A Novel Approach to Content Based Image Retrieval Technique Using Local Tetra Patterns

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Abstract— **Content Based Image Retrieval gives the path to retrieve the needed information based on the image content. In this paper, Local tetra pattern (LTrP) is used for creating a new retrieval algorithm for managing the large database. LTrP encodes the relationship between the referenced pixel and its neighbour pixel based on the directions that are calculated using the first-order derivatives in vertical and horizontal directions. We proposed a system in which, the image is segmented first by K-means algorithm and Local Tetra Patterns (LTrP) is calculated from the segmented region and finally the entire patterns from the cluster region are combined together. The LTrP pattern of the query image and images in database is compared are shows the retrieved relevant image. Performance analysis shows that the proposed method improves the retrieval result in terms of average precision average recall and average retrieval rate, as compared with the standard LTrP.**

Keywords: **Content-Based Image Retrieval (CBIR),Local Tetra Patterns (LTrPs),Texture, K-means.**

I. INTRODUCTION

In recent years, the volume of visual data in the world is increasing exponentially through the use of digital camcorders and cameras in the mass market. The technology has also evolved so that it is possible to produce and store huge amounts of image data. But storing the images is not enough. There must be, some means available for accessing the images after they have been archived. Many industry including telecommunications, entertainment, medicine, and surveillance, need high performance retrieval systems to function efficiently [1]. Visual searches by text alone are ineffective on images. Descriptive text simply does not reflect the capabilities of the human visual memory and does not satisfy users' expectations. Furthermore the annotation of visual data for subsequent retrieval is almost entirely carried out through manual effort. This is slow, costly and error prone and presents a barrier to the stimulation of new multimedia services. Much research is now being conducted into measures of visual similarity that take account of the semantic content of images in an attempt to reduce the human involvement during database composition. Problems with traditional methods of image indexing have led to the rise of interest in techniques for retrieving images on the basis of automatically-derived features such as color, texture and shape – a technology now generally referred to as *Content-Based Image Retrieval* (CBIR) [2]. After a decade of intensive research, CBIR technology is now beginning to move out of the laboratory and into the marketplace, in the form of commercial products like QBIC and Virage, Retrievalware, Photobook, Visualseek and webseek, Netra, and Mars. [3]. However, the technology still lacks maturity, and is not yet being used on a significant scale. In the absence of hard evidence on the effectiveness of CBIR techniques in practice, opinion is still sharply divided about their usefulness in handling real-life queries in large and diverse image collections.

Texture analysis has been extensively used in computer vision and pattern recognition applications due to its potential in extracting the prominent features [4]. Texture retrieval is a branch of texture analysis that has attracted wide attention from industries since this is well suited for the identification of products such as ceramic tiles, marble, parquet slabs, etc. The Local Tetra Pattern is a stepping stone in the field of texture classification and retrieval. LTrP builds the association between the referenced pixel and its neighbours by computing the gray-level difference [5]. In this paper, a framework for retrieval of images from a given database after due indexing and classification using LTrP is presented. The LTrP considers the direction of pixels calculated by horizontal and vertical derivative for encoding the images. The rest of the paper is organized as follows: Section II investigate the related work about image retrieval strategies and models. In Section III, the detailed description of proposed framework is presented. Section IV comprises the experimental results along with their discussions. Finally, Section V concludes the paper.

II. LITERATURE SURVEY

Content based image retrieval for general-purpose image databases is a highly challenging problem because of the large size of the database, the difficulty of understanding images, both by people and computers, the difficulty of formulating a query, and the issue of evaluating results properly. The common ground for CBIR systems is to extract a signature for every image based on its pixel values and to define a rule for comparing images. The signature serves as an image representation in the "view" of a CBIR system. The components of the signature are called features.

In this research work we address two important issues. We identify the relative advantages of using specific combinations of image segmentation and texture extraction algorithms for scene analysis. This chapter has been structured

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as follows. We review studies on image segmentation first, followed by research focusing on texture analysis, and classification in image analysis. Image segmentation is one of the primary steps in image analysis for object identification. The main aim is to recognize homogeneous regions within an image as distinct and belonging to different objects. Ohlander [7] proposed a thresholding technique that is very useful on segmenting outdoor color images. This is based on constructing color and hue histograms. The picture is threshold at its most clearly separated peak. The process iterates for each segmented part of the image until no separate peaks are found in any of the histograms. The criterion to separate peaks was based on the ratio of peak maximum to peak minimum to be greater than or equal to two. In a number of applications, histogram thresholding is not possible simply because the histogram may be unimodal. In some cases the images may be of such quality that any pre-processing may not improve the contrast between objects sufficiently and hence one may not achieve two or more peaks in the histogram for selecting thresholds for segmentation. Unimodal distributions are typically obtained when the image consists of mostly of a large background area with small, but significant regions. Ahuja et al. [8] describe how pixel neighbourhood elements can be used for image segmentation. For each, its neighbours are first identified in a window of fixed size. A vector of these neighbours as individual grey values or vector of average grey levels in windows of size 1x1, 3x3 and 5x5 is determined. The paper uses both vector representations. The aim is to identify a weight matrix that multiplied with these vectors will yield a discriminate value that allows the classification of pixel in one of the two classes. Perkins [9] uses an edge based technique for image segmentation. It is acknowledged that edge based segmentation has not been very successful because of small gaps that allow merging of dissimilar regions. Image segmentation can be performed effectively by clustering image pixels. Cluster analysis allows the partitioning of data into meaningful subgroups and it can be applied for image segmentation or classification purposes. Clustering analysis either requires the user to provide the seeds for the regions to be segmented or uses non-parametric methods for finding the salient regions without the need for seed points. Clustering is commonly used in a range of applications such as image segmentation and unsupervised learning [10]. A number of issues related to clustering are worth studying including how many clusters are the best and how to determine the validity of clusters. Ng [11] describes an extension to the conventional *k*-means algorithms by modifying the Splitting rule in order to control the number of cluster members. By adding suitable constraints into the mathematical program formulation, the author developed an approach that allows the use of *k*-means paradigm to efficiently cluster data sets with a fixed number of elements in each cluster. The main objective of this algorithm is the minimization of an objective function usually taken as a function of deviations calculated for all patterns from their respective cluster centres. This algorithm minimizes the objective function through a scheme that starts with an arbitrary initial cluster membership in an iterative manner to obtain better clustering results.

Texture analysis has been extensively used in computer vision and pattern recognition applications due to its potential in extracting the prominent features. Ojala et al. [12] presents a simple and efficient multiresolution method to gray-scale and rotation invariant texture classification based on local binary patterns and nonparametric discrimination of sample and prototype distributions. Laio et al [13] proposed an approach, in which features are robust to image rotation, less sensitive to histogram equalization and noise. It comprises of two sets of features: dominant local binary patterns (DLBP) in a texture image and the supplementary features extracted by using the circularly symmetric Gabor filter responses. A combined completed LBP (CLBP) scheme [14] is developed for texture classification in which a local region is represented by its centre pixel and a local difference sign-magnitude transform (LDSMT). Ahonen et al. [15] reported a novel and efficient facial image representation based on local binary pattern (LBP) texture features. The LBP technique has been widely used in numerous applications due to its finest texture descriptor performance. It has proven to be highly discriminative and its key advantages, mainly, its invariance to monotonic gray-level changes and computational efficiency, make it suitable for demanding image analysis task. Zhang *et al.* proposed local derivative patterns (LDPs) for face recognition, in which LDP templates extract high-order local information by encoding various distinctive spatial relationships contained in a given local region[16]. Author et al. [17] proposed a novel approach for face representation and recognition by examining the information jointly in image space, scale and orientation domains. Information collected from different domains is explored and examined to give an efficient face representation for recognition. The main challenge is that the use of LBP, LDP and their extended Techniques are not so much reliable under the unconstrained lighting conditions. To accomplish this challenge the local ternary pattern (LTP) [18] has been introduced for image recognition under different lighting conditions. LTP eliminates most of the effects of changing illumination and presents a local texture descriptor which is unique and less sensitive to noise in uniform region. The LBP, the LDP, and the LTP extract the information based on the distribution of edges, which are coded using only two directions (positive direction or negative direction). Thus, it is evident that the performance of these methods can be improved by differentiating the edges in more than two directions. The local tetra patterns (LTrPs) describes the spatial structure of the local texture using the direction of the centre gray pixel it encodes the relationship between the referenced pixel and its neighbours, based on the directions that are calculated using the first-order derivatives in vertical and horizontal directions [5].

III. PROPOSED SYSTEM

Murala et. al. [5] adopted the LBP, LDP and LTP to define LTrPs. Local tetra pattern technique encodes the relationship

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between the centre pixel and its neighbours, based on the directions that are calculated using the first order derivatives in vertical and horizontal directions.

The first-order derivatives at the centre pixel g_c can be written as

$$I^1_{0^\circ}(gc) = I(g_h) - I(g_c) \quad \text{.......... (1)}$$

$$I^1_{90^\circ}(gc) = I(g_v) - I(g_c) \quad \text{.......... (2)}$$

and the direction of the centre pixel can be calculated as

$$I^1_{Dir}(gc) = \begin{cases} 1, & I^1_{0^\circ}(gc) \geq 0 \text{ and } I^1_{90^\circ}(gc) \geq 0 \\ 2, & I^1_{0^\circ}(gc) < 0 \text{ and } I^1_{90^\circ}(gc) \geq 0 \\ 3, & I^1_{0^\circ}(gc) < 0 \text{ and } I^1_{90^\circ}(gc) < 0 \\ 4, & I^1_{0^\circ}(gc) \geq 0 \text{ and } I^1_{90^\circ}(gc) < 0 \end{cases}$$

.... (3)

From (3), it is evident that the possible direction for each centre pixel can be 1, 2, 3, or 4, and eventually, the image is converted into four values, i.e., directions. The second-order $LTrp^2(g_c)$ is defined as

$$LTrp^2(g_c) = \left\{ \begin{array}{c} f_3(I^1_{Dir}(g_c), I^1_{Dir'}(g_1)), f_3(I^1_{Dir}(g_c), I^1_{Dir'}(g_2)) \\ \dots f_3(I^1_{Dir}(g_c), I^1_{Dir'}(g_p)) \end{array} \right\} \mid p = 8$$

$$f_3(I^1_{Dir}(g_c), I^1_{Dir'}(g_p)) = \begin{cases} 0, & I^1_{Dir'}(g_c) = I^1_{Dir'}(g_p) \\ I^1_{Dir,(g_p)}, & else \end{cases}$$

.... (4)

From (4), we get 8-bit tetra pattern for each centre pixel. Then, we separate all patterns into four parts based on the direction of centre pixel. Finally, the tetra patterns for each part (direction) are converted to three binary patterns. Let the direction of centre pixel $(I^1_{Dir}(g_c))$ obtained using (3) be "1"; then $LTrp^2$, can be defined by segregating it into three binary patterns as follows:

$$LTrp^2|Direction = 2,3,4$$
$$= \sum_{p=1}^{P} 2^{(p-1)} \times f_4(LTrp^2(g_c)) \; |\text{Direction} = 2,3,4$$

$$f_4(LTrp^2(g_c))|\text{Direction} = \emptyset$$
$$= \begin{cases} 1, & if LTrp^2(g_c) = \emptyset \\ 0, & else \end{cases} \quad \text{.......... (5)}$$

Where Ø=2, 3, 4.

Similarly, the other three tetra patterns for remaining three directions (parts) of centre pixels are converted to binary patterns. Thus, we get 12 (4×3) binary patterns. The magnitudes of horizontal and vertical first-order derivatives calculated by using

$$\sqrt{(I^1_{0^\circ}(g_p))^2 + (I^1_{90^\circ}(g_p))^2}$$

$$\sum_{p=1}^{P} 2^{p-1} \times f_1(M_{I^1(g_p)} - M_{I^1(g_c)}) \mid p = 8 \; \text{....... (6)}$$

A. k-means Clustering algorithm

k-means is a classical clustering algorithm (Schalkoff 1992). The algorithm tries to find a self-consistent partitioning of the data points to a predefined number k of clusters [19]. The k-means algorithm consists of the following steps:

1. Initialization: Fix the number k of clusters and choose (e.g. randomly) cluster centres.
2. Iteration step 1: Partition the data points into clusters. Each data point gets assigned to the cluster with the nearest cluster centre.
3. Iteration step 2: Recomputed cluster centres by setting each cluster centre as the mean of the points that got assigned to it in the previous step.
4. Stopping condition: Stop if the clustering is self-consistent. That is, if a partition has been found that does not change any more in further iterations. Otherwise keep iterating iteration steps 1 and 2.

Application of k-means to image segmentation is straightforward. Each image point or non-overlapping group of points, e.g. a small rectangular block, is associated with a set of visual attributes. These could be such as color channel values or texture features. Then the k-means algorithm is run on the set of points, using the desired number of image segments as the value of k.

The proposed image retrieval system and algorithm as given below:

B. <u>Algorithm</u>

Input: Query image; Output: Retrieval result

1. Load the image.
2. Clustering the image.
3. Convert the image into grayscale
4. Apply the first-order derivatives in horizontal and vertical axis.
5. Calculate the direction for every pixel.
6. Divide the patterns into four parts based on the direction of the center pixel.
7. Calculate the tetra patterns, and separate them into three binary patterns.
8. Combine the pattern from all regions.
9. Construct the feature vector.
10. Compare the query image with the images in the database.
11. Retrieve the images based on the best matches.

In Our Proposed method, let consider an input Image as shown in following figure. The input image is clustered into k region by k-means clustering algorithm. The algorithm tries to find a self- consistent partitioning of the data points to a predefined number k of clusters. The k-means algorithm consists of the following steps: Fix the number k of clusters, Partition the data points into clusters. Each data point gets assigned to the cluster with the nearest cluster centre. Recomputed cluster centres by setting each cluster centre as the mean of the points that got assigned to it in the previous step. Stop if the clustering is self-consistent.

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Figure1
Input Image

Figure 2
clustered Image

Figure 3
Greyscale Image

The clustered image is shown in fig. The clustered image is then converted into greyscale as shown in fig. The centre pixel of an image is given by $g_{c,}$ the first-order derivatives along 0^0 and 90^0 directions are at the centre pixel g_c given by the equation 1&2. The possible direction for each centre pixel can be 1, 2, 3, or 4 by the equation3. We get 8-bit tetra pattern for each centre pixel by using equation 4. Then, we separate all patterns into four parts based on the direction of centre pixel. Finally, the tetra patterns for each part (direction) are converted to three binary patterns. Similarly, the other three tetra patterns for remaining three directions (parts) of centre pixels are converted to binary patterns by using equation 5 .The magnitudes of horizontal and vertical first-order derivatives calculated by using equation 5. The tetra pattern of the entire cluster is calculated by using the step4-7. The entire patterns from the cluster region are combined together.

Input Bits Patterns	***If found ,%Match***
1	*12.3 %*
10	*25 %*
101	*38.5 %*
1011	*50 %*
10110	*62.5 %*
101100	*75 %*
1011000	*87.5 %*
10110001	*100 %*

Table 1

The goal is to select the best images that resemble the query image. This involves the selection of top-matched images by measuring the distance between the query image and the images in database. The above table will match the images based on the binary pattern.

IV. RESULT AND ANALYSIS

In this chapter we present an evaluation of the proposed CBIR systems that we introduced in the previous chapters. We also compare their performance with already existing CBIR systems.

Precision and Recall (P-R): The images are retrieved and measured against P-R as:

Precision, P, is defined as the ratio of the number of retrieved relevant images to the total number of retrieved images [20].

$$P = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images retrieved}}$$

Recall, R, is defined as the ratio of the number of retrieved relevant images to the total number of relevant images in the whole database [20].

$$R = \frac{\text{Total number of relevant images in the database}}{\text{Number of relevant images retrieved}}$$

where P is the ratio to measure accuracy and R is used to measure robustness.

Experiment

In this section, the experiments that have been carried out to test the efficiency and effectiveness of proposed Framework is presented. In experiment 1, images from the Corel database have been used. This database consists of a large number of images of various contents ranging from animals to outdoor sports to natural images. These images are collected from five different domains, namely, *Planet ,Sunset, Rose, House ,Dear ,Beaches, Bear and People.* Each category has images with resolution of either 128 X 96 or 128 X 85. Fig 4. shows the sample images of database (one image from each category).

Fig. 4 Sample images from database (one image per category).

Query
Image

5 Matches from Top 5 Retrieved Images

Figure 5 (a) Retrieved Images

Query
Image

5 Matches from Top 5 Retrieved Images

Figure 5 (b) Retrieved Images

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In this experiment, each image in the database is used as the query image. For each query, the system collects database images with the shortest image matching distance computed if the retrieved image belongs to same category as that of the query image, then we say that the system has appropriately identified the expected image, or else, the system has failed to find the expected image. The performance of the proposed method is measured in terms of average precision, average recall and average retrieval rate (ARR) and as shown below. The Average retrieval rate for LTrPs over segmented image on DB2 is 85.40.

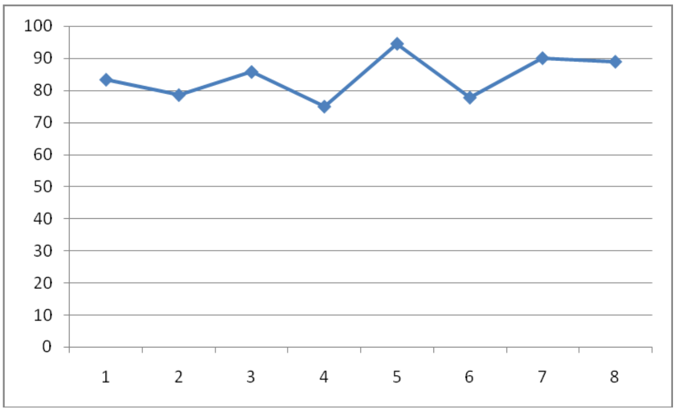

Fig.6 Category wise performance (Precision)

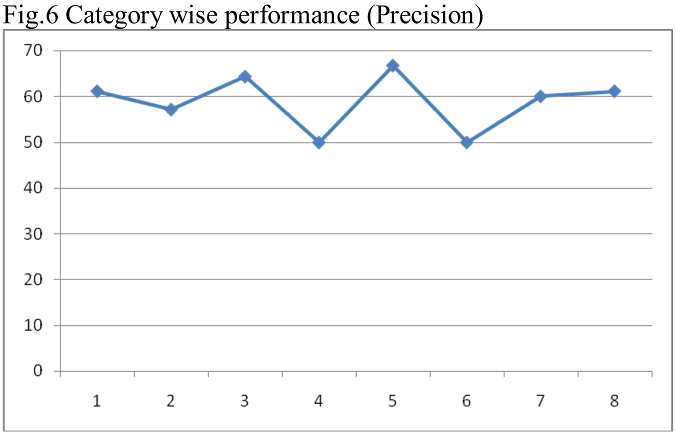

Fig.7 Category wise performance (Recall)

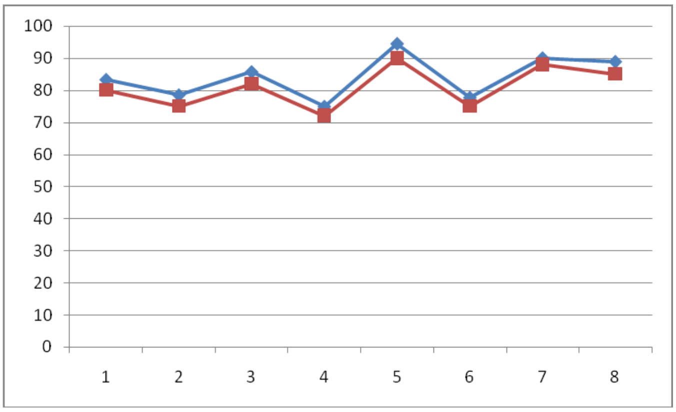

Fig.8 Comparison with other existing methods in terms of average retrieval precision

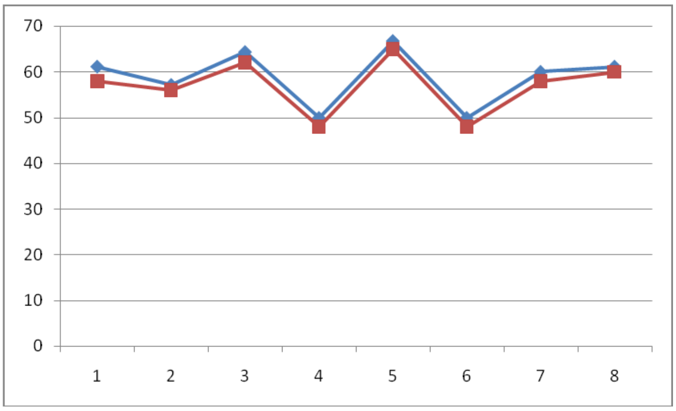

Fig.9 Comparison with other existing methods in terms of average retrieval recall

V. Conclusion & Future Work

We have designed and implemented a content-based image retrieval system that evaluates the similarity of each image in its data store to a query image in terms of textural characteristics, and returns the images within a desired range of similarity. The primary goal of this paper was to explore the effect of using different image segmentation and texture extraction algorithms on natural scene recognition. The performance improvement of the proposed method has been compared with the LBP, the LTP, and the LDP on greyscale images. The average precision, average recall has been significantly improved.

It is clear that the rate at which the number of images available to the public in digital form grows will increase in the coming years, because of new image compression techniques, cheaper storage, and faster Internet connections. Hence, the role of CBIR (certainly within the framework of content-based multimedia retrieval) in the future will become even more important. In this paper, only horizontal and vertical pixels have been used for derivative calculation. Results can be further improved by considering the diagonal pixels for derivative calculations in addition to horizontal and vertical directions. Due to the effectiveness of the proposed method, it can be also suitable for other pattern recognition applications such as face recognition, fingerprint recognition, etc.

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