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A Survey on Feature Extraction Techniques of CBIR and Image Indexing Techniques

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ABSTRACT: The rapid explosion ofcollection of an imagesover the Internet and the evolution of multimedia technology have been attracted significant research efforts. Also in generating tools for effective retrieval of visual data. Some difficulties faced by traditional text-based image retrieval brought the researchers to discover new solutions like CBIR to index visual information. This fresh trend of image retrieval was based on properties that are include in the images themselves called as Content-Based Image Retrieval (CBIR). CBIR uses thefeatures and the contents of an image like color,edge, texture, etc. to represent and index the image. All research efforts are being made to evaluate the performance and accuracy of image retrieval systems. The quality of response is highly dependent on the two things, like choice of the method used to generate feature vectors as well as the similarity measurement for comparison of features.The research also tell the important techniques of images indexing in detail. Theindexing method is toretrieve the best relevant image from the archive that matches the query image.

KEYWORDS: Color, Shape, Lab space, HSV, Content-Based Image Retrieval (CBIR), LocalTetra Patterns (LTrPs), Local Derivative Pattern (LDP), Local Ternary Pattern (LTP).

I. INTRODUCTION

The evolution of modern technology as well as computational power of processors and reduction in the price of memory causes need to switch from the previous non efficient approach to the new approach. Maintenance of very huge databases is very hard and especially when large set of digital images need to be maintained. Over the decade, the volume of digital image is increasing very exponentially because of many areas where digitized images are required like Multimedia, Hospitals, GIS, Crime Prevention, Pattern Recognition, Statistics and many more. Thus several researchers are working on it to maintain the large amount of databases.

Problem with the previous approach leads to another path of accessing the image on the basis of their features. This trend of image retrieval was rely on special properties and contents that are included in the images themselves called as Content-Based Image Retrieval.

Content-Based Image Retrieval (CBIR) uses the visual contents of an image to representation of an image as well as indexing of an image. Figure 1 of a CBIR system can be understood as a building blocks that communicate with each other to retrieve the database images according to a given query. In normal CBIR system, the visual contents/features of the images in the database are extracted by multi-dimensional feature vectors. To retrieve images, users provides query images to the retrieval system and then changes the query image into its internal representation of corresponding feature vectors. The similarities between the feature vectors as well as dissimilarities between the feature vector of the query image and the images in the archives are then matched. In recent days, some CBIR systems uses relevance feedback and user progressively advance the search results by ticking images in the results as "relevant" and "not relevant" to the search query, and then they repeat the search with the improved information. Thus, from the query results, the user can evaluate which images are relevant.Also the system can reuse their information in order to refine their results.

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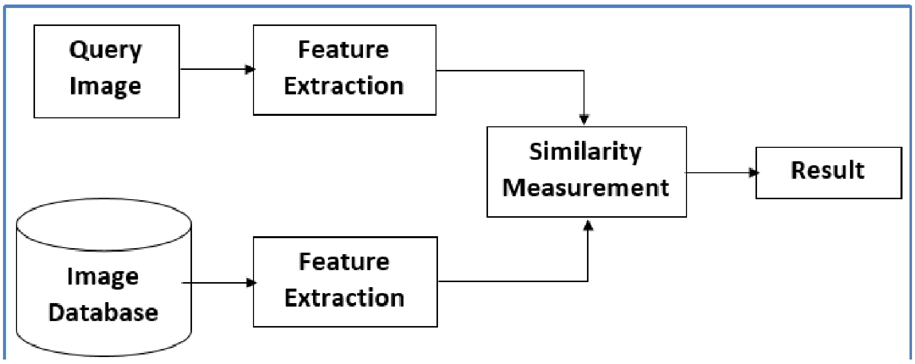

Figure.1.Block diagram of existingContent-Based Image Retrieval System

We noted some Characteristics of CBIR include like Image retrieval by image content, visually similar images to Query image, No keywords, Low level features like color, shape are used, image indexing techniques, etc.

The rest of the paper is as follows. Section 2 briefs the considered different schemes based on CBIR for the analysis and image indexing techniques. Section 3 represents the feature extraction techniques considering different features. Section 4 represents the similarity measurement, Section 5 represents the image indexing techniques and the paper concludes with section 6.

II. Literature Survey

From the last decade, the search for heavily used and efficient techniques of CBIR is alocus of research. The comprehensive works of talwar [3], Bansal [9] provide some of the most useful surveys on the CBIR. The extensive work of Singh [2], Chaudhari[4], Daisy [6] and Apurva [10] also outstands to describe the functionality of CBIR systems with proper references of past systems. Pujari [1], Sarvanan [7] done a great work with color feature. Finally, the recent study of Xie [5], Gui [8] and Demir [11] gives an actual overview of the enhanced of CBIR and tackle its major future challenges by implementing the relevance feedback using supervised learning algorithms (machine learning algorithms).But after feature extraction, some image indexing techniques are evolved. The local binary pattern (LBP) feature has been emerged in recent year in the field of "texture" classification and retrieval. Ojala et al. proposed LBPs [12], which are converted to a rotational invariant version for texture classification [13], [14] as well as improved LBP variance with global matching [15]. Some of the extensions of the LBP like dominant LBPs [16], completed LBPs [17], joint distribution of local patterns with Gaussian mixtures [18], etc., are proposed for rotational invariant texture classification. The LBP on facial expression recognition is successfully reported in [18] and [19]. Xi Li et al. proposed a multiscale heat-kernel-based face representation as heat kernels are known to perform well in characterizing the topological structural information of face appearance for the purpose of capturing texture information of the face appearance [20]. Zhang et al. proposed local derivative patterns (LDPs), here they assumed the LBP as first-order non-directional local patterns for face recognition collected from the first-order derivatives [21]. Lei et al. [22] proved that exploiting the image information jointly in image space, scale, and orientation domains can provide richer clues, which are not evident in any one individual domain. This process involves two phases, where the first phase, the face image is decomposed into different scale and orientation responses by convolving with multi-scale and multi-orientation Gabor filters. In the second phase, LBP analysis is used to describe the neighbouring relationship not only in image space but also in different scale and orientation responses. Thus, it is evident that the performance of these methods can be improved by differentiating the edges in more than two directions. This all observation has emphasis them to propose the quad-direction code, commonly known as local tetra patterns (LTrPs) for CBIR.

III. Feature Extraction

The basis of any content-based image retrieval technique is a visual feature extractionfurther classified as high-level features and low-level features. In a wider sense, features might include both color as well as shape features and text-

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based features (key-words, annotations). One of the keys of a CBIR system is the selection of the features to represent an image exactly query given to it. There does not have any alone best representation for any visual feature. Because of the complex composition it is hard to use only single visual content. Also due to perception subjectivityof visual data it is hard to use only single content. Multiple approaches have been introduced for each of these visual features and each of them characterizes the feature from a different perspective [3].

3.1 Color:

Color is depends on the response of visual system to light as well as the interaction of light with real objects [1] [7]. Color is widely used visual features in content-based image retrieval among all the features relatively robust to background complication. It is independent of image orientation and size. The key issues in color feature extraction include the color space, color quantization, and the choice of similarity function [3]. We have to first determine the color space to use, if we want to describe an image by its color features. There exist different space models such as RGB, HSV, CIE L*a*b*, etc. The best representation depends on the special needs of the application.

3.1.1 Color Space:

There are different color spaces used to show the images in the real world. Choosing an appropriate color space for the implementation of a content based image retrieval system is most important thing to produce the accurate results. Here some of the most commonly used color spaces are:

3.1.1.1 RGB

RGB [1] stands for Red-Green-Blue. RGB is the most popular color space. This space consists of the additive primary color of light Red, Green and Blue. To produce more or less any color in the visible spectrum, varying levels of the three colors are added. RGB color space is basicallyrely on device and non-uniform in behaviour. This means that a color relative club together is hard to be perceived as being close by the human eye. RGB space is normally used in televisions, digital cameras, etcs.

3.1.1.2 HSV

HSV [1] color space are made in terms of Hue, Saturation and Value. Hue represents color. In this model, hue is an anglefrom 0 degrees to 360 degrees. Saturation indicates the range of grey in the color space ranges from 0 to 100%. Sometimes the value is calculated from 0 to 1 and when the value is '0,' the color isgrey and when the value is '1,' the color is a primarycolor. A faded color is due to a lower saturation level. Which means the color contains more grey.Value is the brightness of the color and varies with colorsaturation. It ranges from 0 to 100%. When the value is '0'the color space will be totally black. With the increase inthe value, the color space brightness up and shows variouscolors.

*3.1.1.3 L*a*b*

CIE L*a*b* [1] spaces are used to models for image retrieval as they accomplish the need of spatial uniformity. These are most likely uniform color spaces as well as they are totally device independent. The three components of the model represent the lightness (L*) and two chromatic components; a* and b* showing the distance between magenta and green, and yellow and blue respectively as shown in figure 2. Accordingly the Labcolor space approach gives better performance than RGBand HSV as CIE L*u*v* was an attempt to linearize the perceptibility of the color differences. [1].

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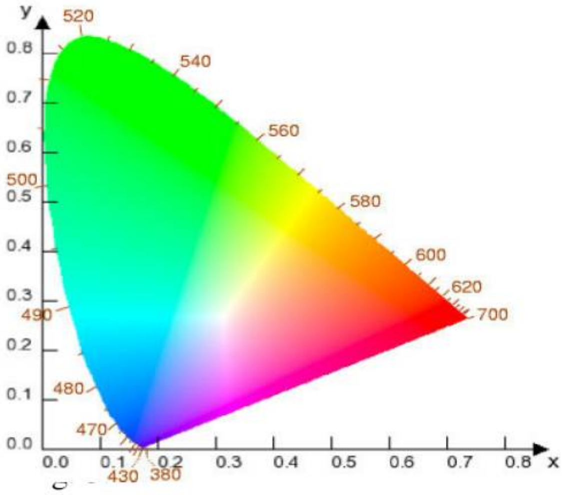

Figure.2.L*a*b color space [1]

3.1.2 Methods of representation

Each contenthave several representations as color histograms [7], color moments [2],image color feature. Moreover, number of variations of the color histogram we studied have been proposed which differs in the selected color-quantization scheme. Certain color space are related to color descriptors represents mathematical operations of the pixel values. Some of the most popular descriptors are as follows:

3.1.2.1 Color histogram

Color histograms [7] is one of the main method of representing color information of images in CBIR systems. In color histogram, we can represent the colors as bars in a bar graph. Here each bar represents a particular color of the color space being used. Statistically, a color histogram is a measure to calculate the joint probability of the three color channels. We get the most common form of the histogram by splitting the range of the data. Split the data into equally sized bins. The number the colors of the pixels in an image for each bins that fall into each bin are counted and normalized to total points. This gives us the probability of a pixel falling into that bin. One of the drawbacks of the color histogram is it does not take into consideration the spatial information of pixel. This can be consider the different images as similar as two images have similar color distributions.

3.1.2.2 Color Moments

To avoid the quantization drawbacks, normally we use the color moments approach [2]. Color moments are one of the statistical moments of the probability distributions of colors. Color moments have been efficiently used in lots of image retrieval systems. The mean, variance and the skewness have been very effective in representing color distributions of images but Color moments are not feasible to encode any of the spatial information surrounding the color content within the image. That's why this also suffer from similar problems as we consider in color histogram approach.

3.2 Shape:

Shape is one of the important content in CBIR and it usually collected verbally as well as in figures, and people use terms such as oval, rounded or unshaped etc. In Computer-based processing of shape, it is necessary to describe even very complicated shapes precisely. Many shape description methods exists, but there is not any universally accepted methodology of shape description. Shape is one of the important visual feature. Shape is one of the primitive features for image content description. It contains all the geometrical information of an object in the image. Image information does not change generally even when orientation or location of the object are changed. Some simple shape features are the perimeter, area, eccentricity, symmetry, etc.

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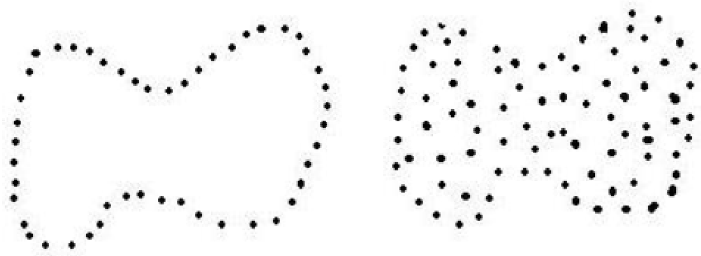

Figure.3.Graph Boundary-based shape and Region-based shape representation[3]

3.2.1 Methods of representation

Two major steps are involved in shape feature extraction: object segmentation and shape representation. Their shape features can be represented and indexed, once objects are segmented. In general, shape representations can be divided into two categories, boundary-based and region-based as shown in figure 3. The boundary-based uses only the outer boundary of the shape while the region-based uses the entire shape region. The most successful representation for thesetwo categories are Fourier descriptors and moment variants.

The canny edge detection algorithm runs in 5 separate steps:

Step 1. Smoothing: Blurring of the image to remove noise.

Step 2. Finding gradients: The edges should be marked where the gradients of the image has large magnitudes.

Step 3. Non-maximum suppression: Only local maxima should be marked as edges.

Step 4. Double thresholding: Potential edges are determined by thresholding.

Step 5. Edge tracking by hysteresis: Final edges are determined by suppressing all edges that are not connected to a very certain (strong) edge.

3.3 Texture

Structure of surfaces formed by specific pattern made by repeating a particular element or number of elements in different relative spatial positions. Image textures are defined as images of natural textured surfaces as well as artificially oriented visual patterns. It contains important information about the structural arrangement of the surface i.e., clouds, leaves, bricks, fabric, etc. It also describes the relationship of the surface to the surrounding environment. It is a feature that describes the distinctive physical composition of a surface [9].

Gabor wavelet is widely used to extract texture from the images for retrieval. Gabor wavelet has been shown to be very efficient compare to other texture extractors. Basically Gabor filters is nothing but a group of wavelets, each wavelet capturing energy set at a specific frequency and specific orientation for capturing the values. The scale and orientation tannable property of Gabor filter makes it especially useful for texture analysis.

Steps for formulation of Texture feature vector of an image [5]:

Step 1. Select an image I(x,y)of size PXQ.

Step 2. Convert the image from RGB to Gray Scale Image.

Step 3. Create 24 Gabor filter images (scale (m)-4 and orientation (n)-6).

Step 4. Convolute the image with 24 Gabor filters fmn (x,y)to form 24 Gabor filters images Gmn (x,y).

Step 5. Calculate Mean (μ) and Standard deviation (σ) for each Gabor filtered images. Thus the feature vector for 4 scales and 6 orientation.

3.4Image Indexing Technique

LTrP algorithm encodes therelationship between the referenced pixel and its neighboringpixel based on the directions which are calculated using the firstorderderivatives in horizontal and vertical direction. Further inorder to improve the performance we are combining LDP andLTP with the LTrP and construct the feature vector. Thepatterns of the query image and images in database arecompared to produce the retrieved relevant image. Theperformance resulting from the combination of LTrP, Ldp andLtp has been analyzed. The analysis shows that the proposedmethod improves the retrieval result in terms of averageretrieval rate, as compared with the existing methods.

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3.4.1 LBPs

The LBP operator was introduced by in [13] for texture classification.Given a center pixel in the image, the LBP value iscomputed by comparing its gray value with its neighbors, as shown in Figure 4, based on

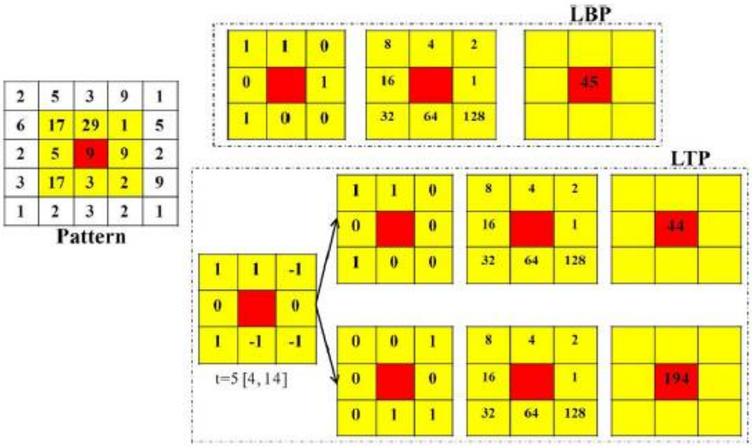

Figure.4.Calculation of the LBP and LTP operators. In the LTP, the obtainedternary pattern is further coded into upper and lower binary patterns. The upperpattern is obtained by retaining 1 and replacing 0 for 1 and 0. Lower patternis coded by replacing 1 with 1 and 0 for 1 and 0.[13]

$$\mathrm{LBP}_{P,R} = \sum_{p=1}^{P} 2^{(p-1)} \times f_1(g_p - g_c)$$

$$f_1(x) = \begin{cases} 1, & x \geq 0 \\ 0, & \text{else} \end{cases}$$

Where g_c is the gray value of the center pixel, g_p is the gray value of its neighbors, P is the number of neighbors, and R is the radius of the neighborhood.

3.4.2. LTPs

Tan and Triggs [24] extended the LBP to a three-valued code called the LTP, in which gray values in the zone of width around are quantized to zero, those above are quantized to 1, and those below are quantized to 1, i.e., indicator is replaced with three-valued function (3) and the binary LBP code is replaced by a ternary LTP code, as shown in Figure 4. LTP is an extension of Local Binary Pattern.Unlike LBP, it does not threshold the pixels into 0 and 1 rather it uses a threshold constant T to threshold pixels into three values.Here T is a user specified threshold, So LTP code more resistant to noise.

3.4.3. LDPs

Zhang et al. proposed the LDPs for face recognition [25].They considered the LBP as the nondirectional first-order localpattern operator and extended it to higher orders (*n*th-order)called the LDP. The LDP contains more detailed discriminativefeatures as compared with the LBP.To calculate the *n*th-order LDP, the (*n*-1)th-order derivativesare calculated along 0 , 45 , 90 , and 135 directions, denotedas . Finally, *n*th-order LDPis calculated as,

$$\mathrm{LDP}_{\alpha}^{n}(g_c) = \sum_{p=1}^{P} 2^{(p-1)} \times f_2\left(I_{\alpha}^{(n-1)}(g_c), I_{\alpha}^{(n-1)}(g_p)\right)\Big|_{P=8}$$

$$f_2(x,y) = \begin{cases} 1, & \text{if } x.y \leq 0 \\ 0, & \text{else.} \end{cases}$$

It encodes the higher order derivative information which contains more detailed discriminative features that the first order local pattern (LBP) cannot obtain from an image.LDP contains more detailed discriminative features as compared with the LBP.

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3.4.4 LTrP

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 g_c (center of pixel in I).Given image, the first-order derivatives along 0, 45 and 90 directions are denoted as $I^1_{\Theta^o}(g_p)$ where $\Theta = 0^o, 45^o, 90^o$. let g_h, g_v and g_d denote the horizontal, vertical and diagonal neighborhoods of g_c, respectively. Then, the first-order derivatives at the center pixel can be written as

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

and the direction of the center pixel can be calculated as

$$I^1_{Dir}(g_c) = \begin{cases} 1. \text{ if } I^1_{0^o}(g_c) >= 0 \text{ and } I^1_{90^o}(g_c) >= 0 \\ 2. \text{ if } I^1_{0^o}(g_c) >= 0 \text{ and } I^1_{90^o}(g_c) >= 0 \\ 3. \text{ if } I^1_{0^o}(g_c) >= 0 \text{ and } I^1_{90^o}(g_c) <= 0 \\ 4. \ I^1_{0^o}(g_c) >= 0 \text{ and } I^1_{90^o}(g_c) <= 0 \\ 5. \text{ if } I^1_{0^o}(g_c) <= 0 \text{ and } I^1_{90^o}(g_c) >= 0 \\ 6. \text{ if } I^1_{0^o}(g_c) <= 0 \text{ and } I^1_{90^o}(g_c) >= 0 \\ 7. \text{ if } I^1_{0^o}(g_c) <= 0 \text{ and } I^1_{90^o}(g_c) <= 0 \\ 8. \text{ if } I^1_{0^o}(g_c) <= 0 \text{ and } I^1_{90^o}(g_c) <= 0 \end{cases}$$

It is evident that the possible direction for each center pixel can be either 1, 2, 3, . . or 8 and eventually, the image is converted into eight values, i.e., directions.

The second-order LTrP(g_c) is defined as

$$\begin{aligned} &\mathrm{LTrP}^2(g_c) \\ &\quad = \left\{ f_3\left(I^1_{\mathrm{Dir.}}(g_c), I^1_{\mathrm{Dir.}}(g_1)\right), f_3\left(I^1_{\mathrm{Dir.}}(g_c), I^1_{\mathrm{Dir.}}(g_2)\right) \right. \\ &\qquad \left. \ldots, f_3\left(I^1_{\mathrm{Dir.}}(g_c), I^1_{\mathrm{Dir.}}(g_P)\right) \right\}\Big|_{P=8} \\ &f_3\left(I^1_{\mathrm{Dir.}}(g_c), I^1_{\mathrm{Dir.}}(g_p)\right) \\ &\quad = \begin{cases} 0, & I^1_{\mathrm{Dir.}}(g_c) = I^1_{\mathrm{Dir.}}(g_p) \\ I^1_{\mathrm{Dir.}}(g_p), & \text{else.} \end{cases} \end{aligned}$$

Similarly, the remaining 3 tetra patterns for remaining 3 directions of center pixels are inverted to binary patterns.Thus, we get 12 (4 x 3) binary patterns. Most of the literatures proved that, the sign component extracts more useful information ascompared with the magnitude component. Still exploiting the combinationof sign and magnitude components can provide betterclues, which are not evident in any one individual component.This concept has motivated us to propose the 13th binary patternby using the magnitudes of horizontal and verticalfirst-order derivatives using

$$M_{I^1} = \sqrt{(I^1_{0^o}(\text{gp}))^2 + (I^1_{45^o}(\text{gp}))^2} + \sqrt{(I^1_{45^o}(\text{gp}))^2 + (I^1_{90^o}(\text{gp}))^2}$$

For the local pattern with neighbourhoods, 2^P combinations of LBPs are possible, resulting in the feature vector length of 2^P. The computational cost of this feature vector is very high. To reduce the actual computational cost, we take the uniform patterns. These pattern refers to the uniform appearance pattern that has restricted discontinuities in this binary representation. In this survey, we represent those patterns that have less than two discontinuities in the binary representation are refer as the uniform patterns, and the other remaining patterns are referred to as non-uniform pattern. Thus, the distinct uniform patterns for a given query image would be P(P-1)+2. Here the actual process become slow but the accuracy increases w.r.t. size of dataset.

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IV. CONCLUSION AND FUTURE WORK

CBIR is a research area that works for different features like color, edge and much more. CBIR is a research area that requires knowledge of computer vision as well as database systems.We can make an accurate system by adding multiple features to retrieve accurate image as an output. Here we studied different image indexing techniques. In future relevance feedback also be our aim of research.

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