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CONTENT BASED IMAGE RETRIEVAL METHODS USING RANDOM VECTOR PROCESS IMAGE RETRIEVAL ALGORITHM

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ABSTRACT

The Content based images retrieval have become the recent key investigation tools for all type of diagnosis and planning. Due to the advent of digital imaging the need of data storage and retrieval of some images increased rapidly. Some difficulties in retrieving images are: medical images have only intensity images that carry less information, more noise and records of medical images are large and complex to analyze. The Similarity measures are extracted on both schemes and a good comparison is made. The experimental results on Random Vector Process Image Retrieval Algorithm RVPIR images indicate reliability, feasibility and efficacy of the proposed method. browsing, searching and retrieving of image in an image databases cannot be underestimated also the efficient management of the rapidly expanding visual information has become an urgent problem in science and technology. This requirement formed the driving force behind the emergence of image retrieval techniques. Image retrieval based on content also called content based image retrieval, is a technique which uses the visual contents to search an image in the scale database

Keywords: *CBIR, Texture, Random Vector Process Image Retrieval.*

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1. INTRODUCTION:

Advances in data storage and image acquisition technologies have enabled the creation of large image datasets. In order to deal with these data, it is necessary to develop appropriate information systems to efficiently manage these collections. Image searching is one of the most important services that need to be supported by such systems developing effective methods for automated annotation of digital images continues to challenge for computer scientist. Image retrieval algorithms are dividing into two categories. Conventional information retrieval is based solely on text, and these approaches to textual information retrieval have been transplanted into image retrieval in a variety of ways, including the representation of an image as a vector of feature values. However, "a picture is worth a thousand words." Text based image retrieval is non-standardized because different users use different keywords for annotation.

Text descriptions are subjective and incomplete because it cannot depict complicated image feature very well. Another method is content based. Image contents are much more versatile compared with text, and the amount of visual data is already enormous and still expanding very rapidly. It has been widely recognized that the family of image retrieval techniques should become an integration of both low-level visual features, addressing the more detailed perceptual aspects, and high-level semantic features underlying the more general conceptual aspects of visual data. Content Based Image Retrieval (CBIR) is an important research area for manipulating large multimedia databases and digital libraries. High retrieval efficiency and less computational complexity are the desired characteristics of CBIR system. CBIR finds applications in advertising, medicine, crime detection, entertainment, and digital libraries. Computational complexity and retrieval efficiency are the key objectives in the design of CBIR system [2]. However, designing of CBIR system with these objectives becomes difficult as the size of image database increases. Features of an image should have a

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strong relationship with semantic meaning of the image. CBIR system retrieves the relevant images from the image data base for the given query image, by comparing the features of the query image and images in the database. The increasing reliance of modern medicine on diagnostic techniques such as radiology, Computerized Tomography (CT) has resulted in an explosion in the number and importance of medical images [1, 2]. The ocean of information available would be useless without the ability to manipulate, classify, archive and access them quickly and selectively. One of the main problems was the difficulty of locating the desired image in a large and varied collection, while it is perfectly feasible to identify the desired image from a small collection simply by browsing. Medical image retrieval systems address this problem [5]. The prime requirement for medical imaging systems is to be able to display images relating to a named patient. The text indexing is often limited, tedious and subjective for describing image content. So there is an increasing interest in the use of CBIR techniques toaid diagnosis by identifying similar past cases. Queries to CBIR system are most often expressed as visual examples of the type of the image or image attribute being sought. For example user may submit a sketch, click on the texture pallet, or select a particular shape of interest. This system then identifies those stored images with a high degree of similarity to the requested feature.

2. MOTIVATION:

The query image and the top 29 target images returned by a CBIR system described in [3] where the query image is on the upper-left corner. From left to right and top to bottom, the target images are ranked according to decreasing values of similarity measure. In essence, this can be viewed as one-dimensional visualization of image database in the "neighborhood" of the query image using a similarity measure. If the query image and majority of the images in the "vicinity" have the same user semantics, then we would expect good results. But target images with high feature similarities to the query image may be semantically quite different from the query image due to semantic gap. For the example the target images belong to several semantic classes where the dominant ones include horses (11 out of 29), flowers (7 out of29), golf player (4 out of 29), and vehicle (2 out of 29).

However the majority of top matches in Figure 1 belong to a quite small number of distinct semantic classes, which suggests a hypothec, is that, in the "vicinity" of the query image, images tend to be semantically clustered in some feature space. Therefore, are trieval method, which is capable of capturing this structural relationship, will be able to render semantically more meaningful results to the user than merely a list of images sorted by a similarity measure. This motivates us to tackle the semantic gap problem from the perspective of unsupervised learning. The major difference between CBICR and CBIR systems lies in the two processing stages, selecting neighboring target images and image clustering. A typical CBIR system bypasses these two stages and directly outputs the sorted results to the display and feedback stage. That CLUE can be designed independent of the rest algorithmic components of the system because the only information needed by CLUE is the sorted similarities.

This implies that CLUE may be embedded in a typical CBIR system regardless of the imagery features being used, the sorting method, and whether there is feedback or not. To mathematically define the neighborhood of a point, we need to first choose a measure of distance. As to images, the distance can be defined by either a similarity measure (a larger value indicates a smaller distance) or a dissimilarity measure (a smaller value indicates a smaller distance). Because simple algebraic operations can convert a similarity measure into a dissimilarity measure, without loss of generality, we assume that the distance between two images is determined by a symmetric dissimilarity measure, d(i; j) = d(j; i) ¸ 0, and name d(i; j) the distance between images i and j to simplify the notation.

3. RELATED WORK:

The recently proposed local binary pattern (LBP) features are designed for texture description. proposed the LBP [8] and these LBPs are converted to rotational invariant for texture classification[1]. Pietikainen et al. proposed the rotational invariant texture classification using feature distributions [2]. Ahonen et al. [2] and Zhao et al [12] used the LBP operator facial expression analysis and recognition. Heikkila et al. proposed the background modeling and detection by using LBP [3]. Huang et al. proposed the extended LBP for shape localization [4]. Heikkila et al. used the LBP for interest region description [5]. Li et al. used the combination of Gabor filter and LBP for texture segmentation [6]. Zhang etal. proposed the local derivative pattern for face recognition [7]. They have considered LBP as a non-directional first order local pattern, which are the binary results of the first-order derivative in images. Texture is one of the crucial primitives in human vision and texture features have been used to identify content of images. Texture refers to the visual patterns that have properties of homogeneity that do not result from the presence of only a single color or intensity. Texture contains important information about the structural arrangement of surfaces and the relationship to the surrounding environment. One crucial distinction between color and texture features is that color is a point, or pixel, property, whereas texture is a local-neighborhood property. As a result, it does not make any sense to discuss the texture content at pixel level without considering the neighborhood. Texture has long been an important topic in image processing [7].Methods of texture analysis are usually divided into two major categories [14]. The first is the structural approach, where texture is considered as a repetition of some primitives, with a specific rule of placement. The traditional Fourier spectrum analysis and wavelet based analysis [8] are often used to determine the primitives and placement rule. Several author shave applied these methods to texture classification and texture characterization with a certain degree of success [8]. The second major approach in texture analysis is statistical method. Its aim is to characterize the stochastic properties of the spatial distribution of gray levels in an image. The gray tone co-occurrence matrix is frequently used for such characteristics. A set of textural features derived from the co-occurrence matrix is widely used to extract textural information from digital images [10]. Study of patterns on textures is recognized as an important step in characterization and classification of textures. Textures are classified recently by various pattern methods, viz., preprocessed images [12], long linear patterns [11], and edge direction movements [2], Avoiding Complex Patterns [10], marble texture description [1]. Textures are also described and classified by using various wavelettrans forms: one based on primitive patterns [3], and another based on statistical parameters

4. PROPOSED RVPIR ALGORITHM:

To improve the performance in terms of retrieval accuracy and computational complexity, in this paper, we considered local derivative patterns (LDP_6_2). Two experiments have been carried out on Corel database and MIT V is Tex databases for proving the worth of our algorithm. The results after being investigated shows a significant improvement in terms of their evaluation measures as compared to LBP_6_2, and other existing transform domain techniques. The system extract the visual attributes of the query image in the same mode as it does for each database image, and then identifies images in the database whose feature vectors match those of the query image, and sorts the best similar objects according to their similarity value. In this system we use approaches that are Spatiogram [1] that is used on color, Gabor filter[2] that is used for texture retrieval and for Edge we use Edge Histogram because Edges convey essential information to a picture and therefore can be applied to image retrieval. In this paper, we introduce an original RF scheme based on graph-cuts.

The latter introduced in [4] are popular in solving many computer vision and image processing problems ranging from stereo vision, 2D image and 3Dmodel segmentation, to in-painting and texture generation. This work is the rest comprehensive study of relevance feedback using graph-cuts. As cited in the sections above, many RF methods rely on popular machine learning tools in cluding support vector machines [10] and Parzen estimators [9]. Even though these approaches were relatively successful in solving RF, none of them take into account the unlabeled data in the learning process. We believe that there limitation comes from the lack of regularities in the structure of the training set when using only the labeled data instead of the whole (mainly the unlabeled) data as shown in the remainder of this paper. Data representation is typically the first step to solve any clustering problem. In the field of computer vision, two types of representations are widely used. One is called the geometric representation, in which data items are mapped to some real normed vector space. The other is the graph representation. It emphasizes the pairwise relationship, but is usually short of geometric interpretation. When working with images, the geometric representation has a major limitation: it requires that the images be mapped to points in some real normed vector space. Overall, this is a very restrictive constraint. For example, in region-based algorithms [3, 7], an image is often viewed as a collection of regions. The number of regions may vary among images. Although regions can be mapped to certain real normed vector space, it is in general impossible to do so for images unless the distance between images is metric, in which case embedding becomes feasible. Nevertheless, many distances for images are non-metric system,

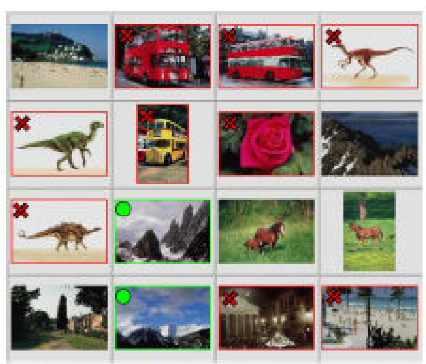

Figure 1: An example of an RF display, using the RVPIR retrieval

Proposed methods for Texture Unit and Texture Spectrum The classification, and recognition of textures becomes complex by the above method due to large number of TU that ranges from 0 to 6561. The proposed scheme reduces the above complexity by reducing overall TU from 0 to 255. For this the proposed paper outlines two methods. The method 1 is named as Reduced Texture Spectrum (RTS) and the method 2 is named as Reduced Texture spectrum with Lag value (RTL) and they are explained below. In RTS, the texture unit is defined by the following equation

$$E_i = \begin{matrix} 0 & \text{if } V_i < V_0 \\ 1 & \text{if } V_i \geq V_0 \end{matrix} \qquad \text{for } i = 1,2,\ldots 8 \tag{1}$$

and the element E i occupies the same position as the pixel I Algorithm:

Input: Image; Output: Retrieval results.
1. Load the input image and convert it into gray scale.
2. Perform the first order derivatives along 00,450, 900 and 1350 directions.
3. Calculate the second order LDPs in 00, 450,900 and 1350 directions.
4. Calculate the LDP histograms in 00, 450,900 and 1350 directions.
5. Form the feature vector by concatenating the both LDP and MLDP histograms.
6. Calculate the best matches using Eq. (1).
7. Retrieve the number of top matches.

Corel database [2] contains large amount of images of various contents ranging from animals and outdoor sports to natural images. These images are pre-classified into different categories of size100 by domain professionals. Some researchers think that Corel database meets all the requirements to evaluate an image retrieval system, because of its large size and heterogeneous content. In this paper, we collected the database DB1contains 1000 images of 10 different categories (groups G). Ten categories are provided in the database namely Africans, beaches, buildings, buses, dinosaurs, elephants, flowers, horses, mountains and food. Fig 2shows that Comparison of proposed method (LDPM) with other existing methods in terms

$$D(Q,I_1) = \sum_{i=1}^{Lg} \left| \frac{f_{I,i} - f_{Q,i}}{1 + f_{I,i} + f_{Q,i}} \right|^2 \tag{2}$$

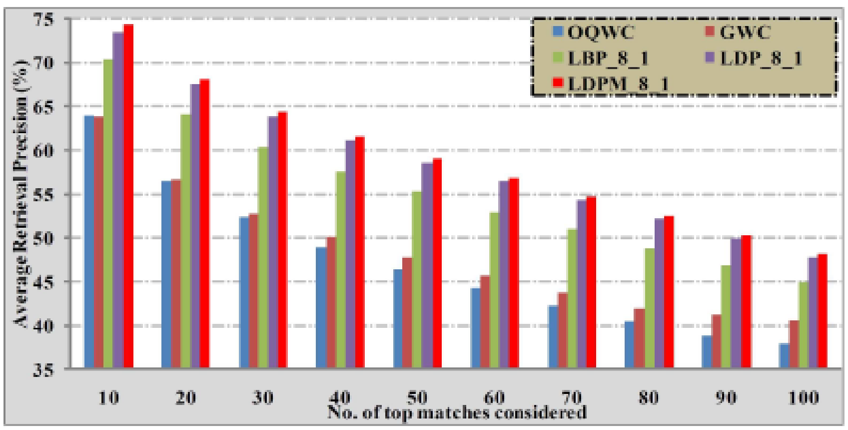

Fig 2 Comparison of proposed method (LDPM) with other existing methods in terms

An edge histogram in the image space represents the frequency and the directionality of the brightness changes in the image. The edge histogram descriptor [6] represents the spatial distribution of five types of edges, namely four directional edges and one non-directional edge. Since edges play an important role for image perception, it can retrieve images with similar semantic meaning. Edge histogram is built by applying an edge detector to the image, then going over all pixels that lie on an edge, and histogramming the local tangent orientation. The Edge Histogram Descriptor represents the local edge distribution in the image which is obtained by subdividing the whole image into 4 × 4 sub images. For each of these sub images we compute the histogram.

5. GABOR FILTER:

The methodology applied on texture that is gabor filter. For texture retrieval we used Gabor filter .Gabor filters area group of wavelets, with each wavelet capturing energy at a specific frequency and a specific direction. Expanding a signal using this basis provides a localized frequency description, therefore capturing local features/energy of the signal. Texture features can then be extracted from this group of energy distributions. The scale (frequency) and orientation tunable property of Gabor filter makes it especially useful for texture analysis. Gabor filters have the ability

to perform multi-resolution decomposition due to its localization both in spatial and spatial frequency domain. Texture segmentation requires simultaneous measurements in both the spatial and the spatial-frequency domains.

$$\hat{q} = \arg\min_{q} \left\{ -\sum_{s=1}^{n} \log f\left(\mathbf{y}(s)|\omega, \boldsymbol{\theta}_{(q)}\right) + \frac{q-1}{2}\log n + \frac{\dim(\mathbf{y})}{2}\sum_{j=1}^{q}\log(m_j\, n) \right\}. \tag{3}$$

Filters with smaller bandwidths in the spatial-frequency domain are more desirable because they allow us to make finer distinctions among different textures .for the accurate localization of texture boundaries requires filters that are localized in the spatial domain. However, normally the effective width of a filter in the spatial domain and its bandwidth in the spatial-frequency domain are inversely related according the uncertainty principle A two dimensional Gabor function consists of a sinusoidal plane wave of some frequency and orientation, modulated by a two-dimensional Gaussian. For generated filter bank we use Gabor function using 3 scales of frequency and 4 orientations we set frequencies and orientations that cover the entire spatial frequency space so as to capture texture information as much as possible in accordance with filter design. Fig 3 shows that No of Images returned for image #10

The lower and upper frequencies of the filters were set at 0.06 octaves and 0.5 octaves respectively, the orientations were at intervals of 30 degrees, and the half-peak magnitudes of the filter responses in the frequency spectrum are constrained to touch each other. Because we use the symmetric property of the Gabor function as explained in Gabor filter explanation.

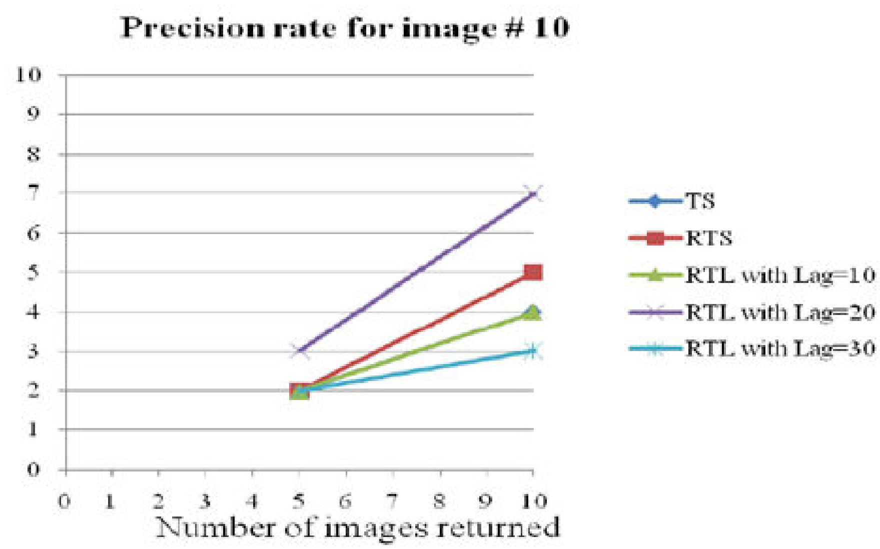

Fig 3: No of Images returned for image #10

6. PERFORMANCE EVOLUTION:

Performance Evolution is calculated using average retrieval rate. The average retrieval rate for the query image is measured by counting the number of images from the same category which are found in the top ‘N’ matches. Retrieval performance of the proposed CBIR system using Spatiogram, Gabor filter and EDH result on the database of 500 images shown in table it is observed that the proposed CBIR system with different method for retrieval (likespatiogram, Gabor, EDH) very effective and give good results. It is well-known that the classification performance depends on the training set size: the more comprehensive a training set, the better the classification performance. the classification accuracies of the indoor/outdoor image classifier (based on spatial color moment features) as the training set size is increased. As expected, increasing the training set size improves the classification accuracy. When we trained the LVQ with all the available 5081 images using the color moment features, a classification accuracy of 95.7% (re substitution accuracy) was obtained. This shows that the classifier still has the capacity to learn, provided additional training samples are available. The above observations illustrate the need for an incremental learning method for Bayesian classifiers. Collecting a large and representative training set is expensive, time consuming, and sometimes not feasible. Therefore, it is not realistic to assume that a comprehensive training set is initially available. Rather, it is desirable to incorporate learning techniques in a classifier [2], [9]. As additional data become available, the classifier should be able to adapt, while retaining what it has already learnt. Since the training set can become extremely large, it may not be feasible to store all the previous data.

7. CONCLUSION:

This paper has presented a brief overview of content based image retrieval area. Firstly, we have presented a set of constructs aiming to define precisely the main related concepts. Next, we have described the main issues that need to be taken into account when designing this kind of image retrieving system. Then we describe new methodology that is integration of different approaches that are Spatiogram, Gabor Filter, Edge Histogram. a novel image retrieval scheme, based on a simple assumption: semantically similar images tend to be clustered in some feature space. The attempts to retrieve semantically coherent image clusters from unsupervised learning of how images of the same semantics are alike. It is a general approach in the sense that it can be combined with any real-valued symmetric image similarity measure (metric or non-metric). Thus it may be embedded in many current systems.

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