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Content Based Image Retrieval - A survey

Kavitha H*

[1]Assistant Professor, Dept. of ISE Siddaganga Institute of Technology Tumkur, India - 03

kavitha.halappa@gmail.com

Dr. M. V Sudhamani

[2]Professor and Head, Dept. of ISE RNS Institute of Technology Benguluru, India - 98

mvsudha raj@hotmail.com

Abstract: This paper focuses on the survey of the technical advancement in the field of Content based image retrieval (CBIR). CBIR refers to any technology that helps in organizing the digital picture archives based on their visual content. The main problem with the current approaches is that they are based on visual similarity that may cause problem due to semantic gap between the low-level content and the higher-level content of an image. Initial phase of research and development in the field of image retrieval based on content can be dated back to the years 1994-2000. Enormous progress has been made during this phase, which has been summarized as high level, that has a clear influence in the current decade and will also influence the CBIR in the future. Effort of this paper is to show the chronological growth in the field of CBIR.

Keywords: Content based image retrieval,digital pictures, low-level content,higher-level content, semantic gap, chronological growth.

I. INTRODUCTION

The recent advances in the data storage and the image acquisition technologies have paved the way for the creation of large image datasets. This scenario, states the need of the appropriate information systems to efficiently manage these collections. The common approach is the use of the CBIR systems. The CBIR approach is looked upon as an automatic retrieval process. When compared to the traditional keyword based approach that is usually very laborious and time consuming, due to the need of previous annotation of database images. CBIR has been an active area of research in image retrieval, since the last three decades and there is considerable image retrieval research activity going on in industry, national/international laboratories and universities. The different stages involved in the general CBIR system may be broadly grouped into four stages [1], namely Query Image, feature extraction or image preprocessing, similarity matching and retrieved images. The Figure 1 shows the steps involved in a general CBIR system. In the CBIR system, the process of searching goes has follows. The user query image acts has the means to query the CBIR system. The features of the images are extracted and are then encoded into feature vectors. These feature vectors are compared with the feature vectors of the images that are put up in the database earlier. The distance measures are computed between the feature vectors and these distance values are used to rank the retrieved images from the database. Each of these steps are discussed in detail in the following sections.

A. Image search:

The way the user specify the query image plays a major role in image search. They are a few different ways for image searching. In [1], the image search was classified into two classes namely narrow and broad and till date this concept is considered the extremely important distinction for the system design. The narrow image domains are characterized by limited variability and well defined visual characteristics (e.g. aviation-related pictures [Airliners.Net 2005]). The board domains tend to have high variability and unpredictability on the same semantic concepts (e.g. Web images), this makes generalization more complex. [2] put forth that the two domains narrow and board are not sufficient for image search, they propose a three category image search:

a. Search by association - suitable when there is no clear intent of a picture; the search is carried out iteratively by refined browsing.
b. Aimed search - search for a specific picture.
c. Category search - single picture of a semantic class is searched for.

There are many other search techniques based on the concepts of syntactic, perceptual and topological similarity. The user can choose any of the searching techniques based on the application.

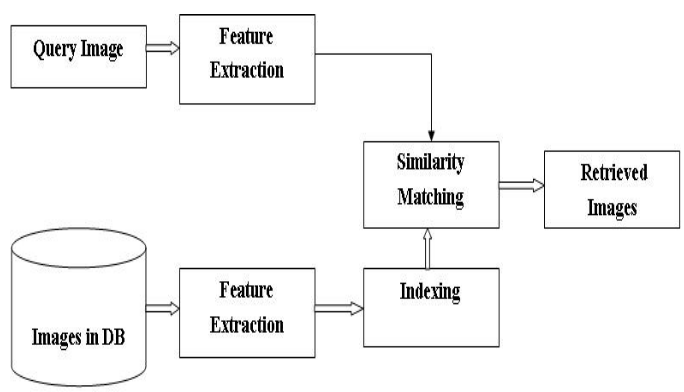

Figure. 1: Generic CBIR System

B. User interface:

The user interface in CBIR is composed of two steps, query formulation and a result presentation part. The query image can be specified in many different ways. One way can be to browse elements one by one from the database. The

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image can be specified in terms of keywords or can be in terms of the image features extracted from the image, for example color histogram. An image itself can be provided or a sketch of an image can be provided. Relevance feedback refers to providing positive or negative feedback about the retrieval result so as to improve the systems performance.

C. Applications:

In the previous three decades, the CBIR techniques has drawn much interest and many image retrieval tech-niques have been put forth in the context of searching information from the image database. The CBIR technol-ogy has been adopted by several applications such as fin-gerprint identification, biodiversity information systems, digital libraries, crime prevention, medicine, historical research, among others. The Chabot project, initiated the study of storage and retrieval of the large digitized database. Concurrently, IBM Almaden Research Centre also came up with another CBIR system proposed by Flickner [3] and Niblack [10]. This approach was im-provised by Tan , Hsu and by Mokhtarian, F S Abbasi and J Kittler, who were working at the Department of Electronics and Electrical Engineering, UK. The CBIR systems that were very much popular in 90's era namely are: IBM QBIC [3], VIRAGE [71] and NEC AMORE [14] these CBIR systems come under the commercial domain. The CBIR system like, MIT Photobook [15] , Columbia VisualSEEK and WebSEEK [16], UCSB NeTra [17] and Stanford WBIIS [26], come under the academic domain.

There are a very few image retrieval systems that are meant for public usage, namely Google Image Search or Yahoo! Image Search. Riya is an image retrieval and also the face recognition, public-domain search engine. Riya is basically meant for searching pictures of the people and also the products mainly in the Web. The CBIR technology has got a diverse application, that ranges from family album management, botany, astronomy, mineralogy, and remote sensing [22], [26], [23], [24], [25]. The Airliners.Net and also the Slashdot, both developed in 2005, are publicly available as the similarity search tool for airline related images. This online database has got over 8,00,000 airline related images [26]. The Global Memory Net proposed in 2006, is a large collection of the art and the cultural images. The Terra galleria of 2001 is basically, an incorporation of image similarity system to a massive picture archive, by the renowned travel photographer, Luong Q T.

Rest of the paper is organized as follows: In Section II, feature extraction techniques, color and texture features are discussed. Similarity measures and indexing scheme are mentioned in Section III. Section IV focuses on conclusion and future work to be carried out.

II. FEATURE EXTRACTION

The feature of an image is the visual property of that image. The feature extraction step is also referred to as image preprocessing step. The features are basically of two types: global features, refer to the overall char-acteristics of an image and the local feature, refers to the visual property for a small group of pixels. Color, texture, shape and salient points of an image are the most commonly used global features. Out of them the color and texture features are discussed in this paper.

A. Color Feature:

Color is one of the most important visual feature identified by the human beings. Hence, color features are looked upon has most important features in the CBIR system. According to the survey there are three important means for color analysis, as shown in Figure 2 and are explained below.

The global color information of the image is consid-ered in global approach. In this approach, there is no partitioning or pre-processing step. The global approach algorithms are simple and fast in extracting the feature vectors. As the spatial distribution of colors information is not considered, these features will have little discrimi-nating power. Usually Histograms are the feature vectors of the global approach, namely, global color histograms [29] and also the cumulative global color histograms [61].

In the fixed region approach the whole image is divided into regions and then the color information is extracted from each of these regions. The features extracted thus will denote the spatial information of the image, at the same time the dimension of the feature vector will be high. Some of the fixed region approach namely are local color histogram [29] and cell/color histogram [62].

In the segmentation based approach the image is divided into regions that differ among images in size and quantity. Segmentation or clustering algorithms are used for division of the image. The algorithms used, adds on the extra complexity to the process of feature extraction. The features obtain by this process are most effective. To name, few such segmentation based approaches are color-based clustering [63] and dominant-color [64], [59].

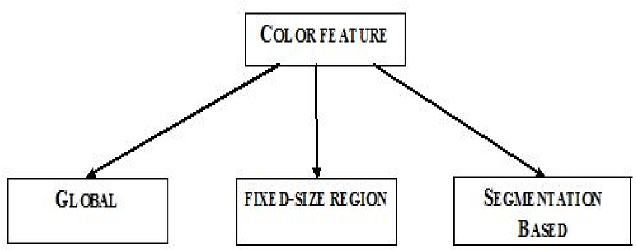

Figure. 2: Color Features Taxonomy

In the CBIR systems, the exploration of the color features was an active area of research. The major color spaces are namely, RGB, Munsell, CIE L*a*b*, CIE L*u*v*, HSV. Among all the color spaces available, the HSV color space is the most preferred one, due to its invariant properties. In this color space hue is invariant to illumination and camera direction, this property makes it more suitable for object retrieval. Some of the research work, in the area of color features have focused on the summarization of colors, that are present in that image. The color histogram is proposed as a color feature in their work by Swain and Ballard [29]. Their work was followed and enhancement by many other feature extraction systems like QBIC [3], Pictoseek [30], and VisualSEEK [16] . [31], Finlayson's work is based on color

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constancy, that refers to perceive similar color irre-spective of specular reflection and shape changes. Huang proposed an enhancement to histograms named as color correlograms, that even counts the spatial distribution of colors. Manjunath, [18] proposed matching and retrieval system based on the local shape feature extraction using Gabor filters. [26], Daubechies' wavelet transform in the WBIIS system improvised the color layout features. [34] received wide recognition for their image retrieval proposal of the viewpoint and occlusion invariant local features.

B. Texture feature:

The texture features usually are meant to capture the granularity and the repetitive patterns of the surfaces present in the picture. For example, grassland and flower petals do differ in the texture pattern in terms of the smoothness and also the patterns. The texture features are used in the field of image processing, computer vision, and computer graphics [35]. The texture features are also used by the multi orientation filter banks [36] and wavelet transforms [37] works. The taxonomy of the texture features is shown in Figure. 3 and the methods are discussed below.

The statistical method is one of the traditional ap-proaches of texture feature extraction. In statistical anal-ysis the gray levels in the image are analyzed based on the spatial distribution. For example, the computation of the probability of the co-occurrence of the gray values, for the different distances and different orientations. The statistics are named as the first order statistics, if the single pixel values are considered for computation. If the pairs of pixels values are considered for computation, then such statistics are known as second order statistics [65]. The co-occurrence matrix is one of the popular statistical methods [35].

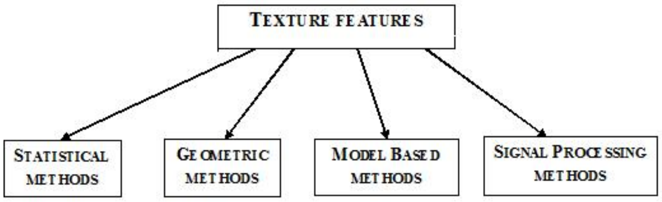

Figure. 3: Texture Features Taxonomy

In the geometrical methods the analysis is based on the geometrical properties of primitives, such as size, shape, area and the length. The identification of the primitives is followed by the extraction of the placement rules (like grids or statistics) from the relative vectors, that joins the primitive centroids [66]. This kind of analysis will be difficult, when the natural textures are considered. As an example, its simple and easy to describe the wall build of bricks by considering the brick as the primitive and the grid as the placement rule. Its not that easy to describe the clouds in the sky, since the clouds can be of different size and shape.

The image models are constructed to describe and syn-thesize the textures in case of the model based methods. The model parameters capture the essential properties of the texture [65]. Examples of texture elements models can be dark or bright spot, lines, horizonal or vertical transition, corners, etc. An example of model based method is the local binary pattern [57].

The signal processing approach apply filters over the image to characterize the textures. The filters used can be both spatial domain and frequency domain filters. The wavelet and Gabor filters follow this approach, for instance like homogeneous texture [18], [64].

The study in [67], identifies the Gabor based approach is more robust to noise when compared to the Fourier based approach. For images with no noise the Fourier based approach has better performance and for the noisy images Gabor based approach does better job. In the MPEG-7 standard, a set of color and texture features are shown to be well suited in case of the natural images and video, by [59]. The work in [38], have applied the affine invariant texture feature extraction technique for the texture recognition. They also have used interest point detection for finding sparsity. The texture features of an image at a point are considered as a function of its neighboring pixels. The scale at which the features are computed, determines the size of the neighboring pixels. Thus the scale selection plays an vital role in defining the meaning of such features. The automatic scale selection problem is been proposed by Carson et al. in their work [39].

Texture has different characteristics from color. So an integration of color and texture features results in more effective image retrieval, than does using color or texture feature alone. WAY-LOOK4 proposed by Samia [4], has taken the advantage of color and texture features for CBIR. Aradhana Katare el al. [5], has used the color and shape features to retrieve those images that are in the query object regardless of the other objects.

C. Local VS Global features:

When the local features of an image are extracted, usu-ally for every pixel its neighboring pixels are considered for computing a set of features. If the image is divided into smaller nonoverlapping blocks. Then for each block the features are computed individually and thus the computation time can be reduced. When compared to the early years of CBIR, there is a major shift from global feature extraction, like color histograms, color correlograms and the global shape features , to local features and descriptors, like region based, interest points based and spatial features. The main reason being that the global features does not reduce the semantic gap. Where as the local features reduce the semantic gap as they correspond with image components like, rigid objects and entities.

In the field of image retrieval also the local invariants like the corner points or interest points are used, these local invariants were traditionally used for stereo matching initially. [7] and [38] have proposed scale and affine-invariant interest points, that can deal with significant affine transformations and il-lumination changes. Salient Invariant Feature Transfor-mation(SIFT) proposed by David G Lowe, is considered the fastest method in most of the situations though its a bit slow.SIFT is invariant to rotation, scale translation and to affine transformations. SIFT does work well in the illumination changes. PCA-SIFT is an enhancement of SIFT, which uses the Principle Component Anal-ysis(PCA), for the dimensionality reduction of SIFT features. The problem with

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PCA-SIFT is mainly because of its blur performance. Speeded Up Robust Features (SURF) proposed by Herbert Bay, is the fastest when compared to the SIFT,SURF and PCA-SIFT.

The perfor-mance of SURF is similar to the performance of SIFT.For rotation and illumination changes the SURF is not that promising. A large number of recent publications in the domain of image retrieval and recognition, show that there is a paradigm shift from global feature extraction to local feature extraction. The experimental results show that the local feature extraction has also improvised the performance of the system. A recent work has combined the local and global features of an image, for the object recognition [8].

III. SIMILARITY MEASURES AND INDEXING SCHEME

A. *Similarity/Distance Measures:*

The CBIR system calculates the visual similarity among the query image and the images present in the database by comparing their visual similarity. The result of the retrieval process will be a set of images ranked upon their similarities to the query image. There are many similarity measures that have been used for image retrieval and the use of different similarity measure will surely affect the retrieval process. In this section we will discuss some of the similarity measures.

If the dimension of the feature vectors are in-dependent and also equally important, then the Minkowski-Form Distance L_p, is the most appropri-ate technique, for comparing the distance between the two images. The distance is defined as given below:

$$D(I, J) = \left(\Sigma_i \mid f_i(I) - f_i(J) \mid^p\right)^{\frac{1}{p}} \qquad (1)$$

Where p=1,2 and ∞ and the D(I,J) can take up the L1,L2(Euclidean distance), $L\infty$ distance re -spectively. The Minkowski-form distance has been widely used in many

a. *Minkowski-Form Distance:*

Applications. The Euclidean distance has been applied to compare the similarity distance of the texture features in MARS system [54]. Netra [17] has also used the Euclidean dis-tance metric for computing the color and shape feature and the texture features are computing using the $L\infty$ distance. The texture and the shape fea-tures are computed in Blobworld [39] by Euclidean distance. The $L\infty$ has been applied to compare the texture similarity in the work of Voorhees and Poggio [68]. The Swain and Ballard [29] have used the Histogram intersection, which is a special form of L1 distance, for comparison of color images.

b. *Quadratic Form (QF) Distance:*

The above mentioned Minkowski distance considers all the bins of the feature histogram as independent and does not consider the similarity between the pairs of bins. This drawback of the Minkowski distance is addressed by the QF distance. The distance in QF is specified as given below:

$$D(I, J) = \sqrt{(F_I - F_J)^T A (F_I - F_J)} \qquad (2)$$

here A= $[a_{ij}]$ denotes the similarity matrix and the term a_{ij} denotes the similarity of the two bins i and j. The vectors F_I and F_J lists the entries of $f_i(I)$ and $f_i(J)$. The image retrieval systems based on color histograms have applied the QF distance [69], [17].The results say that the QF distance does a better job, when compared to Euclidean distance and histogram intersection methods.

c. *Mahalanobis Distance:*

When the dimension of the feature vectors of an image are dependent on one another and each one of them have their own importance, the Mahalanobis distance metric is more appropriate one. The Ma-halanobis distance metric is defined below:

$$D(I, J) = \sqrt{(F_I - F_J)^T C^{-1} (F_I - F_J)} \qquad (3)$$

Here C denotes the feature vectors covariance ma-trix. The Mahalanobis distance can be further sim- plified if the dimensions of the features are inde-pendent.

d. *Kullback-Leibler (KL) Divergence and Jeffrey-Divergence (JD):*

The KL divergence is usually used where the com-pactness of the feature distribution is coded with reference to other one, which has the codebook. For the images I and J the KL divergence is put forth as given below:

$$D(I, J) = \sum_i f_i(I) \log \frac{f_i(I)}{f_i(J)} \qquad (4)$$

In [70] the texture similarity measure is based on the KL divergence. The other divergence method named as Jeffrey-divergence (JD), is defined as shown below:

$$D(I, J) = \sum_i f_i(I) \log \frac{f_i(I)}{\hat{f}_i} + f_i(J) \log \frac{f_i(J)}{\hat{f}_i} \qquad (5)$$

Here $\hat{f}_i = [f_i(I)+f_i(J)]/2$. When there is a need to compare two empirical distribution, JD divergence is more stable in terms of symmetry and numbers, when compared to KL divergence.

B. *Indexing Scheme:*

Effective indexing scheme plays an vital role in the CBIR system. Indexing aids in fast retrieval of images. Dimension reduction is used, since the dimensionality of the feature vector is high in the case of images. The high dimensionality of the feature vector makes the traditional structures of indexing difficult. The Principal Component Analysis (PCA)is the most commonly used method for dimension reduction. In PCA the input data is linearly mapped on to the coordinate space, so that the alignment of the axes reflects the maximum variation present in the data. PCA is used to reduce the twenty dimensional feature of the shape to two or three in QBIC system [10], [3]. Other than PCA many researcher have also applied the Karhunen-Loeve (KL) transform to dimensionality reduction of feature vectors. The most important property of KL is its ability to identify the most important sub space. The most annoying property of KL is that the blind dimensionality reduction, leads to the loss of feature properties that are helpful in identifying a pattern. Along with PCA and KL, the

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neural network is also a important tool in dimension reduction of features, as shown by Carson in [39].

The next step following the dimensionality reduction is the indexing of the multi-dimensional data set. There are many approaches that have been proposed, namely R* tree proposed by N Beckmann et al., linear quad trees proposed by J Vendrig et al., KD trees and grid files proposed by J Nievergelt et al.. A modification of the KD tree algorithm, known as Best Bin First search method proposed by David G Lowe is able to identify the nearest neighbor with limited number of computation [7]. Many of the method for multi-dimensional indexing have better performance for smaller dimension (upto 20), as the dimensionality increases they perform no way better than the sequential search techniques. The other problem is that they assume that the similarity metric used is the Euclidean distance. The Self-Organization Map (SOM) is a solution for these problems. SOM, is a hierarchical indexing scheme proposed by H J Zhang et al. .

IV. CONCLUSION

When we compare the earlier work, prior to 2000 and the current work in the CBIR, noticeable difference can be found in the image signature. The advancement can be seen in both the extraction of the features and also the construction of the signatures, which is based on these features. The advancement in the field of mathematical formulation of signatures, has paved the way for the invention of new methods for similarity matching. In this work, we tried to focus on the development of CBIR right from the early days. We have planned to built a CBIR system for multiobject retrieval based on the local feature and some visual features of an image.

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