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Effective Method of Image Retrieval Using BTC with Gabor Wavelet Matrix

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Abstract— The emergence of multimedia technology and the rapidly expanding image collections on the database have attracted significant research efforts in providing tools for effective retrieval and management of visual data. The need to find a desired image from a large collection. Image retrieval is the field of study concerned with searching and retrieving digital image from a collection of database .In real images, regions are often homogenous; neighboring pixels usually have similar properties (shape, color, texture). In this paper we proposed novel image retrieval based on Block Truncation Coding (BTC) with Gabor wavelet co-occurrence matrix. For image retrieval the features like shape, color, texture, spatial relation, and correlation and Eigen values are considered. BTC can be used for grayscale as well as for color images. The average precision and recall of all queries are computed and considered for performance analysis.

Keywords: *Feature Extraction, Similarity Measures, Image Retrieval.*

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I. INTRODUCTION

Image retrieval is the field of study concerned with searching and retrieving digital images from a collection of database. Image retrieval attracts interest among researchers in the fields of image processing, multimedia, digital libraries, remote sensing, astronomy, database applications and others related area. An effective image retrieval system is able to operate on the collection of images to retrieve the relevant images based on the query image which conforms as closely as possible to human perception. Image compression techniques aim at reducing the transmission file size, by using lesser bits for the images. This is realized by using fewer bits per pixel of the image. The images could be compressed without reduction in quality by employing suitable coding techniques. The 'Compression ratio (CR)', the 'Peak Signal to Noise Ratio (PSNR)' and the 'Contrast (C)' are the parameters used to measure the quality of image compression both time-domain (spatial) and frequency - domain (spectral) image compression techniques are employed in image compression. Block Truncation Coding (BTC) is an apparently elegant and efficient time-domain compression technique, developed by Delp and Mitchell. The wavelet transform could perform multi-resolution time-frequency analysis. Gabor functions provide the optimal resolution in both the time and frequency domains. Then, we propose a texture characterization made through second order statistical measurements based on Grey-Level Cooccurrence Matrix (GLCM), as proposed Haralick. Features computed from GLCM are based on the assumption that the texture information in an image is contained in the overall spatial relationship which grey levels of neighboring pixels have to one another. GLCM contains information about the frequency of occurrence of two neighboring pixel combination in an image. Many classifiers tend to underperform and can lead to false discoveries due to the high dimensional nature. SVM is one of the most powerful non-linear classification methods to date, as it is able to find a separating hyper-plane for non-seperable data on a high-dimensional feature space using the kernel trick.

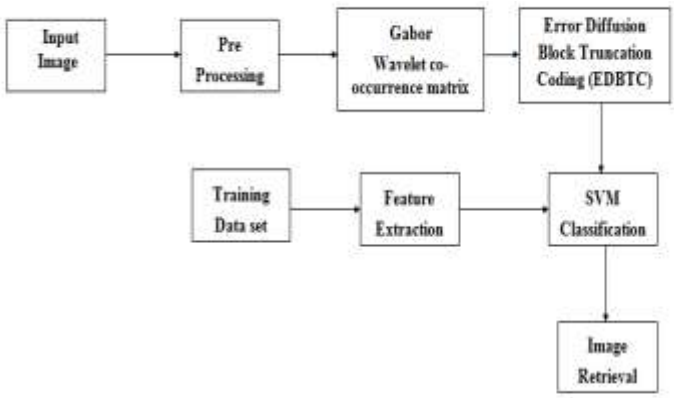

Fig block diagram of image retrieval

II. RELATED WORK

In this section, the related work about feature extraction, similarity measure metrics, and image retrieval in the following sections.

A. Feature Representation and Fusion

Over the last two decades, a variety of feature descriptions has been proposed. They are generally divided into two categories: Block truncation coding and Gabor Wavelet Transform. An image retrieval system is presented by exploiting the BTC encoded data stream to construct the image features, namely gabor wavelet and CCF. The proposed scheme can provide the best average precision rate compared to various former schemes in the literature. The proposed scheme can be considered as a very competitive candidate in the color image retrieval application. Another feature can be added by extracting the BTC data stream, to enhance the retrieval performance. The Gabor wavelet captures the property of spatial localization, orientation, spatial frequency and face relationship. The wavelet transform could perform multi-resolution Time-Frequency analysis. This new application of a well studied image coding technique, namely block truncation coding (BTC). It is shown that BTC can not only be used for compressing color images, it can also be conveniently used for content-based image retrieval from image databases. From the BTC compressed stream and applying Gabor wavelet transform, continued by, we derive image content description features by GLCM like shape, color, texture, spatial relation, and correlation and Eigen values are considered.

B. Similarity Measure Approaches

Similarity measure is often used on the extracted features to identify the images similar to the query. The shape similarity can easily be defined by means of a distance measure (the Euclidean distance).The Euclidean distance can simply be described as the ordinary distance between two values. The Euclidean distances between the feature vectors P=(p1,p2,…..pn) and Q=(q1,q2,…..qn) is expressed by

$$D=\sqrt{\sum_{k=1}^{n}(p_k\text{-}q_k)}^2$$

C. Image Retrieval

In this section, the subjects of image matching and retrieval related to our paper. In a content based image retrieval system was presented, which aimed at classifying and retrieving oceanic structures from satellite images. In semantic matching of multilevel image scenes was utilized to retrieve. In the authors described a content-based shape retrieval of objects from a large-scale satellite images. Ferecatu and Boujemaa developed an active relevance feedback solution based on support vector machines using weighted histograms as descriptors. In a support vector machine approach was employed to recognize land cover information corresponding to spectral characteristics. The smaller kernel size (in time domain) has higher resolution in time domain but lower resolution in frequency domain, and is used for higher frequency analysis; while bigger kernel size has higher resolution in frequency domain but lower resolution in time domain, and is used for lower frequency analysis. This great property makes wavelet transform suitable for applications such as image compression, edge detection, filter design, and some kinds of image object recognition, etc.

III. IMAGE FEATURE DESCRIPTORS

In this section, The procedure for extracting Block truncation coding , Gabor Wavelet Transform and Gray Level Co Occurrence Matrix (GLCM).

3.1GaborWavelet Transform Algorithm

The Gabor wavelet captures the property of spatial localization, orientation, spatial frequency and face relationship. The wavelet transform could perform multi-resolution Time-Frequency analysis. Among various wavelets, the Gabor function provides the optimal resolution in both time & Frequency domain and Gabor transform seems to be optimal basis to extract local features for several reasons to achieve multiresolution and multi-orientation. A Gabor (Kernels, filters) The Gabor wavelet can be defined as follows:

The Fourier transform has been the most commonly used tool for analyzing frequency properties of a given signal, while after transformation, the information about time is lost and it's hard to tell where a certain frequency occurs. To solve this problem, we can use kinds of time-frequency analysis techniques learned from the course to represent a 1-D signal in time and frequency simultaneously. There is always uncertainty between the time and the frequency resolution of the window function used in this analysis since it is well know that when the time duration get larger, the bandwidth becomes smaller. Several ways have been proposed to find the uncertainty bound, and the most common one is the multiple of the standard deviations on time and frequency domain:

$$\sigma t^2 = \int(t^2\,|x(t)|^2 dt)/\int(|x(t)|^2 dt)\ ,\ \sigma f^2 = \int(f^2\,|X(f)|^2 df)/\int(|X(f)|^2 df)\ \ldots\ldots \quad (1)$$

$$\sigma t \times \sigma f \geq 1/\,4\pi\ \ldots\ldots.(2)$$

Among all kinds of window functions, the Gabor function is proved to achieve the lower bound and performs the best analytical resolution in the joint domain. This function is a Gaussian modulated by a sinusoidal signal and shown below:

$$\varphi\ (t) = (-\alpha^2\ t^2\ )(j2\pi f0\ t)\ldots\ldots\ (3)$$

$$(f) = \sqrt{(\pi/\ \alpha^2)}\ (exp(-\pi^2/a^2\ (f - fo)^2\ ))\ldots\ldots..\ (4)$$

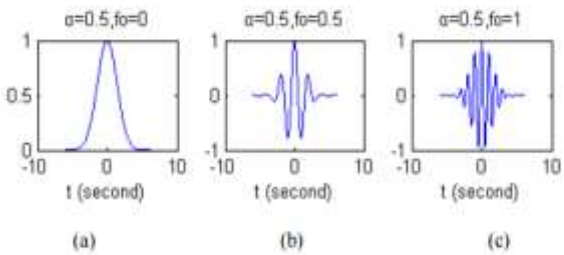

Figure 1: Example of $\varphi\ t$ with three different $f0$ = 0, 0.5, and 1 but the same α = 0.5 and their time-frequency analysis by Gabor transform, where (a)-(c) show the real part of $\varphi\ (t)$

Fig.2 shows the example of this new-defined (t) with three different $f0$ but the same α and their time-frequency analysis by Gabor transform

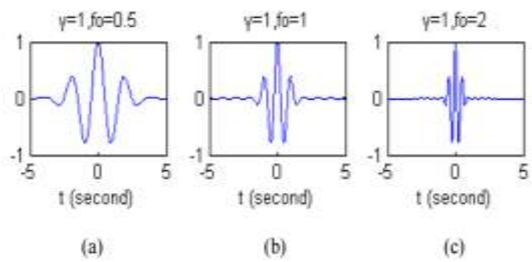

Figure 2: Example of the generalized $\varphi\ t$ with three different $f0$ = 0.5, 1, and 2 but the same γ = 1 and their

time-frequency analysis by Gabor transform, where (a)-(c) show the real part of (t)

We know that a set of 1-D wavelets is defined as:

$\psi\ (t, a, b)$ = ((□ − □)/□)

where (□) is the mother wavelet and a and b determines the temporal shifting and scaling of this function. This definition could be further extended into 2-D wavelet transform as:

(□□, □□, □, □, □0, □0) = (1/√ (□□□□)) □□ ((□−□0)/ □□ + (□−□0)/ □□)

The family of Gabor wavelets with 4 scales and 8 orientations given by

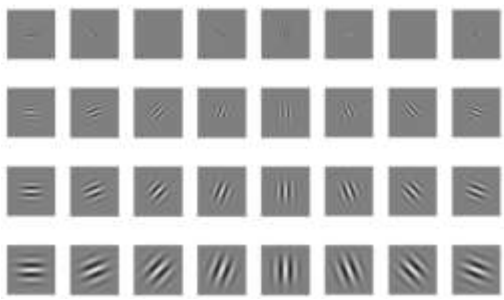

Figure 3: An example of the real part of Gabor wavelets with 4 scales and 8 orientations. The □□□□ is set as 0.35 with □ = □ = 1.2

3.2 Co-occurrence matrix method:

In 1973 Haralick introduced the co-occurrence matrix and texture features for automated classification of rocks into six categories. These features are widely used for different kinds of images. Now we will explore the definitions and background needed to understand the computation of GLCM.

3.2.1 Construction of the Traditional Co-occurrence Matrices

Let I be a given grey scale image. Let N be the total number of grey levels in the image. The Grey Level Co-occurrence Matrix defined by Haralick is a square matrix G of order N, where the (i, j)th entry of G represents the number of occasions a pixel with intensity i is adjacent to a pixel with intensity j. The normalized co-occurrence matrix is obtained by dividing each element of G by the total number of co-occurrence pairs in G. The adjacency can be defined to take place in each of the four directions (horizontal, vertical, left and right diagonal) as shown in figure1. The Haralick texture features are calculated for each of these directions of adjacency.

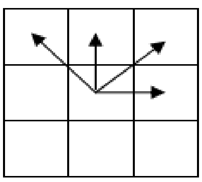

Figure 4. The four directions of adjacency for calculating the Haralick texture features The texture features are calculated by averaging over the four directional co-occurrence matrices.

3.2.2 Generalized Gray Scale Images

In order to extend the concept of co-occurrence matrices to n-dimensional Euclidean space, a mathematical model for the above concepts is required. We treat our universal set as Z^n . Here Z^n= Z x Z x … x Z, the Cartesian product of Z taken n times with itself. Where, Z is the set of all integers. A point (or pixel in Z^n) X in Z^n is an n-tuple of the form X=(x1,x2,…,xn) where xi ∈ Z ∀ i= 1,2,3...n . An image I is a function from a subset of Z^n to Z. That is f :I →Z where I ⊂ Z^n . If X ∈ I , then X is assigned an integer Y such that Y = f (X). Y is called the intensity of the pixel X. The image is called a grey scale image in the n-dimensional space Z^n . Volumetric data can be treated as three dimensional images or images in Z^3.

3.2.3 Generalize Co-occurrenceMatrices

Consider a grey scale image I defined in n Z. The gray level co-occurrence matrix is defined to be a square matrix Gd of size N where, N is the N be the total number of grey levels in the image. the (i, j)th entry of Gd represents the number of times a pixel X with intensity value i is separated from a pixel Y with intensity value j at a particular distance k in a particular direction d. where the distance k is a nonnegative integer and the direction d is specified by d =(d1,d2, d3, ...,dn) , where di ∈{0,k ,-k }, ∀i= 1,2,3...n.

As an illustration consider the grey scale image in Z^3 with the four intensity values 0, 1, 2 and 3. The image is represented as a three dimensional matrix of size 3*3*3 in which the three slices are as follows.

$$\begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & 2 \\ 0 & 2 & 3 \end{bmatrix}, \begin{bmatrix} 1 & 2 & 3 \\ 0 & 2 & 3 \\ 0 & 1 & 2 \end{bmatrix} \text{ and } \begin{bmatrix} 1 & 3 & 0 \\ 0 & 3 & 1 \\ 3 & 2 & 1 \end{bmatrix}$$

The three dimensional co-occurrence matrix Gd for this image in the direction d = (1,0,0) is the 4*

$$G_d = \begin{bmatrix} 1 & 3 & 2 & 1 \\ 0 & 0 & 3 & 1 \\ 0 & 1 & 0 & 3 \\ 1 & 1 & 1 & 0 \end{bmatrix}$$

4 matrix

Note that

$$G_{-d} = \begin{bmatrix} 1 & 0 & 0 & 1 \\ 3 & 0 & 1 & 1 \\ 2 & 3 & 0 & 1 \\ 1 & 1 & 3 & 0 \end{bmatrix} = G_d'$$

It can be seen that X +d = Y , so that G −d =Gd' , where Gd' is the transpose of Gd . Hence Gd+ G-d is a symmetric matrix. Since G−d = Gd' , we say that Gd and G−d are dependent (or not independent). Therefore the directions d and –d are called dependent or not independent. Theorem: If X∈ Z^n, the number of independent directions from X in Z^n is $(3^n - 1)/2$.

3.2.4 Normalized Co-Occurrence Matrix

Consider N= ∑∑Gd(i,j) , which is the total number of co-occurrence pairs in Gd . Let GN(i, j) = 1/N(Gd(i, j)). GNd is called the normalized co-occurrence matrix, where the (i, j)th entry of GNd(i j) is the joint probability of co-occurrences of pixels with intensity i and pixels with intensity j separated by a distance k, in a particular direction d.

3.2.5 Trace

In addition to the well known Haralick features such as Angular Second Moment, Contrast, Correlation etc., we define a new feature from the normalized co-occurrence matrix, which can be used to identify constant regions in an image. For convenience we consider n=2, so that the image is a two dimensional grey scale image and the normalized co-occurrence matrix becomes the traditional Grey Level Co-occurrence Matrix.

Consider the images taken from the Brodatz texture album given in figure 2. The majority of the nonzero entries of the co-occurrence matrices lie along the main diagonal so that we treat the trace (sum of the main diagonal entries) of the normalized co-occurrence matrix as a new feature. Trace of GNd(i j) is defined as

Trace =∑i GNd(i j)

The value of the trace indicates the same.

1) **Contrast:** Contrast is a local grey level variation in the grey level cooccurrence matrix. It can be thought of as a linear dependency of grey levels of neighboring pixels.

   Contrast = $\sum_{i,j} |i-j|^2 p(i,j)$

2) **Homogeneity:** Homogeneity measures the uniformity of the non-zero entries in the GLCM. It weights values by the inverse of contrast weight.

   Homogeneity = $\sum_{i,j} \frac{1}{1-(i-j)^2} p(i,j)$

3) **Dissimilarity**: Dissimilarity is a measure that defines the variation of grey level pairs in an image. It is the closest to Contrast with a difference in the weight – Contrast unlike Dissimilarity grows quadratically.

   Dissimilarity = $\sum_{i,j} |i-j| p(i,j)$

4) **Entropy:** Entropy in any system represents disorder, where in the case of texture analysis is a measure of its spatial disorder

   Entropy = $\sum_{i,j} p(i,j) \log(p(i,j))$

5) **Energy:** Energy is a measure of local homogeneity and therefore it represents the opposite of the Entropy. Basically this feature will tell us how uniform the texture is

   Energy = $\sum_{i,j} p(i,j)^2$

3.3 Block Truncation Coding

BTC can be used for grayscale as well as for color images. The average precision and recall of all queries are computed and considered for performance analysis. Image compression techniques aim at reducing the transmission file size, by using lesser bits for the images. This is realized by using fewer bits per pixel of the image. Normally this bit reduction will affect the quality of the image reproduced at the receiver. This process is known as ‘Lossy Image Compression. But images could also be compressed without reduction in quality by employing suitable coding techniques. Inherently, such ‘Lossless Image Compression’ methods yield less compression, compared to ‘Lossy’ methods. The ‘Compression ratio (CR)’, the ‘Peak Signal to Noise Ratio (PSNR)’ and the ‘Contrast (C)’ are the parameters used to measure the quality of image compression. Both time-domain (spatial) and frequency -domain (spectral) image compression techniques are employed in image compression. Block Truncation Coding (BTC) is an apparently elegant and efficient time-domain compression technique, developed by Delp and Mitchell.

3.4 Support Vector Machine

The Support Vector machines were introduced by Vladimir Vapnik and colleagues. Support Vector machines (SVM’s) are a relatively new learning method used for binary classification. The basic idea is to find a hyper plane which separates the D-Dimensional data perfectly into its two classes. However, since example data is often not linearly separable, SVM’s introduce the notion of a kernel induced feature space which casts the data into a higher dimensional space where the data is separable.

However, SVM classifiers could be extended to be able to solve multiclass problems as well. One of the strategies for adapting binary SVM classifiers for solving multiclass problems is one-against-all (OvA) scheme. It includes decomposition of the M-class problem (M>2) into series of two-class problems. To obtain a decision surface corresponding to a polynomial of degree two, one can create a feature space, Z, which has N = 2&±21 coordinates of the form:

Z1=x1,…….,Zn=Xn. n coordinates

Zn+1=xn2,…….,Z2n=Xn2 n coordinates

Z2n+1=X1X2,……Zn=XnXn-1 n(n-1)/2 coordinates

IV. IMAGE DESCRIPTORS

The basis of any content-based image retrieval technique. In a broad sense, features may include both text-based features (key words, annotations) and visual features (color, texture, shape, etc.).

A.COLOR

Color is a perception that depends on the response of the human visual system to light and the interaction of light with objects. Color is one of the most widely used visual features in visual image retrieval. The key issues in color feature extraction include the color space, color quantization, and the choice of similarity function. Each pixel of the image can be represented as a point in a 3D color space. To describe an image by its color features, and first determine the color space to use.

a. Color space

There are a number of different color spaces currently used for the representation of images in the digital world. Choosing an appropriate color space for the implementation of an image retrieval system is not only important to the production of the accurate results, but to the accurate representation of color in the way the human visual system perceives it. There are a number of color spaces in use of which some of the most commonly used are:

1. RGB

The most popular color space is RGB which stands for Red-Green-Blue these are the additive primary colors. By this added to produce more or less any color in the visible spectrum. This space is device dependant and perceptually non-uniform. This means that a color relative close together in the RGB space may not necessarily be perceived as being close by the human eye. For a monitor the phosphor luminescence consists of additive primaries and can simply parameterize all colors via the coefficients (α, β, γ), such that C = αR+βG+γB. The coefficients range from zero (no luminescence) to one (full phosphor output). In this parameterization the color coordinates fill a cubical volume with vertices black, the three primaries (red, green, blue), the three secondary mixes (cyan, magenta, yellow), and white as shown in Fig 2 .

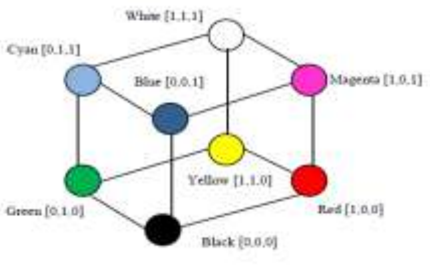

Fig 2: RGB Color space

2. HSV

Colors in the HSV color space are defined in terms of three constituent components; Hue, Saturation and Value. Hue is the type of color (red, blue, etc), saturation is the vibrancy of the color (the lower the saturation the more grayness is present) and the value is the brightness of the color. RGB coordinates can be easily translated to the HSV coordinates by a simple formula.HSV is perceptually uniform so colors close in value are also perceived close by the human eye.

B.TEXTURE

a. Definition

The Texture is defined as the visual patterns that have properties of homogeneity that do not result from the presence of only a single color or intensity. It is a natural property of virtually all surfaces, including clouds, trees, bricks, hair, and fabrics. It contains important information about the structural arrangement of surfaces and their relationship. Fig shows a few types of texture

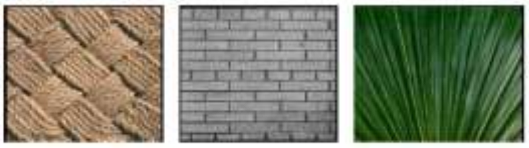

Fig 3. Examples of Texture

b. Methods of representation

Texture representation methods can be classified into three categories:

Statistical techniques: characterize texture using the statistical properties of the gray levels of the pixels comprising an image. Normally, in images, there is periodic occurrence of certain gray levels. The spatial distribution of gray levels is calculated Structural techniques: characterize texture as being composed of texels (texture elements). These texels are arranged regularly on a surface according to some specific arrangement rules.

Spectral techniques: are based on properties of the Fourier spectrum and describe global periodicity of the grey levels of a surface by identifying high-energy peaksin the Fourier spectrum.

C. SHAPE

a. Definition

Defining the shape of an object is often very difficult. Shape is usually represented verbally or in figures, and people use terms such as elongated, rounded etc. Computer-based processing of shape requires describing even very complicated shapes precisely and while many practical shape description methods exists, there is no generally accepted methodology of shape description. Shape is an important visual feature and it is one of the primitive features for image content description.

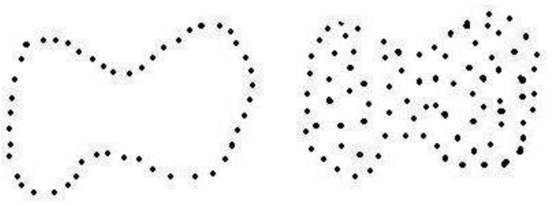

Fig 4: Boundary-based & Region-based shape representations

It contains all the geometrical information of an object in the image which does not change generally change even when orientation or location of the object are changed. Some simple shape features are the perimeter, area, eccentricity, symmetry, etc.

V. SIMULATION RESULT

Fig 1 Input image

Fig 2 HSV image

Fig 3 Block Truncation Coding

VI. CONCLUSION

Image retrieval is a very important research topic which has attracted great interests in recent years. Image coding is a successful field which has been studied for more than three decades. All image coding techniques attempt to extract visually most important features and represent them as compactly as possible. This paper presents a new application of a well studied image coding technique, namely block truncation coding (BTC). It is shown that BTC can not only be used for compressing color images, it can also be conveniently used for content-based image retrieval from image databases. From the BTC compressed stream and applying gabor wavelet transform, continued by, we derive image content description features by GLCM like shape, color, texture, spatial relation, and correlation and Eigen values are considered. After this the images are then classified using SVM classification

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