IMAGE RETRIEVAL BASED ON TEXTURE- A SURVEY

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Abstract— As there are increasing more number of digital images on internet, there is problem in retrieving more similar images from database on internet. So the content based image retrieval (CBIR) system becoming more popular for extracting & browsing more similar images from large image database. CBIR uses visual features of image such as colour, shape, texture, etc. to retrieve required image from image database. In this paper we present a literature survey of the Colour Image Retrieval Technique based on Texture.

Keywords— Content-Based Image Retrieval (CBIR), Texture, Gray-level co-occurrence matrix (GLCM), Colour histogram, Image Retrieval Precision value (IRP).

I. INTRODUCTION

With the rapidly growth of the Internet, and the easily available image capturing devices in market such as digital cameras & scanners, there is increasing more numbers of availability of digital images on Internet. So the efficient image searching, browsing and retrieval tools are required by users from various domains, including remote sensing, fashion, crime prevention, publishing, medicine, architecture, etc. For this purpose, many image retrieval systems have been developed. That’s why, now a days researchers paying their attention on a very interesting system which is nothing but the Content-based image retrieval technique. In CBIR technique, image retrieval is based on similarities in their lower level features, which are textures, colours, shapes, etc. CBIR is the computer vision application to the difficulty in finding of images from large databases. Content Based Image Retrieval (CBIR) is techniques that allow us to access the digital images from a large collection of image databases by using the image features. The increasing number of digital images requires new methods to access. The images can be retrieved using the image features colour, texture and shape. Image retrieval approaches are based on the computation of the similarity between the users query and images. Figure 1 shows the Architecture of CBIR system. In it each image is stored in the large image database and its features are extracted, compared to the features of the query image. In on-line image retrieval, the user gives a query image to the CBIR system to search the required images. The system exhibit a feature vector for the query image. Then similarities between the feature vectors of the query image and the images in the feature database are compared. In last, the system returns the images that are most similar to the query images. The challenge in CBIR is to develop the methods that will reduce the retrieval time and increase the retrieval accuracy. Evaluation of retrieval performance is a crucial problem in content-based image retrieval (CBIR) [2]. The most common evaluation measures used in CBIR are precision and recall.

A. Types of image feature

1) Colour Based Retrieval: Colour is the most important feature in retrieving a digital image. There are many colour feature retrieved methods are present. Such like colour histogram, autocorregrogram, colour moments etc. Colour Histogram is the commonly used method for colour feature extraction in digital images. Colour histograms are widely & commonly used for CBIR systems for predicting the features of an image. The image histogram shows the variations of gray levels from 0 to 255, as the dimension is too big to be stored or compared, these all values cannot be used as a feature vector [7]. The image histogram must be sampled into the number of bins to reduce the size of feature vector. Colour histograms have the speed and low memory space which are its advantages.

2) Texture Based Retrieval: Texture represents the surface and surrounding structure of an image. It can be defined a property as a regular repetition of an element or pattern on a surface [5]. The texture of an image can be extracted using GLCM (Grey level co-occurrence matrix), Wavelets, Fourier transform, entropy, correlation methods [4]. GLCM technique is more commonly used as it is more similar to the human visual system features. The features extracted using GLCM are energy, entropy, correlation etc. Wavelets are the difficult form for texture feature extraction. The wavelets are discretely sampled and decompose into different sub bands [5].

Figure 1. Architecture of CBIR system
3) **Shape Based Retrieval**: shape permits an object to be distinguished from its surroundings by its outline [6]. There are many methods for the extraction of shapes from digital images. Some methods include contour based shape extraction, Region based shape extraction, Boundary based methods and generalized Hough transform(GHT) etc. GHT is the mostly used shape extraction technique. GHT is tolerant to noise and robust to the de-formalities of shape [10].

**II. TEXTURE ANALYSIS APPROACHES**

Texture feature is a common characteristic of all objects, which includes important information about the surface characteristics and their relationship with the surroundings [2]. Figure 2 shows, the texture analysis approaches are categorized into, 1) structural, 2) statistical, 3) model-based
4) transform

In Structural approaches, Haralick (1979) & Levine (1985) represent texture by well defined primitives (microtexture) and a hierarchy of spatial arrangements (macrotexture) of those primitives[1]. The primitives must get defined, in order to describe the texture. To provide a good symbolic description of the image, is the advantage of the structural approach; however, this feature is more useful for synthesis than analysis tasks. Mathematical morphology (Serra 1982, Chen 1994) provides a powerful tool for structural texture analysis. It may prove to be useful for bone image analysis, e.g. for the detection of changes in bone micro structure[1].

Statistical approaches are contrast to the structural methods. General statistical parameters are calculated from pixels intensity values or by pairs of pixels. Methods based on statistics approaches shown achieve higher discrimination rates than the transform & structural methods. Human texture discrimination statistical properties are investigated by Julesz in 1975. The mostly known second-order statistical features for texture analysis are derived from the co-occurrence matrix by Haralick in 1979.

Model based texture analysis is represented by many researchers like Cross in 1983, Pentland in 1984, Chellappa in 1985, Derin in 1987, Manjunath in 1991 & by Strzelecki in 1997. To characterize texture, an approach is being analyzed to determine an analytical model of the textured image. Such models have a set of parameters. To interpret an image texture there are two types of models that are fractal and stochastic models. Firstly the parameters of the model are estimated and only then used for image analysis. But there is one problem that the computational complexity arises in the estimation of stochastic model parameters. For modeling some natural textures, the fractal model has been useful.

Several Transform methods of texture analysis are present, such as Fourier Transforms (Rosenfeld 1980), Gabor Transforms (Daugman 1985, Bovik 1990) and wavelet transforms (Mallat 1989, Laine 1993, Lu 1997). This type of methods represent an image in a space whose co-ordinate system has an interpretation that is closely related to the characteristics of a texture such as frequency or size[1]. Due to lack of spatial localization, Fourier transform performs poorly. The wavelet transforms have several advantages that it’s varying spatial resolution allows it to represent textures at the most suitable scale also one is able to choose wavelets best suited for texture analysis in a specific application as there is a wide range of choices for the wavelet function. These advantages make the wavelet transform attractive for texture segmentation. Wavelet transform is not translation-invariant (Brady 1996, Li 1997) this it’s disadvantage.

**III. FEATURE EXTRACTION TECHNIQUES**

Visual feature extraction is the basis of any CBIR technique. The process of determining the combination of features that is most representative of a particular query image is called the feature selection. Texture is an important feature of an image. The visual features can be further classified as low-level features and high-level features. To represent an image the selection of the features is one of the keys of a CBIR system.[9] The three basic principle approaches are used in image processing to describe the texture of a region that are statistical, structural, and spectral[13]. Multiple approaches have been introduced for texture features are as fallows,

**B. First-order histogram based features**

The histogram of intensity levels is obviously a concise and simple summary of the statistical information contained in the image. Calculation of the grey-level histogram involves single pixels. Thus the histogram contains the first-order statistical information about the image or its fragment[1]. Consider the image is a function \( f(x, y) \) of two space
variables \( x \) and \( y, x=0,1,\ldots,N-1 \) and \( y=0,1,\ldots,M-1 \). The function \( f(x,y) \) can take discrete values \( i = 0,1,\ldots,G-1 \), where \( G \) is the total number of number of intensity levels in the image. The intensity-level histogram is a function showing (for each intensity level) the number of pixels in the whole image, which have this intensity:

\[
h(i) = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} \delta(f(x,y),i),
\]

where \( \delta(i,j) \) is the Kronecker delta function, \( \delta(i,j)=1(i=j), \delta(i,j)=0(j\neq i) \)

The approximate probability density of occurrence of the intensity levels can be obtain by Dividing the values \( h(i) \) by the total number of pixels in the image,

\[
p(i) = h(i) / NM, \ i = 0,1,\ldots,G-1
\]

The histogram is easy to compute. Different image features can be calculated from the histogram to quantitatively describe the first-order statistical properties of the image. Mostly central moments (Papoulis 1965) are derived from it to characterise the texture (Levine 1985, Pratt 1991), as defined by Equations below,

Mean: \( \mu = \sum_{i=0}^{G-1} ip(i) \)

Variance: \( \sigma^2 = \sum_{i=0}^{G-1} (i - \mu)^2 p(i) \)

Skewness: \( \mu_3 = \sum_{i=0}^{G-1} (i - \mu)^3 p(i) \)

Kurtosis: \( \mu_4 = \sum_{i=0}^{G-1} (i - \mu)^4 p(i) - 3 \)

Energy: \( E = \sum_{i=0}^{G-1} p(i)^2 \)

Entropy: \( H = \sum_{i=0}^{G-1} p(i) \log 2[p(i)] \)

The mean is the average level of intensity of the texture being examined, whereas the variance is the variation of intensity around the mean. The skewness is zero if the histogram is symmetrical about the mean, and is otherwise either positive or negative depending whether it has been skewed above or below the mean. The kurtosis represent the flatness of the histogram. Uniformity of histogram is represented by the entropy.

C. Co-occurrence matrix based features

Gray Level Co-occurrence Matrices (GLCM) is a more popular representation for the texture in images[9]. The GLCM presents the joint probability of gray pixels that a pair of gray pixels with the position \( \Delta x, \Delta y \) will occur at the same time. In it \( \Delta x \) and \( \Delta y \) are determined by a specified displacement \( \delta \) between the pair of pixels and angle \( \theta \), and where they are subject to \( \Delta x=\delta \cos \theta \) and \( \Delta y=\delta \sin \theta \)[8]. Usually considers the neighbors of a pixel. Because the distribution of gray intensities will be different at every orientation. For computing GLCM, 8 connected neighbors seem to be the best & there will be \( \delta=1,0,45^\circ, 90^\circ, 135^\circ \) for the 8 connected neighbors[8]. GLCM is the most known texture analysis methods, this estimate image properties related to second-order statistics. Haralick consider that the texture information is contained in this matrix, and then texture features are calculated from it[14].

Figure3. Co-occurrence matrix directions for extracting texture features

 Compute co-occurrence matrices for the images in the database and also for the query image[12]. As shown in figure3, For each R, G, B, and 1 component, calculate the normalized co-occurrence matrix, for each colour connectivity region and then extract the following statistical values from each matrix:

Energy: \( \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} [p(i,j)]^2 \)

This infers that maximum constant values or periodic uniformity in gray level distribution will form maximum energy of texture.

Correlation: \( \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{jp(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \)

Correlation that brings out how correlated a reference pixel to its neighbor over an image, is uncorrelated to energy, contrast and homogeneity.

Inertia (contrast): \( \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i - j)^2 p(i,j) \)

The similar values of pixels in observation results in low contrast, causing a poor dissemination of boundaries between features.

Absolute value: \( \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} |i - j| p(i,j) \)

The absolute value is the difference of distance between the grey levels.

Inverse difference: \( \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{p(i,j)}{1+(i-j)^2} \)
It measures number of local changes in image texture. Inverse Difference is the local homogeneity. It is high when local gray level is uniform.

Entropy: \[-\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} p(i,j) \log_2[p(i,j)]\]

In the image texture Entropy measures randomness. Entropy is minimum when the co-occurrence matrix for all values is equal. On the other hand, if the value of co-occurrence matrix is very uneven, its value is greater. Therefore, the maximum entropy implied by the image gray distribution is random [3].

D. The Wavelet Transform

The Haar transform is given by the set of “difference” values & the “average” value for the last level. In the frequency domain, the values correspond to the output of a low pass filter, thus representing low-frequency information, whereas the values correspond to the output of a high pass filter, thus representing high-frequency information[8].

In this type of transformation, for an N x M image, the first step decomposes the signal into four sub-images of size N/2 x M/2, representing the sub-bands in the frequency domain. The obtained sub-images are labelled as LL; LH ; HL; HH, where L and H represent low- and high-frequency information, respectively. The first and the second position refer to the horizontal and the vertical direction, respectively. The second transformation level decomposes the LL sub-image, obtaining four images of size N/4 x M/4, and so on. Figure 4 shows the decomposition of the frequency domain at different scale levels:

Multiwavelets were defined using several wavelets with several scaling functions [11]. Compared with scalar wavelets, multiwavelets offer the possibility of superior performance and high degree of freedom for image processing applications. 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. This necessitates that all the subbands of the lower resolution image must be refined i.e., have a rate added to them.

Following table shows, the different methods used for texture feature extraction with their respective advantages & limitations.

<table>
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<th>TABLE 1. Different methods used for texture feature extraction</th>
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CONCLUSION

This paper has surveyed the concepts of image retrieval system based on Texture. CBIR is a fast developing technology; researcher’s in CBIR has been focused on low level feature extraction techniques. From the literature survey it is concluded that, a wide variety of texture extraction algorithms have been proposed in different papers. The purpose of this survey is to provide an overview of the some mostly used texture extraction techniques of content based image retrieval systems. GLCM has been used in various areas to improve the performance of the system and to achieve better results in different applications.

REFERENCES

