FEATURE EXTRACTION TECHNIQUES FOR IMAGE RETRIEVAL USING HAAR AND GLCM

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ABSTRACT

Content Based Image Retrieval (CBIR) approach which provides efficient and effective means to extract most similar images stored in the database based on image contents. It aims at retrieving images which are perceptually meaningful by making the best use of a single or combination of visual content descriptors. The major steps are feature extraction and similarity comparison. This paper expands along the two techniques "Haar and GLCM" on Texture based image retrieval. Texture analysis is one of the widely used operations for feature extraction. The first method explores texture features extraction of the image by applying Haar Wavelet Transform (HWT) and then applying Gradient Operator Concept on LH and HL bands of HWT. The implemented second method computes the texture features by applying popular gray level co-occurrence matrix (GLCM) approach. The texture features thus extracted are subjected to similarity comparison and few images with higher similarity value are retrieved. The Brodatz image database that utilizes texture features forms the basis of the comparison and retrieval.It is concluded that the implemented GLCM provides much better results when compared with the popular Haar.

Keywords: CBIR, GLCM, Haar discrete transform

I. INTRODUCTION

The term "Feature Extraction" deals with extracting feature such as energy (energy measures texture uniformity. If an image is completely homogeneous its energy will be maximum), entropy (it measures randomness of an image), randomness, correlation (measure of how correlated a pixel is to its neighbor over the entire image), homogeneity (it measures the spatial closeness of the distribution of elements in co-occurrence matrix to the diagonal. If an image will be completely homogeneous, its energy will be maximum) etc. from an image, then store these feature in an offline database for further use and use these feature for image retrieval. Image retrieval is the process searching images from an offline database which are most similar to a query image specified by the user. The matching of images is done by extracting their features (texture, color & shape) and then applying some similarity measures on these features. This whole process is shown in this Fig1.
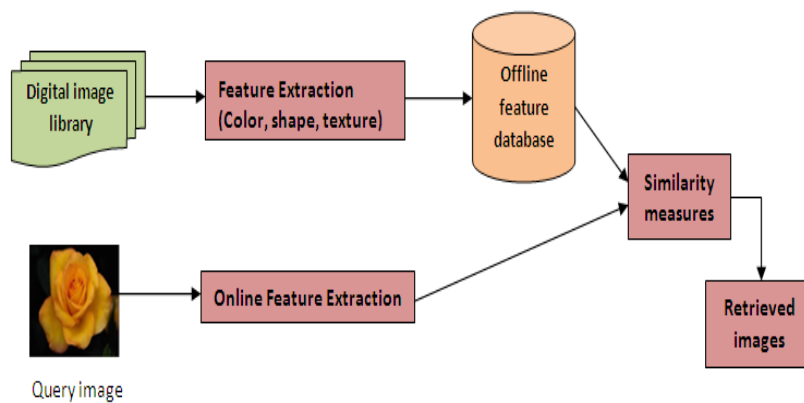
Figure1. CBIR System

Texture can be defined by certain constant, slowly varying or periodic local statistical properties computed over different regions of an image.

Texture analysis is used in many applications such as CBIR, biomedical image processing, automated visual inspection, and remote sensing. Much research work has been done on texture analysis for the last few decades. Despite these efforts, texture analysis is still considered an interesting but difficult problem of image processing. A good approach to study texture is the use of multi resolution analysis specially the Haar Wavelet Transforms. The Gray Level Co-occurrence Matrix (GLCM) method is a way of extracting second order statistical texture features. Using this statistical approach will help to provide valuable information about the relative position of the neighboring pixels in an image.

This paper is organized as follows: This section gives a brief introduction on CBIR. Section 2 explain the image decomposition and feature extraction using Haar discrete wavelet transform, Section 3 covers relative position of the neighboring pixels in an image and feature extraction using Gray Level Co-occurrence Matrix (GLCM) Section 4 covers similarity Measures. Section 5 describes experimental results. Finally conclusions are offered in section 6.

II. HAAR DISCRETE WAVELET TRANSFORM

Discrete Wavelet Transform (DWT) is the combination of pyramid coding, sub band coding and Haar transform. These are under the category of Multi-resolution analysis. Multi-resolution analysis (MRA) concerned with the representation and analysis of signals at more than one resolution. Features that might go undetected at one resolution may be easy to detect at another.

The Haar function $h_k(z)$ is defined on a continuous interval, z belongs to[0,1]

$h_0(z) = h_{00}(z) = 1/\sqrt{N}$, $z \in [0, 1]$

$h_{pq}(z) = 1/\sqrt{N}*2^{p/2}$ if $(q-1)/2^p \leq z < (q-0.5)/2^p$

$h_k(z) = h_{pq}(z) = 1/\sqrt{N}*(-2^{p/2})$ if $(q-0.5)/2^p \leq z < q/2^p$

$h_{pq}(z) = 0$ otherwise, $z \in [0, 1]$

where, k=0, 1, 2, N-1, $N=2^n$, z=0/N,1/N,2/N,…,(N-1)/N . k is defined as $k=2^p+q-1$, where $0 \leq p \leq n-1$, and q=0 or 1 for p=0, and $1 \leq q \leq 2^p$ for $p \neq 0$.

Each step in the Haar Wavelet Transform [1], [2] calculates a set of scaling coefficients and a set of wavelet coefficients. It creates four sub bands named as LL, LH, HL and HH. LL represents approximation of original

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image, HL – horizontal edges, LH –vertical edges, HH – diagonal edges. An L-level discrete wavelet transform decomposes an image into 3*L+1 sub bands. A 2-level DWT decomposes an image into 3*2+1=7 bands as shown in Fig 2.
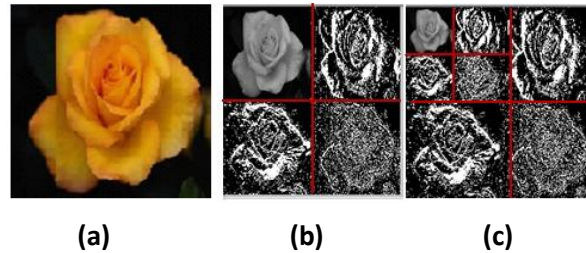

(a) **(b)** **(c)**

Figure 2 (a) The original image (b) Image obtained using 1-level Haar DWT. The levels are distinguished by colored lines. (c) obtained using 2-level Haar DWT. The levels are distinguished by colored lines.

2.1 Texture Feature from Haar

For computing 1- level Haar Gradient operator is applied on HL (channel represents horizontal edges) and LH (channel represents vertical edges) band of 1-Level haar wavelet. Thus with the given horizontal and vertical gradient magnitudes we can calculate gradient direction for each pixel of the sub image by the formula:

$$\theta = \tan^{-1}\left(\frac{gy}{gx}\right)$$

where gx, gy are the convolved image of gradient magnitude in horizontal (from HL data) and vertical direction (from LH data), respectively.

After calculating gradient direction for every pixel, number of regions is calculated as 360/D where D represents the direction range. In other words, D is nothing but size of a bin while plotting graph of number of pixels versus direction. Since the decision of direction range is crucial in affecting retrieval performance, the value of D should be fine tuned to achieve greatest performance. Based on a series of experiments, the value of D was set to 40∘ which has the greatest retrieval performance. [3] Hence we get 9 bins, each of size 40 degrees, and we calculate number of pixels in each bin. After this, for each bin three features, mean, standard deviation and entropy are calculated as shown in equations:

$$\text{Mean} = \frac{1}{N}\sum_{i=1}^{N} \qquad\qquad (1)$$

$$\text{Stddev} = \left(\frac{1}{N}\sum_{i=1}^{N}(\theta_i - mean)^2\right)^{\frac{1}{2}} \qquad (2)$$

$$\text{Entropy} = -\sum_{i=1}^{N} P_i \, log\left(\frac{1}{P}\right) \qquad (3)$$

III. GRAY LEVEL CO-OCCURRENCE MATRIX

The Gray Level Co-occurrence Matrix (GLCM) [4], [5] method is a way of extracting second order statistical texture features. Using only histograms in calculation will result in measures of texture that carry only information about distribution of intensities, but not about the relative position of pixels with respect to each other in that texture. Using this statistical approach will help to provide valuable information about the relative position of the neighboring pixels in an image.

GLCM is a spatial domain technique. It is a tabulation of how often different combinations of pixel brightness values (Gray Levels) occur in an image. The texture features are calculated by following the underlined steps in order:

1. Four co occurrence matrices are computed from the gray scale image by considering distance between pixels to be 1 and the four directions as 0°, 45°, 90° and 135°. Computation of co-occurrence matrix at 0^0 is shown in Fig 3.

2. For each co-occurrence matrix so obtained, four features namely; contrast, correlation, energy and homogeneity are calculated, thus resulting in a feature vector of size 16.
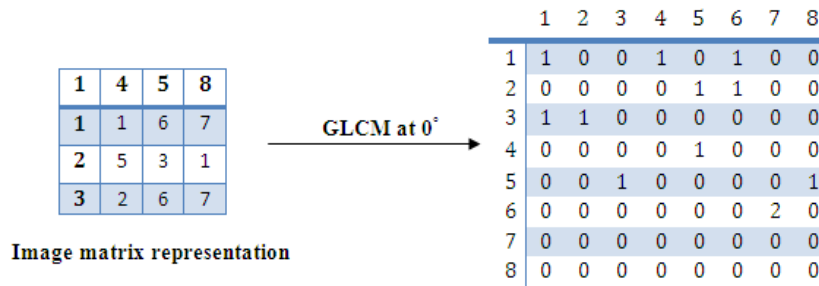
Figure3. Formation of Co-Occurrence Matrix for 0° Direction and a Single Gap Between the Pixels

3.1. Texture Features from GLCM

After calculating GLCM in all four directions 0, 45, 90, 135 degrees features energy, Contrast, Homogeneity and Correlation are calculated as shown in equations:

$$\text{Energy}= \sum_{i,j=0}^{N-1}(P_{i,j})^2 \qquad (4)$$

$$\text{Contrast}= \sum_{i,j=0}^{N-1}P_{i,j}(i-j)^2 \qquad (5)$$

$$\text{Homogeneity}= \sum_{i,j=0}^{N-1}\frac{P_{i,j}}{1+(i-j)^2} \qquad (6)$$

$$\text{Correlation}= \sum_{i=1}^{N}\sum_{j=1}^{N}\frac{(i-m_r)(j-m_c)P_{ij}}{\sigma_r\,\sigma_c} \qquad (7)$$

$$m_r = \sum_{i=1}^{N}i\,\sum_{j=1}^{N}P_{ij} \qquad m_c = \sum_{j=1}^{N}j\,\sum_{i=1}^{N}P_{ij}$$

$$\sigma_r = \left(\sum_{i=1}^{N}(i-m_r)^2\sum_{j=1}^{N}P_{ij}\right)^{1/2} \qquad \sigma_c = \left(\sum_{j=1}^{N}(j-m_c)^2\sum_{i=1}^{N}P_{ij}\right)^{1/2}$$

Here, N is the number of rows/columns of image matrix Q, P_{ij} is the probability that a pair of points in Q will have values (N_i, N_j) , m_r and m_c are the mean of rows and columns respectively, σ_r and σ_c are the standard deviation of rows and columns respectively.

IV. SIMILARITY MEASURE

In general, the accuracy of the retrieved results is directly proportional to the accuracy of the similarity measurement. A comparison of feature vectors of two different images gives the degree of similarity between them. Instead of exact matching of descriptors, content-based image retrieval calculates visual similarities of a query image with images in a database. Accordingly, the retrieval result is not a single image but a list of images

ranked by their similarities with the query image.In both the approaches (described in Section 2 and section 3) we use an as Euclidean distance.

$$\text{Euclidean Distance, } d(x,y) = \left(\sum_{i=1}^{N} |x_i - y_i|^2\right)^{1/2} \quad (8)$$

The process of identifying similar images to query image is shown in Fig 4, using Euclidean distance and various features of image.
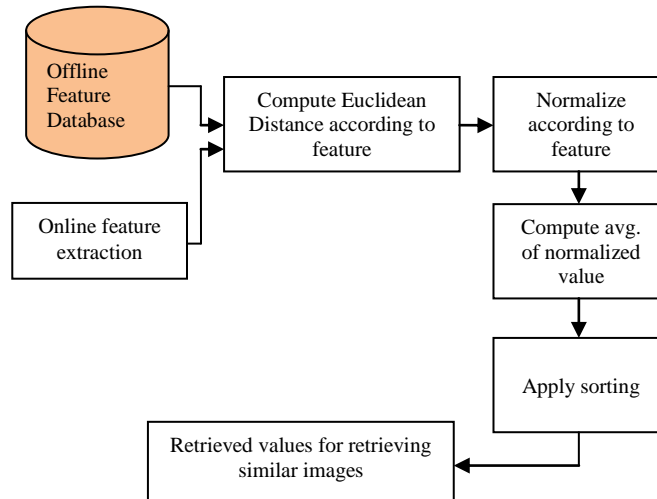

Figure4. Method for Identifying Similar Images

V. EXPERIMENTAL RESULT

The experiments were performed with Java as front end and MySQL as back end. The experiments were performed using the Brodatz [6] Texture Album.18 different textures were taken. The image of each texture type was divided into 16 non overlapping images of size 256X256, resulting in a database of 288 images. Therefore, there are 16 relevant images belonging to each texture type. Samples are shown in Fig 5.
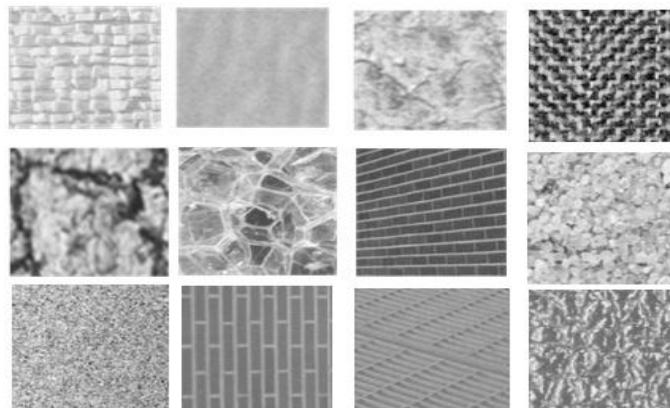
Figure5. Brodatz Database Sample

As an input query image shown in Fig 6 is provided

Figure6. Query Image

Haar transformation is applied on Brodatz database sample images. Then on these Haar transformed images Sobel Gradient operator is applied on HL & LH band. Output obtained after applying Sobel Gradient operator is shown in Fig7.
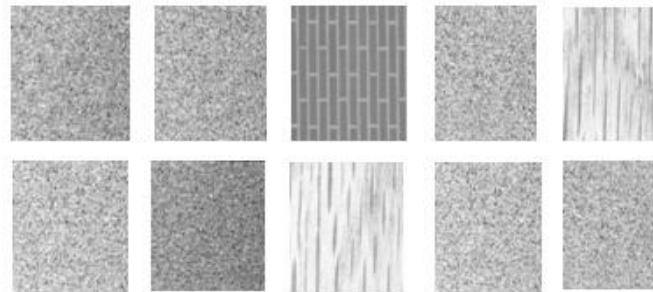
Figure7. Output after Sobel Gradient operator

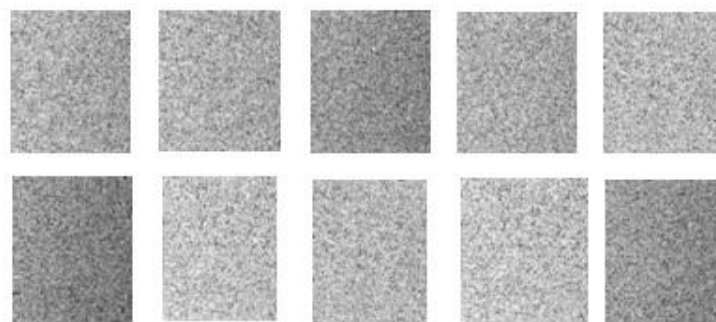After applying GLCM on Brodatz database sample images, following output is obtained. This is shown in Fig 8.
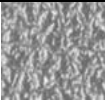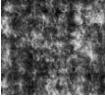
Figure8. Output after GLCM

The precision of the retrieval image is defined as the fraction of the retrieved images that are indeed relevant for the query:

$$\text{Performance analysis} = |X(q) \cap Y(q)| \div |X(q)| \quad (9)$$

Where, total number of images of the texture type in offline database is denoted as $Y(q)$, the total number of images retrieved after computation is denoted as $X(q)$.

By applying the performance analysis on Sobel Gradient operator on Haar transformed and GLCM transformed images, the result obtained is summarized in Table 1.

Table1. Precision Table of Sobel Gradient Operator on Haar Transformed and GLCM images

Texture Image	Sobel Gradient operator applied on HL & LH and features on HL & LH	GLCM
	Precision	Precision
	50	60
	100	80
	50	90
	70	100
	90	100

VI. CONCLUSION

This paper presented efficient image retrieval techniques. It is concluded that the implemented GLCM provides much better results when compared with the popular Haar, shown in Fig 9.
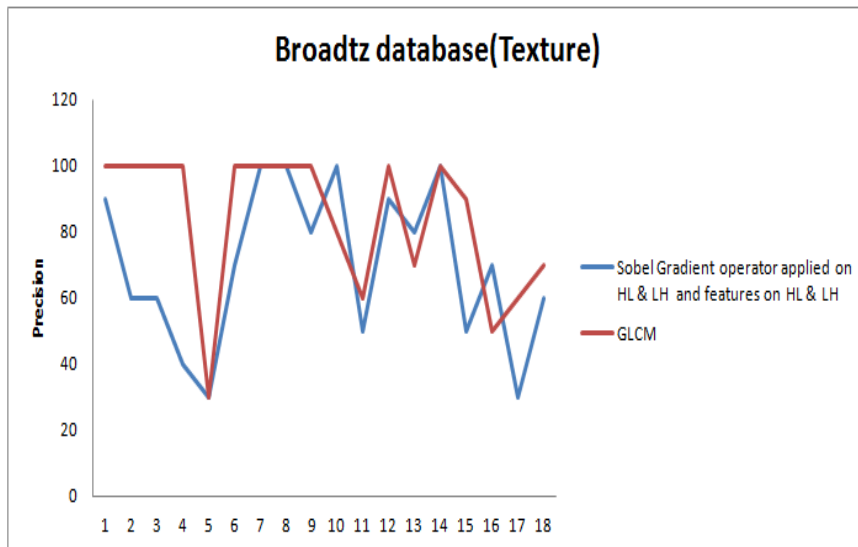

Figure9. Comparison Between Sobel Gradient Operator on Haar and GLCM

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