Abstract: Advances in data storage and image acquisition technologies have enabled the creation of large image database. In order to deal with these data, it is necessary to develop method to efficiently manage these collections. In these systems, image processing algorithms using different method for feature extraction like texture and which method provides better performance.

Keywords: content based image retrieval, gabor algorithm, local directional pattern, feature extraction
1. Introduction:

Content Based Image Retrieval (CBIR) is a technique which uses visual contents, known 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, a lot of human effort can be saved and the problem of searching images from large databases 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. Nowadays, image content is no longer represented only by textual 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 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 LDP.

1.1. 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. 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. The 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:

\[
W_{MN}(x,y) = \sum_{x1}^{x} \sum_{y1}^{y} I(x1,y1) g_{mn}^*(x-x1,y-y1)
\]  

(1)

Where \( g_{mn}^* \) indicates complex conjugate and where \( m, n \) specify the 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:

\[
E(m,n) = \sum_{x} \sum_{y} |W_{MN}(x,y)|
\]  

(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 \( \sigma \) of the magnitude of the transformed coefficients is:

\[
\sigma_{mn} = \sqrt{\frac{1}{P \times Q} \sum_{m,n} (|W_{mn}(x,y)| - \mu_{mn})^2}
\]  

(3)

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

\[
\mathbf{f} = [\sigma_00, \sigma_01, \ldots, \sigma_{(m-1)(n-1)}]
\]  

(4)

\[
f_{\text{Gabor}} = f - \mu / \sigma
\]

where \( \mu \) is the mean and \( \sigma \) 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. transform transforms the image into a representation with both spatial and characteristics. This allows for effective image analysis with lower computational cost. According to this

\[
\Psi(t)
\]

\[
1
\]

\[
T
\]

\[
-1
\]

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

1.2. LDP:

Local Directional Pattern (LDP), for describing local image feature. A LDP feature will be obtained by computing the edge response values in all eight directions at each pixel position and generating a code from the relatively strength magnitude. Each bit of the code sequence
is determined by considering a local neighborhood hence becomes robust in noisy situation. The rotation invariant LDP code is also introduced which uses the direction of the most prominently edge response. Finally an image descriptor is formed to describe image (or image region) by accumulating the occurrence of LDP feature over the whole input image (or image region). We get Experimental results on the Brodatz texture database show that LDP impressively outperforms the other commonly used dense descriptors (e.g., Gabor-wavelet and LBP).

Local image descriptors are employed in many real world applications like object detection and view matching using local invariant features [1], texture classification using micro textons [2], face detection and recognizing using local features [3], [4] etc. Every image descriptors attempt to describe the image robustly in adverse imaging condition like lighting variation, changed view point, alteration due to rotation, zooming etc. Descriptors found in literature can be classified into two groups: sparse descriptor and dense descriptor [5]. The sparse first detects the interest points from a given image for sampling local image patch around detected interest points then it generates a feature vector capable to describe the patch. On the other hand, the dense descriptors extract local image features pixel by pixel over the whole input image without identify the interest points.

Recently researchers use change of gradient magnitude in a specific direction around pixels to encode local texture. [15], [16]. Instead of comparing neighboring intensity value these methods compare neighboring pixel’s gradient magnitude along a specific direction and encode it like trivial LBP. Consequently, these are unable to encode the information which possibly achieved by analyzing different magnitude of edge responses in different directions of a particular pixel. Rather it considers only one directional edge magnitude. Motivated by this observation, we proposed the image feature Local Directional Pattern (LDP) that computes the edge response values in different directions and use these to encode the image texture.
The proposed LDP feature is an eight bit binary code assigned to each pixel of an input image. This pattern will be calculated by comparing the relative edge response value of a pixel in different directions. Kirsch edge detector, Prewitt edge detector, Sobel edge detector are the representative edge detectors which can be used in this regard [17]. Among them, the Kirsch edge detector has been known to detect different directional edge responses more accurately than others because the Kirsch edge detector considers all eight neighbors [18].
Given a central pixel in the image, the eight directional edge response values \( \{m_i\}, \ i=0,1,\ldots,7 \) are computed by Kirsch masks \( M_i \) in eight different orientations centered on its position. These masks are shown in the fig. 2.

The response values are not equally important in all the directions. The presence of the corner or edge show high response values in every particular directions. Therefore, we will be interested to know the \( k \) most prominent directions in order to generate the LDP. Here, the top \( k \) directional bit have responses \( b_i \) are set to 1. The remaining \((8-k)\) bits of 8-bit LDP pattern is set to 0. Finally, the LDP code is derived by (3). Fig. 3 shows the mask response and LDP bit positions, and fig. 4 shows an exemplary LDP code with \( k=3 \).

\[
LD_P_k \prod \sum_{i} b_i (m_i - m_k) \prod 2 \quad (1)
\]

\[
i \neq 0 \quad 1 \quad a \geq 0 
\]

\[
b_i(a) \square \quad (2)
\]

\[
0 \quad a \square 0
\]

where, \( m_k \) is the \( k \)-th the most significant directional response.

![Figure 2: Kirsch masks](image)

![Figure 3: Mask response and LDP bit positions](image)

![Figure 4: Exemplary LDP code with \( k=3 \)](image)
2. 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 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 results. 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 LDP, GABOR, Histogram analysis, edge detection and others according to user requirement.
3. Proposed CBIR Model:

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

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.

4. 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 LDP 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 we try to enhance the work of cbir and hence uses two different approaches are used texture methods were investigated for which one is better and efficient method.
5. 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, Microsoft Office 2007 Pack are used to get desired result. 11 snaps are taken i.e. 1.jpg, 2.jpg, 3.jpg, 4.jpg, 5.jpg etc. To get the desired result, 11 snaps are taken. Here 1.jpg is used for test image 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.
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