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Hybrid Feature of Tamura Texture Based Image Retrieval System

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***Abstract*— Storage and retrieval of images in such libraries has become a real demand in industrial, medical, and other applications. Content-based image indexing and retrieval (CBIR) is considered as a solution. In such systems, in the indexing algorithm, some features are extracted from every picture and stored as an index vector. We apply tamura texture features on digital images and compute the low order statistics from the transformed images. Images are then represented using the extracted texture features. These feature combination integrate the pixels spatial distribution information into a numerical value. The experiment results show that this method is still effective when the data scale is very large, and it has superior scalability than traditional indexing methods.**

***Keywords*— CBIR, Image Retrieval, Image indexing**

I. INTRODUCTION

Technology, in the form of inventions such as photography and television, has played a major role in facilitating the capture and communication of image data. But the real engine of the imaging revolution has been the computer, bringing with it a range of techniques for digital image capture, processing, storage and transmission which would surely have startled. The involvement of computers in imaging can be dated back to 1985, in India which demonstrated the feasibility of computerised creation, manipulation and storage of images. Once computerised imaging became affordable, it soon penetrated into areas traditionally depending heavily on images for communication, such as engineering, architecture and medicine. The creation of the World-Wide Web in the early 1990s, enabling users to access data in a variety of media from anywhere on the planet, has provided a further massive stimulus to the exploitation of digital images. The number of images available on the Web can estimate to be between 100 billion to 200 billion [1]. With such a large volume of unstructured digital media there is a need for effective and additional techniques for image retrieval. Further people quite often need such visual information as it finds a variety of applications like education and training, criminal tracking, law enforcement etc. Even though image search engines do exist like Google Image Search, Lycos and AltaVista photo tinder but their search relies on text to look for images which yields a great percentage of irrelevant results. Hard information on the effectiveness of automatic image retrieval techniques is difficult to implement. Few of the early systems developers made serious attempts to evaluate their retrieval effectiveness, simply providing examples of retrieval output to demonstrate system capabilities. Few of the researchers take the question of retrieval effectiveness seriously; though even they glossed over some of the problems of determining whether a given image did in fact answer a given query. The position is changing as more researchers with an information retrieval background enter the field, the problems of evaluating multimedia information retrieval systems are substantial [2]. In this new approach, images are retrieved directly based on their visual content features such as texture, color, texture [3].

Mathematically, an image feature is an n-dimensional vector, with its components which can be calculated by some image processing analysis. The most commonly used visual features are texture, color, texture etc. For example, a feature may represent the texture information in an image — such as internal, external, and region based textures.

For the solution to this problem, we proposed a multi-feature image retrieval system. The best well-known tamura texture features based are being used for the similar image retrieval. In this paper we focused on texture based features of images and aimed both to improve retrieval performance and help users to express their queries efficiently.

Core of the system is the image feature extraction process in which all the selected combination of feature vectors (FV) are extracted and calculated for the similarity measurement. The feature extractor executes for both inputs as well database images. The relationship between the user and the system is two-way the user can make a query request to the system; the system returns the query results based on the query requirements. A content-based image retrieval process has two key steps first is Image Selection, Feature extraction and indexing based on the visual features of the image and another is Feature vector similarity-based image retrieval processing. The search is usually based on similarity rather than on exact match and the retrieval results are then nearest indexed image.

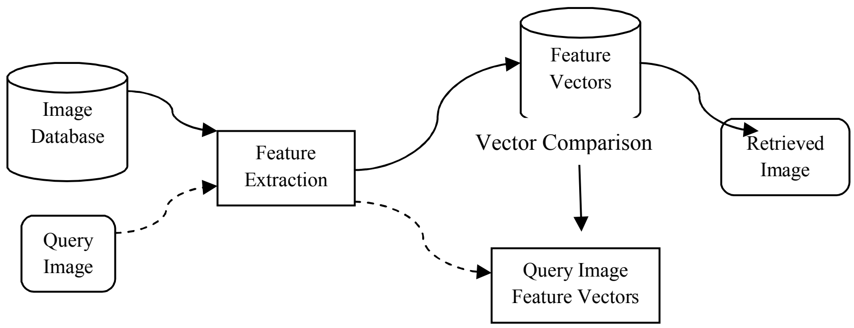

Fig. 1 System Architecture

II. RELATED WORK

In the earlier work some work has been observed in image retrieval system, which is based on different features of the images. F.A. Andaló et.al [4] presents a work using texture based features. In this paper, they exploit the concept for binary images and propose a texture salience detector and a texture descriptor method as Tensor Scale Descriptor with Influence Zones. They also introduce a robust method to compute tensor scale, using a graph-based approach—the Image Foresting Transform. Experimental results are provided, showing the effectiveness of the proposed methods, when compared to other relevant methods, such as Beam Angle Statistics and Contour Salience Descriptor, with regard to their use in content-based image retrieval tasks.

The color feature is described by the CH, which is translation and rotation invariant. The Haar wavelet transformation is used to extract the texture features and the local characteristics of an image, to increase the accuracy of the retrieval system. The lifting scheme reduces the processing time to retrieve images. The experimental results indicate that the proposed technique outperforms the other schemes, in terms of the average precision, the average recall and the total average precision/recall [5].

H.-W. Yoo et al. [6] suggests two kinds of indexing keys to prune away irrelevant images to a given query image: major colors' set (MCS) signature related with color information and distribution block signature (DBS) related with spatial information. After successively applying these filters to a large database, they got only small amount of high potential candidates that are somewhat similar to a query image. Then they make use of the quad modeling (QM) method to set the initial weights of two-dimensional cell in a query image according to each major color. Finally, system retrieve more similar images from the database by comparing a query image with candidate images through a similarity measuring function associated with the weights. In that procedure, they also use a relevance feedback mechanism.

III. FEATURE EXTRACTION

Image feature extraction and expression is the basis of the content -based image retrieval technology. Broadly speaking, the image feature comprises a texture-based feature (such as keywords, comments, etc.) and visual features (such as color, texture, texture and surface of the object, etc.) categories. Because texture-based image feature extraction in database systems and information retrieval field has in-depth research, this paper introduces us to extract and express the image visual features. For a particular image features, usually there are many different methods of expression. Due to the subjective understanding of the vastly different people, a feature not presents the best for a so-called expression. In fact, the image characteristics expressed in different ways from different angles characterize the nature of some of the features. In this, we introduce the practice that proved to be more effective image search feature and corresponding expression methods. We used the color, texture and texture features of the image, as described.

Texture Based Features

The texture of an image is an important and basic visual feature for describing image content. Texture based feature is the most widely used visual features in image retrieval, mainly due to the different direction of the object and contained in the image is very relevant.

Roughness can be divided into the following calculation steps. First, calculate the average image intensity values of size $2^k \times 2^k$ pixels of pixels in the active window , that

$$A_k(x,y) = \sum_{i=x-2^{k-1}}^{x+2^{k-1}-1} \sum_{j=y-2^{k-1}}^{y+2^{k-1}-1} g(i,j)/2^{2k} \quad ..(1)$$

Where k = 0, 1….5 and g (i, j) is located in the (i, j) pixel intensity values. Then, for each pixel, which are calculated in the horizontal And the average intensity in the vertical direction between the windows do not overlap the difference.

$$\left.\begin{aligned} E_{k,h}(x,y) &= \left|A_k(x+2^{k-1},y) - A_k(x-2^{k-1},y)\right| \\ E_{k,v}(x,y) &= \left|A_k(x,y+2^{k-1}) - A_k(x,y-2^{k-1})\right| \end{aligned}\right\} \quad \text{…. (2)}$$

Wherein for each pixel, can make the maximum value E (either direction) to set the optimum value of k dimensions. Finally, the roughness can be obtained by calculating the whole image and expressed as

$$F_{crs} = \frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} S_{best}(i,j) \quad \text{…. (3)}$$

Another form of the roughness characteristics of the intake is used to describe best histogram distribution, and not as simple as the above-described method of calculating the average S_{best}. This feature improved roughness can express a variety of different texture features of an image or region, and therefore more favorable for image retrieval.

Contrast is a statistical distribution of the pixel intensity obtained. Rather, it is defined by the $\alpha_4 = \mu_4/\sigma^4$ where μ_4 is the fourth moment and σ^2 is the variance. Contrast is measured by the following formula:

$$F_{con} = \frac{\sigma}{\alpha_4^{1/4}} \quad \text{…. (4)}$$

This value gives the entire image or regions in contrast global metrics.

Direction degrees we need to calculate the direction of the gradient vector is calculated at each pixel. And the direction of the vector mode are defined as

$$\begin{aligned} |\Delta G| &= \left(|\Delta_H| + |\Delta_V|\right)/2 \\ \theta &= \tan^{-1}(\Delta_V/\Delta_H) + \pi/2 \end{aligned} \quad \text{…. (5)}$$

Where in Δ_H and Δ_V are the following two 4x4 operator variation resulting horizontal and vertical directions by the image convolution.

$$\begin{matrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{matrix} \qquad \begin{matrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{matrix}$$

When the gradient vector of all the pixels is calculated, a histogram is constructed for the expression of H_D θ value. The first range of values θ histograms were discrete, then the corresponding statistics for each bin of | ΔG | is greater than the number of pixels in a given threshold. The histogram of an image for a clear directional exhibit a peak, for no apparent direction of the image is relatively flat performance. Finally, the overall image can be calculated by the directional sharpness of peaks in the histogram obtained is expressed as follows:

$$F_{dir} = \sum_{p}^{n_p} \sum_{\phi \in w_p} \left(\phi - \phi_p\right)^2 H_D(\phi) \quad \text{.... (6)}$$

P represents the histogram of the peak type, n_p is the histogram of all the peaks. For a peak p, W_p represents all peaks included in the bin, and the bin having the highest φ_p value.

Coarseness has a direct relationship to scale and repetition rates and was seen by Tamura et al as the most fundamental texture feature. An image will contain textures at several scales; coarseness aims to identify the largest size at which a texture exists, even where a smaller micro texture exists. Computationally one first takes averages at every point over neighborhoods the linear size of which are powers of 2. The average over the neighborhood of size $2^k \times 2^k$ at the point (x, y) is

$$A_k(x,y) = \sum_{i=x-2^{k-1}}^{x+2^{k-1}-1} \sum_{j=y-2^{k-1}}^{y+2^{k-1}-1} f(i,j)/2^{2k} \quad \text{.... (7)}$$

Then at each point one takes deference between pairs of averages corresponding to non-overlapping neighborhoods on opposite sides of the point in both horizontal and vertical orientations. In the horizontal case this is

$$E_{k,h}(x,y) = |A_k(x+2^{k-1},y) - A_k(x-2^{k-1},y)| \quad \text{.... (8)}$$

At each point, one then picks the best size which gives the highest output value, where k maximizes E in either direction. The coarseness measure is then the average of $S_{opt}(x, y)=2^{kopt}$ over the picture.

Edge Directions

Every object in an image has edges and with their direction we calculate a feature vector for image identification. The histogram of edges in an image is translation invariant and it gives the general texture information of the image. The edge histogram can be calculated with few computational steps. The input image is first, transformed to the HSI scale and hue channel is removed. The other two channels are convolved with the eight Sobel masks. Each pixel is given the maximum of the responses and the corresponding 8-quantized direction. The gradient is threshold next. The threshold values are manually fixed to 15% of the maximum gradient value on the intensity channel and to 35% on the saturation channel. The threshold intensity and saturation gradient images are combined by the logical OR operation. In the OR operation, if the gradient directions differ between the saturation and intensity, the originally stronger gradient direction is chosen. A gray level image $I(x, y)$ is hence transformed as

$$I(x, y) \rightarrow \{Ie(x, y), Id(x, y)\}$$

Where $Ie(x, y) \in \{0, 1\}$ represents the binary edge image, and $Id(x, y) \in \{0 . . . 7\}$ the direction image.

Texture FFT

This feature is based on the Fourier Transform of the binarize edge image. The image is normalized to 512X512 pixels before the FFT. Then the magnitude image of the Fourier spectrum is low-pass filtered and decimated by the factor of 32, resulting in a 128-dimensional feature vector.

Object Texture Moment

Perhaps the most popular method for texture description is the use of moment invariants , which are invariant to affine transformations. For a 2-dimensional function f (x, y), the moments of order p + q are defined as:

$$m_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^p y^q f(x, y)\, dx\, dy$$

For p, q = 0, 1, 2 …

The width and height of a region are defined as the maximum value of the vertical and the horizontal projection, respectively [7].

Color features

Color feature is the most widely used visual features in image retrieval, mainly due to the color of an object or scene and often contained in the image is very relevant. In addition, compared with the other visual features , color characteristics of the image itself, the size, orientation , viewing angle dependence is small , which has high robustness.

Color Histogram

It describes the proportion of different colors in the proportion of the whole image, and does not care about which the spatial position of each color, i.e., does not describe the object or objects in the image. Color histogram is particularly suitable for those images are difficult to describe the automatic segmentation. The color histogram is based on the type of color space and the coordinate system. The most common color space is a RGB color space, because the majority of the digital image in this color space is expressed. It is necessary to calculate the color histogram; the color space is divided into several small color intervals between each cell into a bin of the histogram. This process is called color quantization. Then, by calculating the number of pixels between the colors of each cell falls within the color histogram can be obtained.

Color Moment

In addition, due to the color distribution information mainly concentrated in the low-order moments, so using only colors the first moment (mean), second moment (variance) and third moment (skewness) is sufficient to express the color distribution of the image. Compared with the color histogram, another advantage of this approach is that the features do not need to be quantified. Three low-order moments of colors expressed mathematically as:

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} p_{ij}$$

$$\sigma_i = \left(\frac{1}{N}\sum_{j=1}^{N} (p_{ij} - \mu_i)^2\right)^{\frac{1}{2}}$$

$$s_i = \left(\frac{1}{N}\sum_{j=1}^{N} (p_{ij} - \mu_i)^3\right)^{\frac{1}{3}}$$

Here p_{ij} is the image of the j^{th} pixel in the i^{th} color component. Thus, the total moment of the color image has only nine components (three color components, each component of the three low-order moments).

IV. Image Indexing

In content-based image retrieval queries by calculating the similarity matching between the visual features retrieve candidate images. Therefore, the selection of a suitable visual feature similarity measurement method has a great impact on search results. Distances between feature vectors were calculated using the Euclidian distance. The resultant distances were then median normalized to give even weighting when combined. The plain vector space model was used for retrieval on the Corel data set as these involved only simple one image queries. The similarity between the query image feature vectors and the feature vectors of the images in the database is computed using the Euclidean distance formula.

$$Sim_{FV}(QI, DBI) = \sqrt{\sum_{n=1}^{m} (QI_n - DBI_n)^2}$$

QI represents the query image and the DBI is the database image, FV is the feature vector.

V. Experimental Results

In this section we evaluate the proposed method of image retrieval using on texture based features. As for implementation tool we used MATLAB version 2009b. As shown in the Fig 2. number of images to be retrieved, and query image is set. Further we have to move on the next section which a single button for searching the image as shown in the GUI. When we click on the search button of second section system retrieved the images on the screen specified for the images according to the ranking of distance from query image feature vector. After searching the image it is found that all five related image of the same class has shown on the GUI. If the match found for the same index or range of the index it returns most related image from the dataset.

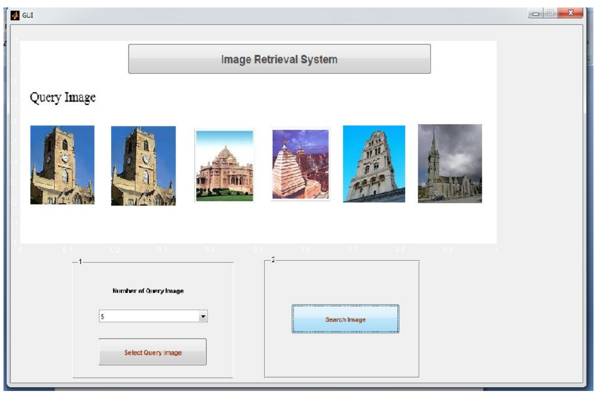

Fig. 2 Retrieved images corresponding to the query image

The performance evaluation of the system carried out on the input images taken under different conditions. The proposed method expressed here in this paper is tested on 500 different images selected from the standard Corel Database. We selected different images to give multiple categories that were visually similar in concern with texture as well as color. A set of single-image category queries was executed to test performance across all categories.

All the testing images are basically divided into five classes according to the nature of images. Images are basically taken from the Corel standard database for specifically designed for the content based image retrieval. Our benchmark test results are summarized in a tabular form where four classes of image database indicated with number of images in each class. Our system detected the number of images from testing database indicated in the "image detected" column and corresponding accuracy presented. The overall system performance calculated on the basis of these four classes. Precision and recall for different class of images evaluated one by one and then create graph for the corresponding values. At the very first we evaluated the 100 images of class-I and the corresponding precision and recall graph shown in Fig.3.

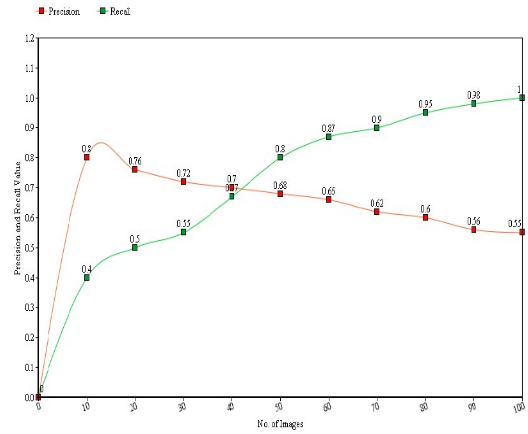

Fig.3 Precision and Recall graph

In the above graphs demonstrates that our approach has very high accuracy. This confirms the effectiveness of our approach for image retrieval detection and removal. In this research we need to know how accurately the feature segmentation results can be used for image retrieval. We found from the results that shape and color features are very strongly retrieve images with high accuracy on the databases.

VI. CONCLUSION

In this paper we tried to show an approach for the best result in the image retrieval system. We have proposed an efficient image retrieval method based on tamura texture features of the image. To improve the discriminating power of shape indexing techniques, we encode a minimal amount of spatial information in the index by extracting features like color moment and RGB histogram. Feature extraction process is an important part in this approach, in which we have selected shape based as well as color based features. This system and gives more accurate result and it has greater success rate. In this research the distance similarity based indexing scheme is used. The method of storing the images in the database can be changed to improve the accuracy. The performance of the system can be better evaluated by the standard precision and recall graphs, with the increasing number of images. This system can be further improved and used as a tool to compare the images in real time applications.

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