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An Adaptive Approach to Extract Texture Feature from an Image in Image Retrieval Process

Kranthi Kumar.K[1], D.V.Priyanka[2], K.Sai Suraj[3], Y.Sai Krishna[4]
[1]*Assistant Professor, Department of IT, SNIST, Yamnampet, Ghatkesar, Hyderabad, AP, INDIA*
[2-4]*B.Tech students of IT, SNIST, Yamnampet, Hyderabad, AP, INDIA.*

Abstract: Images and graphics are among the most important media formats for human communication and they provide a rich amount of information for people to understand the world. In many areas of commerce, government, academia, and hospitals, large collections of digital images are being created. Many of these collections are the product of digitizing existing collections of analogue photographs, diagrams, drawings, paintings, and prints. Usually, the only way of searching these collections was by keyword indexing, or simply by browsing. Traditional text based methods are proven to be insufficient for retrieval of images from the large image data base. To overcome the drawbacks of text-based image retrieval, images are retrieved with the help of contents present in that image (i.e using the low-level features of an image such as Color, Shape and Texture). Among these three features texture plays an important role in many image retrieval systems such as surface inspection, scene classification, and surface orientation and shape determination.

In this paper, we are proposing an adaptive approach to extract the texture feature from a given image for an effective retrieval process of images from large image databases. The previous systems are having some limitations of its own, now we want to propose a method in such a way that it can be overcome almost all disadvantages of existing systems. The experiment is conducted on 5000+ images of 45 different categories from COREL image database. The experimental results show the effectiveness of the proposed approach and in comparisons with other work, it is shown that our approach more effective than the previous works.

Keywords: Digital image, Image Retrieval, Texture, Feature and Feature Extraction.

INTRODUCTION

In many machine vision and image processing algorithms, simplifying assumptions are made about the uniformity of intensities in local image regions. However, images of real objects often do not exhibit regions of uniform intensities. For example, the image of a wooden surface is not uniform but contains variations of intensities which form certain repeated patterns called *visual texture*. The patterns can be the result of physical surface properties such as roughness or oriented strands which often have a tactile quality, or they could be the result of reflectance differences such as the color on a surface. We recognize texture when we see it but it is very difficult to define. This difficulty is demonstrated by the number of different texture definitions attempted by vision researchers. Coggins [1] has compiled a catalogue of texture definitions in the computer vision literature and we give some examples here.

"We may regard texture as what constitutes a macroscopic region. Its structure is simply attributed to the repetitive patterns in which elements or primitives are arranged according to a placement rule." [2]

• "A region in an image has a constant texture if a set of local statistics or other local properties of the picture function are constant, slowly varying, or approximately periodic." [3]

• "The image texture we consider is nonfigurative and cellular... An image texture is described by the number and types of its (tonal) primitives and the spatial organization or layout of its (tonal) primitives... A fundamental characteristic of texture: it cannot be analyzed without a frame of reference of tonal primitive being stated or implied. For any smooth gray-tone surface, there exists a scale such that when the surface is examined, it has no texture. Then as resolution increases, it takes on a fine texture and then a coarse texture." [4]

• "Texture is defined for our purposes as an attribute of a field having no components that appear enumerable. The phase relations between the components are thus not apparent. Nor should the field contain an obvious gradient. The intent of this definition is to direct attention of the observer to the global properties of the display — i.e., its overall "coarseness," "bumpiness," or "fineness." Physically, non enumerable (a periodic) patterns are generated by stochastic as opposed to deterministic processes. Perceptually, however, the set of all patterns without obvious enumerable components will include many deterministic (and even periodic) textures." [5]

• "Texture is an apparently paradoxical notion. On the one hand, it is commonly used in the early processing of visual information, especially for practical classification purposes. On the other hand, no one has succeeded in producing a commonly accepted definition of texture. The resolution of this paradox, we feel, will depend on a richer, more developed model for early visual information processing, a central aspect of which will be representational systems at many different levels of abstraction. These levels will most probably include actual intensities at the bottom and will progress through edge and orientation descriptors to surface, and perhaps volumetric descriptors. Given these multi-level structures, it seems clear that they should be included in the

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definition of, and in the computation of, texture descriptors." [6].

This collection of definitions demonstrates that the "definition" of texture is formulated by different people depending upon the particular application and that there is no generally agreed upon definition. Some are perceptually motivated, and others are driven completely by the application in which the definition will be used.

Image texture, defined as a function of the spatial variation in pixel intensities (gray values), is useful in a variety of applications and has been a subject of intense study by many researchers. One immediate application of image texture is the recognition of image regions using texture properties. For example, in Fig 1(a), we can identify the five different textures and their identities as cotton canvas, straw matting, raffia, herringbone weave, and pressed calf leather. Texture is the most important visual cue in identifying these types of homogeneous regions. This is called *texture classification*. The goal of texture classification then is to produce a classification map of the input image where each uniform textured region is identified with the texture class it belongs to as shown in Figure 1(b). We could also find the texture boundaries even if we could not classify these textured surfaces. This is then the second type of problem that texture analysis research attempts to solve — *texture segmentation*. The goal of texture segmentation is to obtain the boundary map shown in Figure 1(c). *Texture synthesis* is often used for image compression applications. It is also important in computer graphics where the goal is to render object surfaces which are as realistic looking as possible. Figure 2 shows a set of synthetically generated texture images using Markov random field and fractal models [7]. The *shape from texture* problem is one instance of a general class of vision problems known as "shape from X". This was first formally pointed out in the perception literature by Gibson [8]. The goal is to extract three-dimensional shape information from various cues such as shading, stereo, and texture. The texture features (texture elements) are distorted due to the imaging process and the perspective projection which provide information about surface orientation and shape.

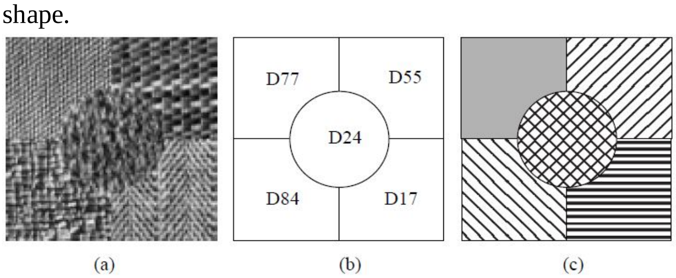

Fig 1. (a) An image consisting of five different textured regions: cotton canvas (D77), straw matting (D55), raffia (D84), herring bone weaves (D17), and pressed calf leather. [8]. (b) The goal of texture classification is to label each textured region with the proper category label: the identities of the five texture regions present in (a). (c) The goal of texture segmentation is to separate the regions in the image which have different textures and identify the boundaries between them. The texture categories themselves need not be recognized. In this example, the five texture categories in (a) are identified as separate textures by the use of generic category labels (represented by the different fill patterns).

The remainder of the paper is organized as follows. In the next section, we focus on image retrieval based mostly on texture and introduce our textural prototype. Section III gives an overview of our proposed approach. Experimental setup and results are presented in section IV. Conclusions are drawn in section V.

II. RELATED WORK

Texture is a key component of human visual perception. Like color, this makes it an essential feature to consider when querying image databases. Everyone can recognize texture but, it is more difficult to define. Unlike color, texture occurs over a region rather than at a point. It is normally defined purely by grey levels and as such is orthogonal to color. Texture has qualities such as periodicity and scale; it can be described in terms of direction, coarseness, contrast and so on [9]. It is this that makes texture a particularly interesting facet of images and results in a plethora of ways of extracting texture features. To enable us to explore a wide range of these methods we chose three very different approaches to computing texture features: The first takes a statistical approach in the form of co-occurrence matrices, next the psychological view of Tamura's features and finally signal processing with Gabor wavelets.

CBIR field has become the dynamic subject interesting both industrial and academic communities [10], [11]. Images entered into multimedia databases are indexed automatically by their own low-level visual features. The most commonly used visual features include color, texture and shape [12], [13]. Feature extraction and signature (index) organisation concern the first stage of retrieving images: *indexing process*. The second phase focuses on the search itself. When the user's query is launched, the system performs a similarity measure between the query's signature and those organised in database then returns the most visually closest images to the user's query. A large number of commercial products and academic retrieval systems that have been developed ongoing the last decade such as IBM QBIC [14], MIT Photobook [15], VisualSEEK [16], Virage [17], Netra [18], IKONA [19]. Comprehensive surveys on the feature extraction techniques and systems in CBIR domain can be found in [11]–[13].

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The search of images in earlier works which concentrated on color is effective if the images are partially or exactly matching the query. Unfortunately, image retrieval results fail if the images are in addition to color, texture like models. The richness of the world in textures do not allow to give a unique and formal definition. Despite this difficulty, the use of textures proved its effectiveness and usefulness in many areas such as pattern recognition and computer vision. The diversity of applications and their objectives keep the field of texture analysis in CBIR yet opened for further research.

In 70's, Haralick et al. [4] were the first to propose a statistical method co-occurrence matrices (COM) to solve the classification and description problems of textured images. The co-occurrence method describes the grey level spatial dependency of two pixels where fourteen numerical features are excerpts to describe different texture properties. Generally, the most works and CBIR systems use only a subset of these fourteen COM-features.

Conners and Harlow in [20] and in Lin's system [21] represent texture images by five COM-features including energy, entropy, correlation, local homogeneity and inertia. A competing method to COM-features is the one proposed by Tamura [22] based on psychological studies on human perception. Six statistical features are presented by Tamura to describe texture properties including coarseness, contrast, directionality, line likeness, regularity and roughness. These features are strongly closest to human perception, thus, make Tamura features very attractive in CBIR systems. Such systems are QBIC system of IBM [23] which use the three features coarseness, contrast and directionality to represent texture images. The literature is rich in extraction texture techniques, we refer the reader to surveys [11]–[13].

III. Proposed System

Fig.1. shows the general scheme of the proposed system to extract texture feature from an Image in Image Retrieval (IR) process. The basic idea of this system is to extract texture feature efficiently from image. The following sections are discussed about various steps involved in the proposed system in the both side i.e online and offline. Online side is provides interface (UI) to user. Offline is discussed about background work of proposed system it plays a major role in the retrieval process to display the similar images to given query image. The following paragraph is gives abstract level proposed algorithm.

Algorithm for proposed system is as follows:

Stage I:

Online	**Offline**
Step 1: Submit query image. Step 2: Extract texture feature from given image step 3: Texture Analysis step 4: find Co-occurrence features step 5: find Similarity Inference	Step 1: Select image database or texture database step 2: Texture Analysis Step 3: find Co-occurrence features Step 4: find Similarity Inference

Stage II:

Step 1: find similarity distance using Manhattan distance between the results of online and offline sides

Step 2: Retrieve the images in ascending order with respect to the value of distance.

Step 3: Display image set to the user.

Stage III:

If user is satisfied with result then stop process. Otherwise repeat all the steps once again until user gets satisfied with results.

3.1 Texture Feature

3.1.1 Co-occurrence

Statistical features of grey levels were one of the earliest methods used to classify textures. Haralick [4] suggested the use of grey level co-occurrence matrices (GLCM) to extract second order statistics from an image. GLCMs have been used very successfully for texture classification in evaluations.

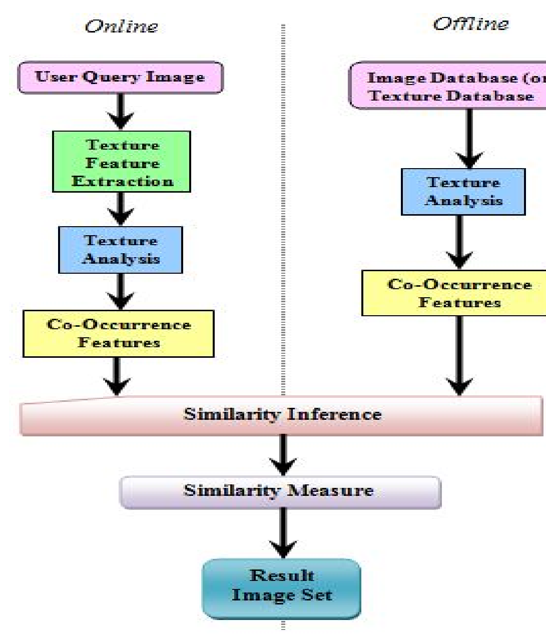

Fig 1: Proposed System Architecture

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Haralick defined the GLCM as a matrix of frequencies at which two pixels, separated by a certain vector, occur in the image. The distribution in the matrix will depend on the angular and distance relationship between pixels. Varying the vector used allows the capturing of different texture characteristics. Once the GLCM has been created, various features can be computed from it. These have been classified into four groups: visual texture characteristics, statistics, information theory and information measures of correlation. We chose the four most commonly used features, listed in Table 1, for our evaluation.

3.1.2 Tamura

Tamura et al took the approach of devising texture features that correspond to human visual perception. They defined six textural features (coarseness, contrast, directionality, line-likeness, regularity and roughness) and compared them with psychological measurements for human subjects. The first three attained very successful results and are used in our evaluation, both separately and as joint values.

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 $2k \times 2k$ at the point (x, y) is

Table 1. Features calculated from the normalized co-occurrence matrix $P(i, j)$

Feature	Formula
Energy	$\sum_i \sum_j P^2(i,j)$
Entropy	$\sum_i \sum_j P(i,j) log P(i,j)$
Contrast	$\sum_i \sum_j (i-j)^2 P(i,j)$
Homogeneity	$\sum_i \sum_j \frac{P(i,j)}{1+\lvert i-j\rvert}$

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

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

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

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.

Contrast aims to capture the dynamic range of grey levels in an image, together with the polarization of the distribution of black and white. The first is measured using the standard deviation of grey levels and the second the kurtosis $\alpha 4$. The contrast measure is therefore defined as

$$F_{con} = \sigma/(\alpha_4)^n \qquad \text{where } \alpha_4 = \mu_4/\sigma_4 \longrightarrow (3)$$

μ_4 is the fourth moment about the mean and $\sigma 2$ is the variance. Experimentally, Tamura found $n = 1/4$ to give the closest agreement to human measurements. This is the value we used in our experiments.

Directionality is a global property over a region. The feature described does not aim to differentiate between different orientations or patterns, but measures the total degree of directionality. Two simple masks are used to detect edges in the image. At each pixel the angle and magnitude are calculated. A histogram, H_d, of edge probabilities is then built up by counting all points with magnitude greater than a threshold and quantizing by the edge angle. The histogram will reflect the degree of directionality. To extract a measure from H_d the sharpness of the peaks are computed from their second moments.

Tamura Image is a notion where we calculate a value for the three features at each pixel and treat these as a spatial joint coarseness-contrast-directionality (CND) distribution, in the same way as images can be viewed as spatial joint RGB distributions. We extract color histogram style features from the Tamura CND image, both marginal and 3D histograms. The regional nature of texture meant that the values at each pixel were computed over a window. A similar 3D histogram feature is used by MARS.

3.1.3 Gabor

One of the most popular signal processing based approaches for texture feature extraction has been the use of Gabor filters. These enable filtering in the frequency and spatial domain. It has been proposed that Gabor filters can be used to model the responses of the human visual system. Turner first implemented this by using a bank of Gabor filters to analyse texture. A bank of filters at different scales and orientations allows multichannel filtering of an image to extract frequency and orientation information. This can then be used to decompose the image into texture features.

Our implementation is based on that of Manjunath et al [24, 25]. The feature is computed by filtering the image with a bank of orientation and scale sensitive filters and computing the mean and standard deviation of the output in the frequency domain. Filtering an image $I(x, y)$ with Gabor filters g_{mn} designed according to [10] results in its Gabor wavelet transform:

$$W_{mn}(x,y) = \int I(x,y) g^*_{mn}(x-x_1, y-y_1) dx_1 dy_1 \longrightarrow (4)$$

The mean and standard deviation of the magnitude $|W_{mn}|$ are used to for the feature vector. The outputs of filters at different scales will be over differing ranges. For this reason each element of the feature vector is normalized using the standard deviation of that element across the entire database.

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IV. EXPERIMENT SETUP AND RESULTS

We followed a two-stage approach: Initial evaluation and modifications to the features were tested using a carefully selected subset of the COREL image library and the vector space similarity measure. Image Collections, We selected 5000 images from the COREL collection to give 45 categories that were visually similar internally, but different from each other [26].

The experimentation was performed on the Windows platform powered by a Core 2 duo processor 2.4 GHz CPU using 2 GB of RAM. The prototype system is implemented using JAVA and eclipse IDE framework. Images and their associated feature data are stored to an Oracle 10 g database located locally.

Precision and *recall* are used to evaluate the performance of the proposed approach. *Precision* is the number of the retrieved relevant images over the total number of retrieved images, and *recall* is the number of the retrieved relevant images over the total number of relevant images in the database. In table.2 shows the values of precision and recall in percentage, which shows our proposed method is outperforms other three approaches to extract the texture feature from an image to improve the retrieval performance.

Table 2: Comparison results with respect to the precision and recall

Feature	Precision	Recall
GLCM	1.93%	2.31%
Tamura	2.85%	3.03%
Gabor	2.57%	3.43%
Proposed method	3.65%	3.72%

In fig .2 is discussed about comparison graphs of the Precision and Recall percentage values with respect to three texture feature approachs (GLCM, Tamura, and Gabor) and proposed method.

V. CONCLUSION

In this paper, we proposed an adaptive approach to extract texture feature from an image in image retrieval system. The approach analyzes the feature distances calculated between the query image and the resulting set of images to

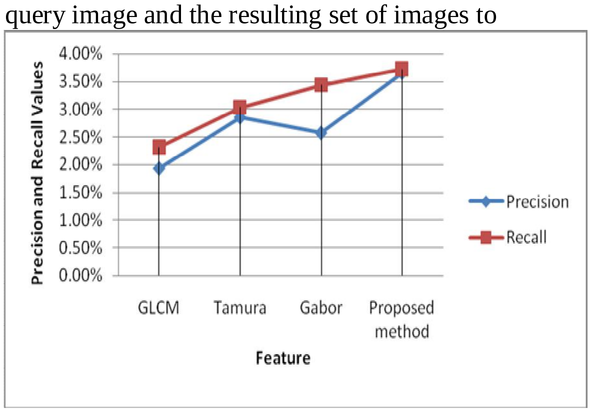

Fig 2: Comparison of precision and recall of GLCM, Tamura, Gabor and our method

approximate the feature distances based on effective feature representation of the entire set of images in the database. We have shown in the results with respect to the precision and recall on relevant images with retrieved set and relevant images with total relevant images. The proposed approach outstands with respect to the existing works (GLCM, Tamura, and Gabor).

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AUTHORS PROFILE

Kranthi Kumar K. is currently with Sreenidhi Institute of Science and Technology, Hyderabad, India, working as Asst. Professor in the department of Information Technology. He has 11 years of experience in Teaching. Graduated in B.Tech (CSE) from JNTU Hyderabad in 2003. Masters Degree in M.Tech (CSE), from JNT University, Anantapur, AP in 2007. He is pursuing his Ph.D in Computer Science & Engineering from JNT University, Hyderabad. He has 15 publications in various national/international journals and conferences. His areas of Interests are Image Processing, Content Based Image Retrieval, Information Retrieval Systems, Database Management Systems, Distributed Databases, Computer Networks.

D.V.Priyanka, is a B.Tech student in Sreenidhi Institute of Science and Technology, Yamnampet, gatkesar, Hyderabad. She is studying in the Department of Information Technology. Her Area of Interest is Image Processing, Data warehouse and Data mining and Computer Networks.

K.Sai Suraj, is a B.Tech student in Sreenidhi Institute of Science and Technology, Yamnampet, gatkesar, Hyderabad. He is studying in the Department of Information Technology. His Area of Interest is Image Processing, Information Security, Data Structures and DBMS.

Y.Sai Krishna, is a B.Tech year student in Sreenidhi Institute of Science and Technology, Yamnampet, gatkesar, Hyderabad. He is studying in the Department of Information Technology. His Area of Interest is Image Retrieval, Security, Object Oriented approaches and Software Engineering..