Review Article — *ISSN: 2319-507X*
Vinayak Ukinkar, IJPRET, 2013; Volume 1(8): 687-697 — *IJPRET*

INTERNATIONAL JOURNAL OF PURE AND APPLIED RESEARCH IN ENGINEERING AND TECHNOLOGY

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A NEW CONTENT BASED IMAGE RETRIEVAL TECHNIQUE USING LOCAL TETRA PATTERNS: A REVIEW

VINAYAK G UKINKAR, PROF. PRAVEEN BHANODIYA, PROF. MRUDULA MUKADA

1. Department of Computer Science, Patel College of Science and Technology, Indore.
2. HOD, Department of Computer Science, Patel College of Science and Technology, Indore.
3. Department of Computer Science, Patel College of Science and Technology, Indore.

Accepted Date:

27/02/2013

Publish Date:

01/04/2013

Keywords

CBIR,

DT-CWT,

Local tetra pattern,

Mahalanobis distance

Classifier.

Corresponding Author

Mr. Vinayak G Ukinkar

Abstract

The volume of visual data found on www and in both private and commercial collection is increasing exponentially through the use of digital camcorders and cameras. The large volume of image and video archive has led to rise of a new research and development of efficient method to searching, locating and retrieval of image. The traditional approaches rely on metadata such as keywords, tags, and/or descriptions associated with the image and this produces a lot of garbage in the results. CBIR system is a technique to the image retrieval problem associated with text based approach, which will search the image based on content e.g., shape, color, texture. The CBIR technology has been used in several applications such as fingerprint identification, biodiversity information systems, digital libraries, crime prevention, medicine, historical research, among others. In this proposed system, The Local Tetra Pattern is used for texture classification and retrieval. In this paper, the association of Mahalanobis Distance with local tetra pattern is also explored. The DT-CWT is used, which provides good directional selectivity and has a limited redundancy.

I. INTRODUCTION

Content-based image retrieval (CBIR), also known as query by image content (QBIC) and content-based visual information retrieval (CBVIR) is the application of computer vision techniques to the image retrieval problem, that is, the problem of searching for digital images in large databases "Content-based" means that the search will analyze the actual contents of the image rather than the metadata such as keywords, tags, and/or descriptions associated with the image. The term 'content' in this context might refer to colors, shapes, textures, or any other information that can be derived from the image itself. CBIR is desirable because most web based image search engines rely purely on metadata and this produces a lot of garbage in the results. Also having humans manually enter keywords for images in a large database can be inefficient, expensive and may not capture every keyword that describes the image. Thus a system that can filter images based on their content would provide better indexing and return more accurate results.

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). 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. The concepts which are presently used for CBIR system are all under research.

Most image database systems are products of research, and therefore emphasize only one aspect of content-based retrieval. Set of images are collected, analyzed and stored in multimedia information systems, office systems, Geographical information systems(GIS), robotics systems , CAD/CAM systems, earth resources systems, medical databases, virtual reality systems, information retrieval systems, art gallery and museum catalogues, animal and plant atlases, sky star maps, meteorological maps, catalogues in shops and many other places.

There exist three basic levels of feature extraction; namely - global, local and pixel. The simplest of all visual image features are based on the pixel values of the image without any deviation. Images are first scaled to a common size and then compared with database images. Local features are extracted from small sub images which are derived from the original image. The global feature can be extracted to describe the whole image in an average fashion. The low-level features extracted from images and their local patches constitute the color, texture, and shape [3].Texture is an important and extensively used feature in the human visual system for recognition and interpretation [8]. The LBP operator was introduced by in [16] for texture classification. Given a center pixel in the image, the LBP value is computed by comparing its gray value with its neighbors. Tan and Triggs [17] extended the LBP to a three-valued code called the LTP, Zhang *et al.* proposed the LDPs for face recognition [18]. They considered the LBP as the non directional first-order local pattern operator and extended it to higher order (nth-order) called the LDP. The idea of local patterns (the LBP, the LDP, and the LTP) has been adopted to define LTrPs. The LTrP describes the spatial structure of the local texture using the direction of the center gray pixel. 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 neighbors by computing the gray-level difference [7]. The LTrP considers the direction of pixels calculated by horizontal and vertical derivative for encoding the images. The rest of this paper is organized as follows. We briefly review previous CBIR techniques in Section II, thereby introducing our proposed method which consists of LTrP, DT-CWT and similarity measure functions in Section III. Application of CBIR presented in Section IV. Finally Section V presents the conclusions.

II. LITERATURE SURVEY

A great deal of research has been carried out in recent years and a few of the most relevant approaches are highlighted here. The first retrieval approach is based on attaching textual metadata to each image and uses traditional database query techniques to retrieve them by keywords. However, these systems require a previous annotation of the database images, which is a very laborious and time-consuming task. Furthermore, the annotation process is usually inefficient because users, generally, do not make the annotation in a systematic way. In fact, different users tend to use different words to describe a same image characteristic. The lack of systematization in the annotation process decreases the performance of the keyword-based image search. [1]

CBIR systems use visual content such as color, texture, and simple shape properties to search images from large scale image databases (Del Bimbo, 1999). Although they improve text-based image retrieval systems, these systems are not yet a commercial success. One of the major reasons for this limited success is that CBIR rely upon a global view of the image, sometimes leading to a lot of irrelevant image content that is used in the search process. A solution for the global view problem can be found in localized CBIR. These systems only focus on the portion of the image the user is interested in. [3]

Shape is one of the primary visual features in CBIR. Shape descriptors fall into two categories i.e., contour-based and region-based. Contour-based shape descriptors use only the boundary information by ignoring the shape interior content while region-based shape descriptors exploit interior pixels of shape. Region-based shape descriptors can be applied to more general shapes. However, contour-based shape descriptors have limitations of extracting complex shapes. Hence, region based shape descriptors viz., Moment Invariants (MI), Zernike Moments (ZM), and Legendre Moments (LM) are preferred to represent the shape content of an image. [2] Few of the region based retrieval systems, compare images based on individual region-to-region similarity. The problems of over segmentation or under segmentation will hamper the shape analysis process.

Color represents one of the most widely used visual features in CBIR systems. First a color space is used to represent color images such as RGB. In image retrieval a histogram is employed to represent the distribution of colors in image. Besides the color histogram several other colors feature representation like color moments and color sets have been applied. [6]

There are however, several difficulties associated with the color histogram (CH) viz a) CH is sensitive to noisy interferences such as illumination changes and quantization errors; b) large dimension of CH involves large computation on indexing, c)It does not take into consideration color similarity across different bins, d)It cannot handle rotation and translation. It means that information about object location, shape and texture is discarded. e) Two perceptually very different images with similar color distribution will be deemed similar by a color histogram based retrieval system

Relevance feedback is often proposed as a technique for overcoming many of the problems faced by fully automatic systems by allowing the user to interact with the computer to improve retrieval performance [5]. This reduces the burden on unskilled users to set quantitative pictorial search parameters or to select images that come closest to meeting their goals.

Texture analysis has been extensively used in computer vision and pattern recognition applications due to its potential in extracting the prominent features. Moghaddam *et al.* have introduced the concept of wavelet correlogram and have further shown that the performance improvement can be obtained by optimizing the quantization thresholds using genetic algorithm for CBIR application. [7] Ahmadian *et al.* have used the discrete wavelet transform (DWT) for texture classification [9].However, the DWT can extract only three directional (horizontal, vertical, and diagonal) information from an image. To address this directional limitation, Gabor transform (GT) have been proposed for texture image retrieval [7]. Fourier transform is used to generate the feature vectors based on the mean values of real and imaginary parts of complex numbers of polar coordinates in the frequency domain. Fourier Descriptors (FDs) have a disadvantage of giving equal weights to all its 8-neighbours. So, the Fourier coefficient formula must be completely recomputed so that horizontal and vertical neighbors are given more weight when compared with the diagonal neighbors. [14]The DT-CWT is a recently suggested transform, which provides good directional selectivity in six different fixed orientations. It has a limited redundancy and is much faster than the Gabor transform to compute. Therefore, it arises as a good one to replace Gabor transform in applications, where the speed is a critical issue [13].Distance measure function is used to measure the similarity for a given pair of images as represented by their feature vectors. Euclidean distance is one of the most commonly used similarity distance metric. Mahalanobis Distance is a metric better adapted than the usual Euclidean distance and it involves non spherical symmetric distributions. [15] Mahalanobis distance is widely used in cluster analysis and classification techniques.

III. PROPOSED METHOD

Faster and efficient CBIR algorithms are required for real time applications. To achieve this we have proposed the method, which consist of LTrP used for texture classification, Dual-Tree Complex wavelets transform (DT-CWT) in association with LTrP and Mahalanobis distance is used for the purpose of similarity comparison. The following fig. illustrates the flowchart of the proposed image retrieval System and the algorithm is as follows:

Algorithm:

Input: Query image; Output: Retrieval similar image

Step1: Convert the RGB image into gray level.

Step2: Apply the first-order derivatives in horizontal and vertical axis.

Step3: Calculate the tetra patterns.

Step4: Construct the feature vector.

Step5: Compare the query image with the images in the database using similarity distance measure.

Step6: Retrieve the similar images.

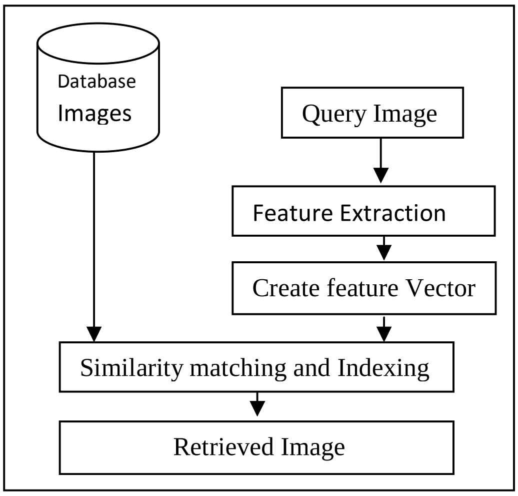

Fig.1 Block diagram of CBIR

A. *Local Tetra Pattern (LTrP)*

The local pattern (the LBP, the LDP, and the LTP) has been adopted to define LTrPs. The Local Tetra Pattern (LTrP) by using the direction of the center gray pixel $g_{c,}$ describes the spatial structure of the local texture. Given image I, the first-order derivatives along 0^0 and 90^0 directions are denoted as $I^1_{\Theta}(g_p)|_{\Theta=0^0,90^0}$. Let g_c *be* the center pixel in I, and let g_h and g_v denote the horizontal and vertical neighborhoods of g_c, respectively. Then, the first-order derivatives at the center pixel g_c can be given by:

$$1^1_{0^0}(g_c) = I(g_h) - I(g_c)$$

$$1^1_{90^0}(g_c) = I(g_h) - I(g_c)$$

And the direction of the center pixel can be calculated as $I^1Dir\ (g_c)$

$1,\ I^1_{0^0}(gc) \geq 0$ *and* $I^1_{90^0}(gc) \geq 0$ $I^1Dir\ (g_c) =$

$2,\ I^1_{0^0}(gc) < 0$ and $I^1_{90^0}(gc) \geq 0$

$3,\ I^1_{0^0}(gc) < 0$ *and* $I^1_{90^0}(gc) < 0$

$4,\ I^1_{0^0}(gc) \geq 0$ *and* $I^1_{90^0}(gc) < 0$

Next step is to calculate the second order derivative ($LTrP^2$) and from it an 8-bit tetra pattern is obtained for each center pixel. Then, this tetra pattern is divided into four parts based on the direction of center pixel. Finally, the tetra patterns for each direction are converted to three binary patterns. The second-order is defined as

$$LTrP^2(g_c) = \{f_3(I^1_{Dir,}(g_c), I^1_{Dir,}(g_1)), f_3(I^1_{Dir,}(g_c), I^1_{Dir,}(g_2)), \ldots, f_3(I^1_{Dir,}(g_c), I^1_{Dir,}(g_p))\}|_{p=8}$$

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

B. *Dual-Tree Complex wavelets transform (DT-CWT)*

Dual-Tree Complex Wavelet Transform (DT CWT), which uses two trees of real filters to generate the real and imaginary parts of the wavelet coefficients separately. This transform leads to approximate shift invariance, good selectivity and directionality, fast to compute and Limited Redundancy. LTrp methods also make use of the DT CWT to analyze the effectiveness of their methods for applications in pattern recognition.

Since DT-CWT produces complex coefficients ($R_{i,s}$,$C_{i,s}$) for each directional sub band at each scale, we use the magnitude of the coefficients, i.e.,

$$Mi,s = \sqrt{R2_{i,s} + C2_{i,s}}$$

where s refers to scale, i ∈ {±15◦,±45◦,±75◦} is a set of 6 sub bands and Mi,s is magnitude of the coefficients of sub band i at scale s.

C. *Similarity Comparison*

The similarity measure is a *matching function*, which gives the degree of similarity for a given pair of images as represented by their feature vectors. In proposed system, Mahalanobis distance is used for the purpose of similarity comparison. It is based on correlations between variables by which different patterns can be identified and analyzed. Formally, the Mahalanobis distance of a multivariate vector $x=(x_1, x_2\ x_{3....}\ x_{n)}^T$ from a group of values with mean $u=(u_1, u_2\ u_{3....}\ u_{n)}^T$ and covariance matrix S is defined as:

$$D_M(x) = \sqrt{(x - \mu)^T S^{-1} (x - \mu)}$$

IV. APPLICATION

A wide range of possible applications for CBIR technology has been identified. Some potentially fruitful areas are described in the following subsections:

a. *Crime Prevention*

Law enforcement agencies typically maintain large archives of visual evidence, including past suspects facial photographs, fingerprints, tire treads and shoeprints. Whenever a serious crime is committed, they can compare evidence from the scene of the crime for its similarity to records in their archives.

b. *Medical Diagnosis*

The increasing reliance of modern medicine on diagnostic techniques such as radiology, histopathology, and computerized tomography has resulted in an explosion in the number and importance of medical images now stored by most hospitals.

c. Web Searching

The well-publicized difficulty of locating images on the Web [Jain 1995] indicates that there is a clear need for image search tools of similar power. Several experimental systems for content-based image searching on the Web have been demonstrated over the last two to three years.

d. The Military

Military applications of imaging technology are probably the best-developed, though least publicized. Recognition of enemy aircraft from radar screens, identification of targets from satellite photographs, and provision of guidance systems for cruise missiles are known examples.

e. Cultural Heritage

Museums and art galleries deal in inherently visual objects. The ability to identify objects sharing some aspect of visual similarity can be useful both to researchers trying to trace historical influences, and to art lovers looking for further examples of paintings or sculptures appealing to their taste

V. CONCLUSION AND FUTURE WORK

Content based image retrieval is a challenging method of capturing relevant images from a large storage space. Although this area has been explored for decades, no technique has achieved the accuracy of human visual perception in distinguishing images. In this paper, we presented a content based image retrieval that proposed local tetra pattern, Dual-Tree Complex Wavelet Transform (DT CWT), Mahalanobis distance classifier for efficient retrieval of image from database. Features are drawn local tetra pattern and matching scheme used to match the image and find the similar images from the database. The future work includes the comparison of various classification methods with the proposed method and analyzes the results.

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