Texture Based Image Retrieval Using Correlation on Haar Wavelet Transform

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Abstract. Content Based Image Retrieval deals with the retrieval of most similar images corresponding to a query image from an image database. It involves feature extraction and similarity computation. This paper proposes a method named Correlation Texture Descriptor (CTD) which computes the correlation between the sub bands formed after applying Haar Discrete Wavelet Transform. Fuzzy Logic is used to compute the similarity of two feature vectors. Experiments determined that the proposed method, CTD, showed a significant improvement in retrieval performance when compared to other methods such as Weighted Standard Deviation (WSD), Gradient operation using Sobel operator and Gray Level Co-occurrence Matrix (GLCM).

Keywords*:* CBIR, Haar Wavelet Transform, Correlation, Fuzzy, GLCM.

1 Introduction

Image retrieval is used to retrieve similar images corresponding to a query image specified by the user. The images are represented by texture, color or any other low level features. The features of the query image are matched with the corresponding features of the images in the database by applying some similarity criteria. Images with high similarity values are then retrieved.

Texture analysis [1] attempts to quantify intuitive qualities described by terms such as rough, smooth, silky, or bumpy as a function of the spatial variation in pixel intensities. An efficient tool to study texture is the use of multi resolution analysis. The Haar wavelet transform is a discrete wavelet transform and is therefore preferred since it provides temporal resolution i.e. it captures both frequency and spatial information. The Haar Wavelet Transform decomposes the image into three detailed sub bands and an approximation image which can be decomposed further.

The objective of this paper is to introduce the Correlation Texture Descriptor method which computes the correlation between LL, HL and LH sub bands formed

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after applying Haar Wavelet Transform on the image at each level along with other statistical features. Furthermore, a comparison of CTD with other methods such as WSD[2], Gradient operation using Sobel operator[3] and GLCM[4] shows a significant improvement in retrieval performance.

This paper is organized as follows: This section gives a brief introduction on CBIR. Section 2 elaborates on Haar Wavelet Transform in Image Processing. Section 3 introduces the proposed method for texture feature extraction. Section 4 gives an idea of the other three approaches. Section 5 covers the similarity criteria. Section 6 presents the experimental results. Finally, the paper is concluded with Section 7.

2 Haar Wavelet Transform

In numerical analysis and functional analysis, a discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. For a one dimensional input signal represented by a list of 2^n numbers, where n>1, the Haar wavelet transform may be considered to simply pair up input values, storing the difference and passing the sum [5]. A standard decomposition of a two dimensional signal (image) is easily done by first performing a one dimensional transformation on each row followed by a one dimensional transformation on each column.

Let The Haar wavelet function [6] be defined by:

$$\Psi(t) = \begin{cases} 1 & t \in [0, \frac{1}{2}] \\ -1 & t \in [\frac{1}{2}, 1] \\ 0 & otherwise \end{cases} \quad (1)$$

Let us consider two 2*2 matrices: H and Y. We may first transform the columns of H by pre multiplying with T and then transform the rows of the result by post multiplying with T^T.

$$\text{Hence:} \quad Y = THT^T \quad (2)$$

$$\text{If } H = \begin{pmatrix} a & b \\ c & d \end{pmatrix} \quad (3)$$

$$\text{Then} \quad Y = \begin{pmatrix} a+b+c+d & a-b+c-d \\ a+b-c-d & a-b-c+d \end{pmatrix} \quad (4)$$

By applying the operations given above, the top left band acts as a 2D low pass filter and gives the approximation image [7]. Similarly, the top right band acts as an average horizontal gradient or horizontal high pass filter and vertical low pass filter , the lower left band as an average vertical gradient or horizontal low pass filter and vertical high pass filter and the lower right band as a diagonal curvature or 2D high pass filter.

3 Proposed Work for Feature Extraction (Ctd)

In statistics, dependence refers to any statistical relationship between two random variables or two sets of data. Correlation refers to any of a broad class of statistical relationships involving dependence. The most familiar measure of dependence between two quantities is the cross correlation coefficient [8]. It is obtained by dividing the covariance of the two variables by the product of their standard deviations:

$$\rho_{xy} = corr(x, y) = \frac{cov(x, y)}{\sigma_x \sigma_y} = \frac{E[(x - \mu_x)(y - \mu_y)]}{\sigma_x \sigma_y} \tag{5}$$

Where E is the expected value operator, cov means covariance, μ_x and μ_y are the mean values and corr stands for correlation.

Correlation Texture Descriptor (CTD) uses the wavelet coefficients of all the sub bands obtained after Haar Discrete Wavelet Transform. To compute CTD, an image is first subjected to gray scale conversion using the formula:

$$I_{ij} = (11 * Cij\ (R) + 16 * Cij\ (G) + 5 * Cij\ (B)) / 32 \tag{6}$$

Where I_{ij} is the intensity assigned to pixel (i,j) of Image C, C_{ij} (R, G, B) denotes the red, green and blue color values of (i, j) pixel of image C.

The gray scale image is subjected to level 1 Haar DWT decomposing it into 4 sub bands. The approximation image is then subjected to level 2 Haar DWT decomposing it into 4 sub bands, thereby resulting in a total of 8 sub bands. The correlation between LL and HL sub bands, LL and LH sub bands and between HL and LH sub bands is calculated using the formula [9] :

$$\rho_{A,B} = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} (a_{ij} - \bar{a})(b_{ij} - \bar{b})}{\sqrt[2]{(\sum_{i=1}^{N} \sum_{j=1}^{N} (a_{ij} - \bar{a})^2)(\sum_{i=1}^{N} \sum_{j=1}^{N} (b_{ij} - \bar{b})^2)}} \tag{7}$$

Where a and b are NXN matrices containing the pixel intensity values of image sub bands A and B respectively and $\bar{a}$, $\bar{b}$ represent the mean of a and b respectively.

The standard deviation of each sub band along with the mean and energy of the approximation image is computed at each level. Since the number of pixels in LH, HH and HL sub bands keep on decreasing with an increase in the level of decomposition, the standard deviation of these sub band images at i^{th} level is weighted by the factor $\left(\frac{1}{2}\right)^{i-1}$ thus assigning higher weights to lower level bands.

The 18 CTD Features (CF) for a two level haar image are:

CF = { σ_1^{LL} ,σ_1^{LH}, σ_1^{HL}, σ_1^{HH}, μ_1^{LL},E_1^{LL},σ_2^{LL} ,½ σ_2^{LH}, ½ σ_2^{HL}, ½ σ_2^{HH}, μ_2^{LL}, E_2^{LL},corr(LL1-HL1),corr(LL1-LH1),corr(HL1-LH1),corr(LL2-HL2),corr(LL2-LH2),corr(HL2-LH2) }

Where CF stands for CTD Features,

σ_i^{MM} is the Standard Deviation of the MM sub band (MM stands for LL, LH, HL or HH sub band) at decomposition level i,

μ_i^{LL} is the mean of the approximation image (i=1 for level1 and i=2 for level2),

E_i^{LL} is the energy of the approximation image (i=1 for level 1 and i=2 for level 2),

corr(mmi-nni) stands for the correlation of sub band mmi and nni (mm and nn stand for LL,HL or LH sub bands; i=1 for level1 and i=2 for level2).

4 Other Feature Extraction Techniques

WSD [2] (Weighted Standard Deviation) is a texture descriptor which uses the wavelet coefficients of all the sub bands obtained after Haar Discrete Wavelet Transform. The standard deviation of 6 sub bands (3 at each level) along with the mean and standard deviation of the approximation image obtained at the 2^{nd} level of decomposition is computed. The standard deviation of each HH, HL and LH sub band image at i^{th} level is weighted by the factor $\left(\frac{1}{2}\right)^{i-1}$. Thus a total of 8 features for each image are extracted.

The Gradient Operation technique [2][3] applies Sobel gradient mask directly on the gray scale image to obtain the gradient direction and theta of each pixel. Nine bins each of 40 degrees are then calculated. Computing the mean, standard deviation and entropy of each bin results in the formation of a total of 27 features.

In the GLCM technique [2][4], four co-occurrence matrices are computed from the gray scale image by considering distance between pixels to be 1 and the four directions as 0^0, 45^0, 90^0 and 135^0. For each co-occurrence matrix so obtained, four features namely: contrast, correlation, energy and homogeneity are calculated resulting in a total of 16 features for each image.

5 Similarity Measure

CBIR requires the computation of similarity between the query image and those in the image database. A specified number of images with the highest similarity are then required to be retrieved. In all the above approaches, Fuzzy Logic [10] is used as a similarity measure. There was a significant improvement in retrieval results by using Fuzzy Logic as similarity measure when compared to Minkowski distance and Euclidean distance. Fuzzy logic uses membership functions to find the similarity between the feature vectors of any two images. In our study, we have used triangular functions as membership functions. The base of the triangular functions was experimentally determined.

6 Experimental Results

The experiments were performed with Java as front end and MySQL as back end. 16 different images were taken from a database containing 681 images from the VisTex Album [11], each of size 256X256.

For the discussed methods, the respective features of each database image were computed offline and stored. The feature computation process was carried out online for the query image. For each of the 16 images, 10 most similar images were retrieved. The retrieval accuracy was then measured using the formula given below:

$$R(q) = |A(q) \cap S(q)| \div |A(q)| \tag{8}$$

Where R(q) is the retrieval accuracy, |S(q)| is the total number of images of the texture type in the database, |A(q)| is the total number of images retrieved for display and |A(q) ∩ S(q)| is the number of relevant images retrieved belonging to the texture type of the query image. The following graph depicts the retrieval accuracy of the above mentioned techniques.

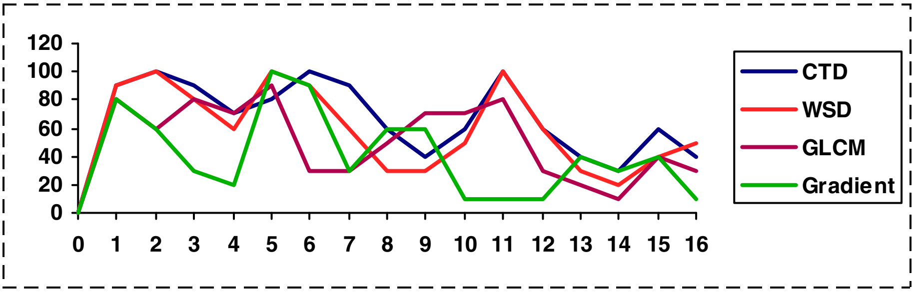

Fig. 1. Plot of Retrieval Accuracy vs. Texture type for the four texture based techniques

The CTD approach was also applied on the Brodatz texture album [2] and a comparison [2] of its results with those of the other three techniques showed a pattern similar to the graph given above i.e. the retrieval accuracy of CTD was better than that of the other three techniques.

7 Conclusion

The graph given above clearly depicts a significant improvement in precision of the proposed CTD approach over the other three methods, namely: WSD, Gradient and GLCM. It can also be seen that both CTD and WSD give significantly better results compared to GLCM and Gradient methods. This can be attributed to the fact that both CTD and WSD methods use detailed information of all the sub bands, after decomposing the image by applying Haar Discrete Wavelet Transform. Also, the use of correlation between sub bands at each level and incorporation of features of the approximation image obtained after applying Haar Transform may be responsible for the marginal improvement in results when the proposed CTD method is used as compared to the WSD approach.

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