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A Study on Content Based Image Retrieval using Texture Features and Security Analysis

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ABSTRACT

This paper suggests discrete wavelet based texture features for Content Based Image Retrieval (CBIR). The Proposed methodology uses Discrete Wavelet Transform for reducing the size of test images. To extract the texture feature of the images, a grey level co-occurrence matrix (GLCM) is applied for all test images of Low Level components of level 2 decomposed images. Related images are retrieved by using different distance measure classifiers. The experimental result shows that the proposed method achieves comparable retrieval performance for correlation property of GLCM of texture feature.

Keyword-Texture, Discrete Wavelet Transform, gray level co-occurrence matrix, Distance Measures

I.INTRODUCTION

The open spread use of digital and multimedia knowledge, storeroom; finding and recovery of images beginning the huge database become not easy. To facilitate economical searching and retrieving of pictures as of the digital collection, new software and techniques have been emerged. The need to discover a preferred image from a huge collection is mutual by many skilled groups including the media persons, drawing engineers, art historians and scholars etc. Content Based Image Retrieval (CBIR) is compared with text or content related advance for recover similar images from the database [1, 2].

Content Based Image Retrieval (CBIR) does not need manual annotation for each image and is not incomplete by the availability of lexicons as a substitute this framework utilizes the low level features that are natural in the images, color, shape and texture. In CBIR, some forms of parallel between images are computed using image futures extracted from them. Thus, users can look for images just like query images quickly and effectively.

Fig. 1 shows the architecture of a typical CBIR system. For each image in the image database and its image features are extracted and the obtained feature space (or vector) is stored in the feature database. once a query image comes in, its feature space are going to be compared with those within the feature database one by one and the similar images with the smallest feature distance will be retrieved.

CBIR may be divided in the following stages:

• Preprocessing: The image is first processed in order to extract the features to describe the contents. The processing involves normalization, filtering, segmentation and object identification. The output of this stage could be a set of significant regions and objects.

• Feature extraction: Features such as color, shape, texture, etc. are used to describe the content of the image. Image features can be classified into primitives.

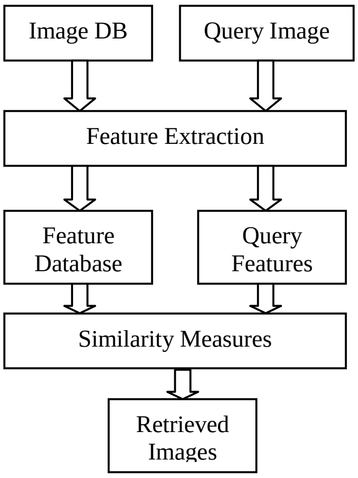

Fig.1: Image Retrieval Process

II. FEATURE EXTRACTION

For the given image database [3], features are extracted first from individual images. The visual features like color, shape, texture or spatial features or some compressed domain features. The extracted features are delineate by feature vectors. These feature vectors are then stored to form image feature database. For a given query image, we similarly extract its features and form a feature vector. This feature vector is matched with the already stored vectors in image feature database.

Sometimes dimensionality reduction techniques are employed to reduce the computations. The distance between the feature vector of the query image and those of the images in the database is then calculated. The distance of a query image with itself is zero if it is in database. Then, the distances are stored in increasing order and retrieval is performed with the help of indexing scheme.

The feature is distinct as a role of one or more capacity, every of which specifies some experimental property of an object and it quantifies some significant characteristics of the object. Here, to classify the various features currently employed as follows:

• General features: Function self-regulating features such as shape, color and texture. Independent of the abstraction level, they can be advance in divided into:

- Pixel level: Features considered at each pixel level, e.g. location, colour.

- Local features: Features considered above the outcome of results is subdivision of the image band on image segmentation or edge detection.
- Global level features: Features measured over the whole image or simply expected sub-area of an image.
• Domain-specific level: Application reliant features like human faces, fingerprints, and conceptual features.
These features are typically a synthesis of low-level features for some specific domain.

On the other hand, all features can be closely secret into low level features and high level features. Low level features can be extracted directly from the original images, whereas high-level feature extraction must be based on low level features [4].

The vital problems of content based image retrieval system, which are: i. Image database selection, ii. Similarity measurement, iii. Performance evaluation of the retrieval process and iv. Low-level image features extraction.

III. TEXTURE FEATURES

Among thoroughly diverse visual features resembling color and shape for the analysis of several forms of images, texture is reported to be outstanding and very important low level feature [5, 6]. Even though no standard definition exists for texture, Sklansky [7] outlined the texture collection of native properties among the image region with a continuing, slowly varied or about periodic pattern. Texture gives the information on structural arrangement of surfaces and objects on the image. Texture is not defined for a separate pixel; it depends on the distribution of intensity over the image. Texture possesses regularity and scalability properties; it is represented by main directions, contrast and sharpness. It is measured using its distinct properties like periodicity, coarseness, directionality and pattern complexity for efficient image retrieval particularly on the aspects of orientation and scale [8].

Tuceryan and Jain [9] divided the different methods for feature extraction into four main categories, namely: structural, statistical, model-based and transform domain. Basically, texture representation methods can be classified into two categories: structural and statistical. Statistical methods, including Fourier power spectra, co-occurrence matrices, shift-invariant principal component analysis (SPCA), Tamura features, Wold decomposition[10], Markov random field[11], fractal model[12] and multi-resolution filtering techniques such as Gabor[13] and wavelet transform[14], characterize texture by the statistical distribution of the image intensity.

D. A. Clausi et. al [15] designed the fusion texture feature with Gabor filter and co occurrence probabilities for texture segmentation and demonstrated that it outperforms well for noisy images and the high dimensional feature vector. The DWT based color cooccurrence feature for texture classification is explained in [16].

Haralick et. al [17] proposed the methods for representing texture features of images was grey level co-occurrence matrices (GLCM). Haralick et. al [17] also suggested 14 descriptors including the contrast, correlation, entropy and others. Each descriptor shows one texture property. Therefore, many works for example as described in [18], are devoted to selecting those statistical descriptors derived from the co-occurrence matrices that describe texture within the best approach.

In [19], firstly, transforming color space from RGB model to HSI model and then extracting color histogram to form color feature vector. Secondly, extracting the texture feature by using gray co-occurrence matrix. The

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texture of image is an illustration of spatial relationship of gray level image. Co-occurrence matrix is make it up based on the point of reference and distance between image pixels. The co-occurrence matrix C(i, j) counts the co-occurrence of pixels with gray values i and j at a given distance d. The distance d is outlined in polar coordinates (d, θ), with discrete length and orientation. In practice, θ takes the values 0◦; 45◦; 90◦; 135◦; 180◦; 225◦; 270◦; and 315◦. The cooccurrence matrix C(i, j) can now be defined as follows:

$$C(i,j) = \text{ card } \left\{ \begin{matrix} ((x_1,y_1),(x_2,y_2)) \in (XY)\times(XY) \text{ for } f(x_1,y_1)=i, f(x_2,y_2)=j \\ (x_2,y_2)=(x_1,y_1)+(d\cos\theta, d\sin\theta); \text{ for } 0<i, j<N \end{matrix} \right\} \quad (1)$$

where card {.} denotes the number of elements in the set. Let G be the number of gray-values in the image, then the dimension of the co-occurrence matrix C (i, j) will be N ×N. So, the computational complexity of the co-occurrence matrix depends quadratically on the number of gray-scales used for quantization.

A. Wavelet-Based Texture Representation

In wavelet based texture Representations, a specific feature of this method is representation and analysis of signals in different scales, i.e., under different resolutions. The image is described by a hierarchical structure each level of which represents the original signal with a certain degree of detail.

Tamura et al. [20] presented an approach to describing texture on the basis on human visual perception. They suggested coarseness, contrast, directionality, line-likeness, regularity and roughness equivalent to the six texture properties that were recognized as visually significant in the course of psychological experiments. Howarth and Ruger [18, 21] noticed that the parameters describing the primary three properties coarseness, contrast and directionality are rather effective in classifying and searching images by texture. The set of all points for one image is referred to as Tamura image.

Texture analysis by means of the Gabor filters is a special case of the wavelet approach. This is the most frequently used method in image retrieval by texture. In most of the CBIR systems primarily based in Gabor wavelet [22, 23], the mean and standard deviation of the distribution of the wavelet transform coefficients are used to construct the feature vector.

B. Correlation property

Correlation property shows the linear dependency of gray level values in the co-occurrence matrix. It presents how a reference pixel is related to its neighbour, 0 is uncorrelated, 1 is perfectly correlated.

$$\text{Correlation} = \frac{\sum_i \sum_j (ij)C(i,j) - \mu_i \mu_{ij}}{\sigma_i \sigma_j} \quad (2)$$

where

$$\mu_i = \sum_i i \sum_j C(i,j)$$

$$\mu_j = \sum_j j \sum_i C(i,j)$$

$$\sigma_i = \sum_i (i-\mu_i)^2 \sum_j C(i,j)$$

$$\sigma_j = \sum_i (j-\mu_j)^2 \sum_j C(i,j)$$

IV .SECURITY ANALYSIS

Honest-but-curious (HBC) cloud server is considered as the security model. We analyze the security of the proposed scheme in the ciphertext-only attack (COA) model and known background attack (KBA) model.

Security under COA Model:

***Theorem*:** The scheme proposed is secure against HBC probabilistic polynomial time adversaries. The security strength is used to measure security of the proposed scheme.

Security of the encrypted image**.** Simulator S simulates a image set **I**S. The simulator S knows the image number and the image size of the image database, so it can simulate a hypothetical image database **I**S similar to real image database EDH-CBIR contains the encrypted order difference histogram-based CBIR scheme (EODH-CBIR) and the encrypted disorder difference histogram-based CBIR scheme (EDDH-CBIR).

Security under the KBP Model:

In addition to the previously mentioned information leakage, the statistical characteristics of plaintext images may be inferred by the ciphertext images. The pixel values of each color component have a range of [0, 255], and the theoretical difference values have a range of [255, 255], i.e., simulator

S needs to solve 500! sequences for color permutation encryption. However, some difference values will not occur in an image, and the number of resolved sequences is reduced.

Efficiency

Efficiency is a significant measurement standard, and it includes the time consumptions of image encryption, index construction, and image searching. For comparison, this section considers the contrast experiments in the ciphertext domain.

- The time consumption of image encryption. The encryption process of ECH-CBIR includes value replacement and position scrambling. The encryption processes of EODH-CBIR and GDDH-CBIR include the difference matrix calculation, difference value replacement, and pixel scrambling. EDDH-CBIR includes the block difference matrix calculation, the difference value replacement, and pixel permutation.

- The time consumption of index construction. A linear index is built for all the schemes so as to observe them more intuitively.

V. CONCLUSION

In this paper, discrete wavelet based texture features, associated with different distance measures have been evaluated in Corel data sets. The efficiency and performance of the proposed system are measured using average precision of three different distance measures. Performance analysis comparison of Correlation with different distance classifier therein one Euclidean distance gives best performance than city block and Standard Euclidean distance. However, both the EDDH-CBIR and the EODH-CBIR scheme have the problem of security risks under the KBP model. Future work will focus on more efficient encryption methods to improve the security of the EDH-CBIR scheme.

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