measures	Description	Limitation	Formulae
Sum of absolute difference(SAD)	SAD is simple method to search for similar image in the database to the query image automatically.	Sensitive towards the consequence of background issues of image such as variation in color, size, illumination	$D = \sum_{i=1}^n  Q_i  -  D_i $
Sum of squared absolute difference(SSAD)	SSAD can be used in both pixel domain and transformed domain	Computational complexity higher	$D = \sum_{i=1}^n ( Q_i  -  D_i )^2$
Euclidian Distance(L2)	Commonly used for similarity measurement because of its efficiency and effectiveness	Most expensive operation is the computation of square root.	$D = \sqrt{\sum_{i=1}^n ( Q_i - D_i )^2}$
City block distance(L1) or Manhattan distance	Distance function computationally less expensive because only the absolute difference in each feature consider	Give large value for the two similar image which create dissimilarity between similar image	$D = \sum_{i=1}^n  Q_i - D_i $
Canberra distance	Each feature pair difference is normalized by dividing it by sum of a pair of features	Distance matrix not robust to outliers	$D = \sum_{i=1}^n  Q_i - D_i  /  Q_i  +  D_i $
Chebyshev or $L_\infty$ Or Maximum value distance	This matrix is used to get the largest value of absolute difference of paired features of feature vector	More emphasis on the features	$D = \max\{ Q_1 - D_1 ,  Q_2 - D_2 , \dots,  Q_n - D_n \}$
Minkowski distance	This is a family of distance function parameterized by p. For $L_1, L_2, L_\infty$ metrics the value of p is 1, 2, $\infty$	For p=3 take the cube root so computation is high	$D = [\sum_{i=1}^n  Q_i - D_i ^p]^{\frac{1}{p}}$

Histogram intersection distance	Calculate the cross distance between two histogram	Neglects the feature occurring in a single histogram	$D = 1 - \frac{\sum_{i=1}^n \min(Q_i, D_i)}{\sum_i D_i}$
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Fig 5: Similarity distance measures for image retrieval

#### IV. PERFORMANCE MEASURE

The successfulness of the image retrieval system is measured with the precision, recall, and average retrieval rate. These values indicate the percentage of relevant image returned by a CBIR system with a specific number of retrieved images. A higher value in precision and recall exhibits the better retrieved result. Precision and Recall can be calculated using equation

$$\text{Precision} = \text{No of relevant image retrieved} / \text{Total no of image retrieved} \quad (4)$$

$$\text{Recall} = \text{No of relevant image retrieved} / \text{Total no of relevant image in database} \quad (5)$$

The other metric employed to measure the retrieval performance is the ARR value which can be formally defined as, where the |DB| denotes the total number of image in the database

$$\text{ARR} = \frac{1}{|DB|} \sum_{i=1}^{|DB|} \text{Recall} \quad (6)$$

#### V. CBIR APPLICATION AND CHALLENGES

##### A. Application

- Content based tile retrieval system: The computer-aided tile consulting system retrieves tiles from digital tile catalogs, so that the retrieved tiles have similar patterns and colors to the query tile as possible. During browsing of digital tile catalogs, the system can offer another tile that you may like based on similar color or pattern which would be integrated into an internet tile shop.
- Medical Diagnosis: Content Based Image Retrieval (CBIR) systems retrieve brain images from that database which are similar to the query image. The goal of diagnostic medical image retrieval is to provide diagnostic support by displaying relevant past cases, along with proven pathologies as ground truth. fMRI (functional Magnetic Resonance Imaging) is a technique used to “monitor” brain activities. Many of the proposed retrieval systems in the area of medical domain are adopted from general image retrieval schemes which perform satisfactorily with databases consisting of heterogeneous images of different modalities and anatomical regions [29].

##### B. Challenges

The implementation of CBIR system raises several research challenges, such as

- Semantic gap is the lack of coincidence between the information that one can extract from the visual data and the interpretation that the same data have for a user in a given situation.

Relevance feedback is a powerful technique in order to improve the performance. It allows reducing semantic gap between low level feature and high level semantics. Relevance feedback method iteratively refines and updates the retrieved result by learning the user-labeled examples (as relevant or irrelevant image set) to further improve the overall retrieval performance.

- How to retrieve images efficiently
- Size of the image database
- Time complexity for feature extraction
- How to choose best similarity measure

## VI. CONCLUSION

This paper has surveyed the various methodologies used for extracting the low level features such as color, texture, shape features. Also this paper provides a detailed review of various distance measures to find the similarity between images. This survey attempts to introduce the theory and practical application of CBIR technique. To achieve a higher retrieval accuracy, color and texture feature combined together in to the indexing scheme with the other color spaces such as YCbCr, hue-saturation-intensity and lab. Relevance feedback tries to reduce the semantic gap. Image retrieval used for various applications like medical diagnosis, crime prevention, fingerprint and iris recognition.

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