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Content Based Image Retrieval

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,Abstract-There are different methods prevailing for Image Mining Techniques. This Paper includes the features by two techniques Gabor algorithm, LBP, Content Based Image Retrieval is the retrieval of images based on visual features such as colour, texture and shape. In CBIR, each image that is stored in the database has its features extracted and compared to the features of the query image. It consist two main steps:
Feature Extraction: *The first step in the process is extracting image features to a distinguishable extent like texture, colour using different methods*
Matching: *The second process involves matching these features to yield a result that is visually similar and providing best output from the database of system*

I. INTRODUCTION

Content Based Image Retrieval (CBIR) is a technique which uses visual contents, know as features, to search images from large scale image databases according to users' requests in the form of a query image . Content-based image retrieval (CBIR) is therefore proposed, which finds images that have visual low-level image features similar to those of the query image example, such as colour histogram, texture and shape, so that visual features are automatically extracted from images, lot of human effort can be saved and problem of searching images from large database can be avoided by building the image databases for CBIR systems Using a Content Based Image Retrieval (CBIR) images can be analysed and retrieval automatically by automatic description which depends on their objective visual content. Content based retrieval of visual data requires a paradigm that differs significantly from both traditional databases and text based image understanding systems. Now a days image content is no longer represented only by texual descriptor thus, Retrieval of image should be on basis of similar images that is defined in terms of Visual features Texture analysis plays an important role in many image analysis applications .Even though colour is an important clue in interpreting images, there are situations where colour measurements just are not enough — nor even applicable. In industrial and for commercial uses, texture information can be used in enhancing the accuracy and also helping in color measurements in image. In some applications, for example in the quality control of paper web, there is no colour at all. Texture measures can also scope better with varying illumination conditions, for any instance outdoor or indoor conditions. Therefore, they can be useful tools for high-level interpretation of natural scene image content. Texture methods is also useful in medical image analysis, biometric identification and in remote sensing search, content-based image retrieval, document analysis, in environment modeling, synthesis of texture and model-based image coding. In this paper apart from the usual features like colour histogram, color moment it uses texture for new feature extraction using algorithm called Gabor and Lbp

Gabor algorithm

Gabor algorithm is introduced. Gabor filters are a collection of wavelets, with each wavelet capturing energy at a specific type of frequency and in a specific direction. Expanding the signal with these basis provides a localized description of frequency, therefore it is capturing local features/energy of the signal. Features like texture can then be extracted from this group of energy distributions. The scale (frequency) and orientation tunable property of Gabor filter makes it especially useful for texture analysis.

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The filters of a Gabor filter bank are designed to detect different frequencies and orientations. We use them to extract features on key points detected by interest operators .From each filtered image, Gabor features can be calculated and used to retrieve images. l distribution of edges . Our model expects the input as Query by Example (QBE) and any combination of features can be selected for retrieval. The focus of this paper is to build a universal CBIR system using low level features. These are mean, median, and standard deviation of Red, Green, and Blue channels of color histograms. Then the texture features consist of contrast, energy, correlation, and homogeneity that are retrieved from any image. Finally the edge features that include five categories are vertical, horizontal, 45 degree diagonal, 135 degree diagonal, and then isotropic are added.

For a given image I(x,y), the discrete Gabor wavelet transform is
given by a convolution:

$$W_{MN}=\sum_x\sum_y I(x1,y1)g_{min}{}^*(x-x1,y-y1) \qquad (1)$$

Where it indicates complex conjugate and where m, n specify it scales and orientations of wavelet respectively.

After applying the Gabor filters on the image with different
Orientation at different scale, we obtain an array of magnitudes:

$$E(m,n) \quad \sum_x\sum_y \left|W_{MN}(X,Y)\right| \qquad (2)$$

The magnitudes which we get represent the energy content at different scale and orientation of the image. The main purpose of texture-based image retrieval is to search images or regions with similar texture. The standard deviation σ of the magnitude of the transformed coefficients is:

$$\sigma\ mn = x = \frac{\sqrt{\sum\sum(\left|Wmn(x,y)-\mu mn\right|)2}}{p*q}$$

where $\mu mn = E(m,n)/P*Q$
is the mean of magnitude A feature vector **f** (texture representation) is created using *mn*
And mn as the feature components [1, 4]. *M* scales and *N* orientations are used and the feature vector is given by:

$$f=[\sigma 00,\sigma 01 \ldots\ldots,\sigma(m-1)(n-1)] \qquad (4)$$

$$f\ \ Gabor=f-\mu/\sigma$$

where µis the mean and σ will be the standard deviation of f .Texture is an innate property of all describes visual patterns, each having contains important information about arrangement of a surface, such as; clouds, fabric, etc. It also describes the relationship surfaces to the surrounding environment. In feature that describes the distinctive composition of a surface. Textures can be modeled as quasi-per with spatial/frequency representation. transforms the image into a representation with both spatial and characteristics. This allows for effective image analysis with lower computational cost According to this

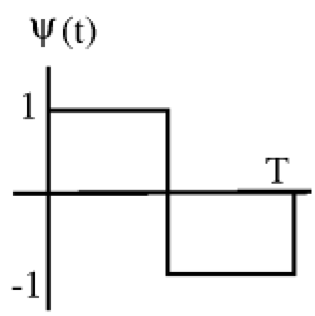


Figure 1 : Haar Wavelet Example

Transformation, a function, which can represent an image, a curve, signal etc., can be described in terms of coarse Level description in addition to others with details and range from broad to narrow scales .Unlike the usage of Sine functions signals in Fourier transforms, in wavelet to use functions known as wavelets. Wavelet time, yet the average value of a wavelet .wavelet is a waveform that is bounded in both frequency and duration.

While the Fourier transform signal into a continuous series function of sine waves ,each with constant frequency and amplitude and infinite

LBP

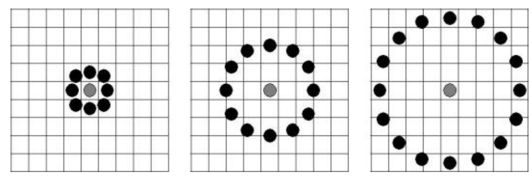
LBP operator was first introduced for the complementary measure for local image contrast inHarwood et al. 1993, . The first incarnation of the operator worked with the eight-neighbors of a pixelin image , taking the value of the center pixel as a threshold. An LBP code was produced by multiplying the thresholded values with weights given to the corresponding pixels ,and summing up the result LBP feature is gaining much attention as a local image descriptor due to its simplicity and excellent performance in texture analysis and face image analysis . Though LBP is robust to monotonic illumination change but it is sensitive to non-monotonic illumination variation The derivation of the LBP follows that Due to the lack of a universally accepted definition of texture, the derivation must start with a custom one. therefore define texture T in a local neighborhood of a grayscale image as the joint distribution of the gray levels of $P + 1$ ($P > 0$) image pixels:

$T = t(g_c, g_0, \ldots, g_{P-1})$, (3.1)

where g_c is taken as the gray value of the center pixel of a local neighborhood.

$g_p(p = 0, \ldots, P - 1)$ similar to the gray values of P equally spaced pixels on a circle of radius R ($R > 0$) that form a circularly symmetric set of neighbors. This set of $P + 1$ pixels is later denoted by GP . In a digital image domain, the coordinates of the neighbors of g_p are given by

$(x_c+R\cos(2\_p/P), y_c-R\sin(2\_p/P))$, where (x_c, y_c) are the coordinates of the center pixel. Taking illustrates three circularly symmetric neighbor sets for different values of P and R. The values of neighbors that will not fall exactly on pixels are estimated by the bilinear interpolation. Since correlation among pixels decreases with distance, lot of the textural information in an image can be obtained from local neighborhoods. If the value of the center pixel is subtracted



P=8,r=1.5 p=12 ,r=2.5 p=16,r=4

from the values of the neighborsand the local texture can be represented — without losing information — as a joint distribution of the value of the center pixel and the differences:

$T = t(g_c, g_0 - g_c, \ldots, g_{P-1} - g_c)$. (3.2)

Assuming that the differences are independent of g_c, the distribution can be factorized:

$T = t(g_c)t(g_0 - g_c, \ldots, g_{P-1} - g_c)$. (3.3)

In practice, the independence assumption may not always hold. Due to the limited nature of the values in digital images, very high or very low values of g_c will obviously narrow down the range of possible differences. However, accepting the possible small loss of information allows one to achieve invariance with respect to shifts in the gray scale.

Since $t(g_c)$ describes the overall luminance of an image, that is unrelated to local image texture, which does not provide useful information for texture analysis. Therefore, much of the information about the textural characteristics in the original joint distribution (Eq. 3.2) is preserved in the joint difference distribution

$T \_ t(g_0 - g_c, \ldots, g_{P-1} - g_c)$. (3.4)

The P−dimensional difference distribution records the occurrences of different texture patterns in the neighborhood of each pixel. For constant or slowly varying regions, the

differences in the cluster near zero. And on spot, all differences are relatively large. On an edge, differences in some directions are larger than the others. Although invariant against gray scale shifts, the differences that are affected by scaling.To achieve invariance with respect to any monotonic
transformation of the gray scale, are only the signs of the differences are considered:

T _ t(s(g0 − gc), . . . , s(gP−1 − gc)), (3.5)

where

s(x) = 1 x > 0
0 x < 0 . (3.6)

Now, a binomial weight 2p is assigned to each sign s(gp −gc), transforming the differences of a neighborhood into a very unique LBP code. The code specifies the local image texture around (xc, yc):

LBPP,R(xc, yc) = PX−1
p=0
s(gp − gc)2p. (3.7)

In practice, Eq. 3.7 means that the signs of the differences in a neighborhood are interpreted as a P-bit binary number, resulting in 2P the distinct values for the LBP code. The local gray-scale image distribution, i.e. texture, thus it can be approximately
described with a 2P -bin discrete distribution of LBP codes:

T =t(LBPP,R(xc, yc)). (3.8)

Let us assume we are given an N ×M image sample (xc 2 {0, . . . ,N −1}, yc ϵ {0, . . . ,M − 1}). In calculating the LBP P,R distribution (feature vector) for this image, the central part is only considered because a sufficiently large and cannot be used on the borders. The LBP code is calculated for each and every pixel which is the cropped portion of the image, and the distribution of the codes and used as the feature vector, is denoted as S:

S = t (LBPP,R(x, y)),

x ϵ {dRe, . . . ,N − 1 − dRe}, y 2 {dRe, . . . ,M − 1 – [Re]}.

the3×3neighborhood are interpolated in LBP Our model expects the input as Query by Example (QBE) and any combination of features can be selected for retrieval. The focus of this paper is to build a universal CBIR system using texture features example image contrast, energy, correlation, and homogeneity are retrieved. Using gabor and Lbp method is indexed circularly, to LBP8,1, with two differences .First, the neighborhood in the general definition is indexed circularly, making it easier to derive rotation invariant texture descriptors. Second, the diagonal pixels in the 3×3 neighborhood are interpolated in LBP making it easier to derive rotation invariant texture descriptors. and, the diagonal pixels in The original LBP is very similar

II. RELATED WORK

An content based image retrieval system is a computer system for browsing searching and retrieving images from a large data base of digital images Image Retrieval. A lot of work already has been done in this area. In many areas of industries, commercial, government, academia, commerce and the hospitals, very large collections of digital images are being created. Many of these collections of images are the product of digitizing existing collections of many analogue collection of photographs, diagrams, drawings, paintings, and prints. normally, the only way of searching these ,GABOR ,Histogram analysis ,edge detection and others according to user requirementWe try to enhance theworkofcbirandhenc

collections by the keyword indexing, or by simply browsing. Digital images of databases however it open the way to content-based image searching**.** Multimedia information retrieval as a broader research area covering all main parts video-, audio-, image-, and text analysis has been extensively surveyed Local features based methods proved good resuls . For a successful CBIR, note that the indexing scheme to be efficient for searching in the image database. Recently used retrieval systems have incorporated users' relevance feedback to modify the retrieval process in order to generate perceptually and semantically more meaningful retrieval results. Thus now days instead of searching images by keywords or wasting so much time CBIR is being used so that retrieval of image became so easy and saving time of user by using any of the method which user find more efficient like texture, shape ,colour and by any method LBP,Gabor

III. PROPOSED CBIR MODEL

The proposed CBIR framework is shown in Figure. The images are kept in a database called Imag Database.

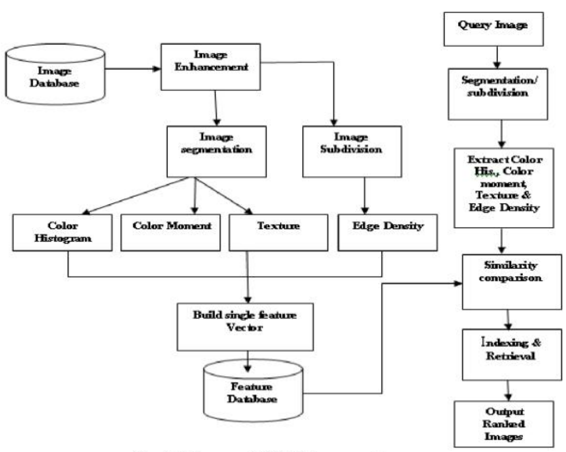


Fig. 4.3 Proposed CBIR Framework

A combination of four feature extraction methods namely color Histogram, texture ,shape and edge histogram descriptor. There will always a provision to add new features in future for better retrieval efficiency. Any combination from these retrieval methods, which provide more appropriate result , can be used for retrieval. This is provided through User Interface (UI) in the form of relevance feedback.

two different approaches are used texture methods were investigated for which one is better and efficient method and rest 11 snaps are used for object images .we can use any snaps for test(query) as well as object image ,.we can use other extension for same result but this project is used to browse only.jpg images .we can give other extension by using minor change and different algorithm or method for extracting information from images And analyzing which method is better for extracting image feature and which algorithm is good for matching images And database can be made larger ,according to the requirement of user

IV. CONCLUSION AND FUTURE WORK

In this Paper, proposed a Multi feature model for the Content Based Image Retrieval System by texture. Using two important methods LBP and Gabor were given options to select the appropriate feature extraction method for best results. The results are quite good for most of the query images and it is possible to further improve by fine tuning the threshold and providing feedback. In this paper

V. EXPERIMENTAL SETUP AND RESULTS

This chapter is used to explain the result analysis.To get required result,P-4,genuine intel CPU 1.60 GHz with 512 MB RAM, 40GB hard Disk ,10 MBPS Ethernet Card, MatLab7.0P. Window-XP Operating System,

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