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Fast Query Indexing and Searching Techniques for Content-Based Image Retrieval

J. DIVYA

Department of Computer science and Engineering, Dhaanish Ahmed College of Engineering

E-mail :div2288@gmail.com

***Abstract*--The process of dealing with or controlling the manipulations of any image database has become extremely tedious due to its intense growth. Thus our approach dealt in this paper relies on an efficient CBIR technique that focuses on low-level image features such as the color, texture and shape. The proposed system aims on an automatic image search and retrieval system that works best even in its average and worst case scenarios. This system incorporates a new indexing technique along with few other feature extraction techniques that extracts various multi-resolution color, texture and shape features from the images in the database. The system also contains a very simple but very effective retrieval method and all these put together have reduced the number iterations that were there in the existing systems. Experiments were stimulated using corel database and were proved that this system has minimized the effects of user's inaccurate relevance feedback and appropriate images were retrieved very efficiently with less iteration.**

Along with the existing approaches, we have included another variety of area in data mining that is extracting data from Knowledge cubes. This can be achieved with the tool SQL Server Analysis Services. The data will be taken and it will be transformed into knowledge cubes. This can be achieved with Multi Dimensional queries. In addition to that, this project introduces a performance evaluation on three methods CASE, SPJ and PIVOT. Experiments with large tables compare the performance of proposed method with existing three methods. Extracting the data from knowledge cube by multi dimensional query is much more efficient and time complexity is less comparing the three methods.

Key words: Content Based Image retrieval (CBIR)

1.INTRODUCTION

The explosive growth of digital libraries due to Web cameras, digital cameras, and mobile phones equipped with such devices is making the database management by human annotation an extremely tedious and clumsy task. Thus, there exists a dire need for developing an efficient expert technique that can automatically search the desired image from the huge database. Content-based image retrieval (CBIR) is one of the commonly adopted solutions for such applications.

A. Related Works

One of the feature extraction technique used in CBIR is LBPs, it converts a rotational invariant version for texture classification. Various extensions of the LBP, such as LBP variance with global matching, dominant LBPs, completed LBPs, joint distribution of local patterns with Gaussian mixtures, etc., were proposed by **Ojala *et al.[7]*** for rotational invariant texture classification. The LBP operator on facial expression analysis and recognition were successful.

For face recognition local derivative patterns (LDPs) were used, **Zhang *et al. [3]*** considered the LBP as non-directional first-order local patterns collected from the first-order derivatives and extended the same approach for i-th order LDPs. Lei *et al.* proved that exploiting the image information jointly provide richer clues, which are not evident in any one individual domain. This process involves two phases. In 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.

Xiaoyan Li et al., [4] have designed and implemented the research on content based image retrieval in gallery image of the flowers and textual descriptors using Punning algorithm. Image retrieval, aims to provide effective and efficient tools for querying the large image data bases. Pure text based retrieval techniques ignore the useful image features. This technique extracts the image via multimedia analysis; as a result some relevant images might be missing in the query output. The proposed algorithm measures the image semantic similarity, this improves the query accuracy. The proposed algorithm has the advantage that reduces the search cost in semantic space. It has the disadvantage that hierarchy search takes more time to retrieve the image and lexical hierarchy will not give the exact result. In conclusion the proposed algorithm gives the good accuracy for search image.

B. Main Contribution

One of the feature extraction technique used in CBIR is LBPs, it converts a rotational invariant version for texture classification. Various extensions of the LBP, such as LBP variance with global matching, dominant LBPs, completed LBPs, joint distribution of local patterns with Gaussian mixtures, etc., were proposed by **Ojala *et al.[7]*** for rotational invariant texture classification. The LBP operator on facial expression analysis and recognition were successful. For face recognition local derivative patterns (LDPs) were used, **Zhang *et al. [3]*** considered the LBP as non-directional first-order local patterns collected from the first-order derivatives and extended the same approach for i-th order LDPs. Lei *et al.* proved that exploiting the image information jointly provide richer clues, which are not evident in any one individual domain. This process involves two phases. In 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.

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C. Main Contribution

The proposed system uses a indexing technique along with various other image feature extraction techniques, re-ranking techniques and query matching technique. The various feature extraction techniques discussed below are Local Tetra Patterns (LTPr's), Color Layout descriptor (CLD), Edge Histogram Descriptor (ECD), Auto Color Correlogram , Fuzzy Color and Texture Histogram (FCTH), Color and Edge Directivity Descriptor (CEDD), Joint Composite Descriptor(JCD), Tamura Texture Feature, Gabor Texture Feature, RGB Color Histogram and Speeded Up Robust Features (SURF) & Bag Of Visual Words (BOVW). Latent Semantic Analysis is used for re-ranking and distance formula for query matching.

2 INDEXING

Indexing is done using an implementation of the DocumentBuilder interface. A simple approach is to use the DocumentBuilderFactory, which creates DocumentBuilder instances for all available features as well as popular combinations of features (e.g. all MPEG-7 features or all available features). A DocumentBuilder is basically a wrapper for image features creating a Document from a Java BufferedImage. The signatures or vectors extracted by the feature implementations are wrapped in the documents as text. The document output by a DocumentBuilder can be added to an index.

3 FEATURE EXTRACTION TECHNIQUES

A. Color Layout Descriptor (CLD)

Once the input image is fed to the CLD, it calculates the dimensions of the image and accordingly the image is divided into 8 sub images. If the dimensions were not divisible by 8, then truncation is used such that the outer most pixels are not considers. Using the obtained information, the data is parsed into three 4D arrays, one for each color component. Indices are provided to each sub image and also to their pixels so that we can access both of them as required. Average of pixels in each sub image is calculated with which the representative color is chosen and as a result we will have three 8x8 arrays, each one representing a color component. Now each 8x8 matrix is transformed to YCbCr color space which is further converted into 8x8 DCT matrices of coefficients, one for each YCbCr component.Finally the descriptor has an array of 12 values which is formed by zig-zag reading. That is 6 coefficients from Y-DCT matrix and 3 coefficients from each chrominance component matrix are taken in zig-zag order.

B. Edge Histogram Descriptor (EHD)

The EHD basically deals with 5 types of edge distributions. They are vertical, horizontal, 45-degree diagonal, 135-degree diagonal and non-directional edges. This descriptor divides the input image into 4x4 non-overlapping blocks thus yielding 16 equal-sized sub images. Now histograms are developed for all sub images and these histograms for each sub-image is based on the relative frequency of occurrence of the 5 types of edges in the corresponding sub-images, thus each local histogram has 5 bins. As we have 16 such sub-images we need a total of 80 histogram bins such that each bin has its own location and edge type. The bins are arranged accordingly by visiting the sub-images in raster scan order. Finally all the obtained values are normalized and quantized.

D. Fuzzy Color and Texture Histogram (FCTH)

In FCTH [6] the input image is divided into 1600 blocks and histograms are formed using the fuzzy systems. The first fuzzy system is used for texture classification and the other fuzzy system is used for color classification. The texture feature constitutes of 8 regions as given in fig.(i),These 8 regions are obtained as a result of calculations on the values of fLH, fHl and fHH. Each of these regions is again classified into 24 bins that represent various colors in the YIQ color space thus forming 192bins as a whole. With these values histograms are developed which is further transformed into a Haar wavelet transform. In the fuzzy color system HSV color space is used here the image blocks are classified into 10 color bins which is further expanded as 24 color bins. With these values histograms are formed, now the texture information and color information are combined and the final output is quantized.

	0	1	2	3	4	5	6	7
CEDD	Linear	Non Directional	Horizontal Activation	Vertical Activation	45 Degree Diagonal	135 Degree Diagonal	-	-
FCTH	Linear Low Energy	Horizontal Low Energy	Vertical Low Energy	Both Directions Low Energy	Linear High Energy	Horizontal High Energy	Vertical High Energy	Both Directions High Energy

Fig. i. Texture Areas

E. Color and Edge Directivity Descriptor (CEDD)

In CEDD [5] the input image is divided into 1600 blocks and histograms are formed using the fuzzy systems. The first fuzzy system is used for texture classification and the other fuzzy system is used for color classification. The texture feature constitutes of 6 regions as given in fig.(i), These 6 regions are obtained from the values of the sub-blocks and it is the mean value of the luminosity of the pixels that participate in it. The texture fuzzy system has five filters to filter the texture information, each of these regions is again classified into 24 bins that represent various colors in the YIQ color space thus forming 192bins as a whole. With these values histograms are developed. In the fuzzy color system HSV color space is used here the image blocks are classified into 10 color bins which is further expanded as 24 color bins. With these values histograms are formed, now the texture information and color information are combined and the final output is quantized.

F. Tamura Texture Feature

Tamura [8] deals with 6 visual features such as Coarseness, Contrast, Directionality, Likeliness, Regularity and Roughness. Coarseness is the distances of notable spatial variations of grey levels forming the texture. Contrast measures how grey levels vary in the image and to what extent their distribution is biased to black or white. Degree of directionality is measured using the frequency distribution of oriented local edges against their directional angles. The line likeness feature F_{lin} is defined as an average coincidence of the edge directions that co-occurred in the pairs of pixels separated by a distance d along the edge direction in every pixel. The regularity feature is defined as $F_{\text{reg}}=1-r(s_{\text{crs}}+s_{\text{con}}+s_{\text{dir}}+s_{\text{lin}})$ where r is a normalizing factor and each 's' means the standard deviation of the corresponding feature '$F_{.}$' in each sub image the texture is partitioned into. The roughness feature is nothing but $F_{\text{rgh}}=F_{\text{crs}}+F_{\text{con}}$

A. Joint Composite Descriptor (JCD)

The Joint Composite Descriptor (JCD) [2] utilizes two sets of keywords in order to map the low-level features of the descriptor to the high-level features. One set consists of colors-keywords and the other set consists of texture keywords. Joint Composite Descriptor (JCD) combines CEDD and FCTH. This new descriptor is made up of 7 texture areas, with each area made up of 24 sub regions that correspond to color areas. Fig (i) is considered for the following equations.

$$JCD(j)_0^i = \frac{FCTH(j)_0^i + FCTH(j)_4^i + CEDD(j)_0^i}{2}$$

$$JCD(j)_1^i = \frac{FCTH(j)_1^i + FCTH(j)_5^i + CEDD(j)_2^i}{2}$$

$$JCD(j)_2^i = CEDD(j)_4^i$$

$$JCD(j)_3^i = \frac{FCTH(j)_2^i + FCTH(j)_6^i + CEDD(j)_3^i}{2}$$

$$JCD(j)_4^i = CEDD(j)_5^i$$

$$JCD(j)_5^i = \frac{FCTH(j)_0^i + FCTH(j)_4^i + CEDD(j)_0^i}{2}$$

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$$JCD(j)_6^i = CEDD(j)_1^i$$

Where i € [0,23]

G. Auto Color Correlogram

This approach is very small but still very effective and efficient, it includes spatial correlation of colors, and it is very easy to compute and is used to describe global distribution of local spatially correlated colors. This method outperforms all other histogram techniques. The correlogram method is more stable to color change and to large appearance change than the histogram method. It is also more stable to contrast and brightness change than the histogram method. This approach considers both the local color spatial correlation as well as the global distribution of this spatial correlation. Any scheme that is based on pure local properties is likely to be sensitive to large appearance changes, but this approach is more stable to these changes; any scheme that is based on purely global properties is susceptible to false positive matches, but this approach proves to be quite effective.

H. Speeded Up Robust Features (SURF) & Bag Of Visual Words (BOVW)

This approach is used for shape extraction. SURF is an extension of SIFT; here the complexity is much more reduced. It consists of two main steps in which initially interest points are set in circular orientations and then square regions are aligned in the selected regions. BOVW feature is used to detect the key-points of an image; key-points are nothing but the more prominent local information of the image. With these key-points similar images are clustered. The combination of SURF and BOVW is more efficient for image search.

I. RGB Color Histogram

Comparing the color distribution of two images will often say something about their similarity. Comparing all the colors in two images would however be very time consuming and complex, and so a method of reducing the amount of information must be used. One way of doing this is by quantizing the color distribution into color histograms. Here different colors are divided into various bins, a three dimensional 8x8x8 RGB histogram would therefore contain a total of 512 such bins. While indexing the image, according to the color of the pixel the corresponding bin's count is incremented by one.

J. Local Tetra Patterns (LTPr's)

It is a combination of local binary pattern (LBT), local ternary pattern (LTP), and local derivative patterns (LDP). LBP and LTP encode the relationship between the referenced pixel and its surrounding neighbours by computing gray-level difference. LBP stores 2 bit values, each pixel is compared with the 8 neighbouring pixels and if the pixel values are equal then 0 is set else 1 is set. LTP uses 3 bit values where 0 is set for equal pixels, 1 for higher pixels values and -1 for lower pixels values. LDP extends LBP by considering higher order derivatives.

4 RE-RANKING AND RETRIEVAL

A. Latent Semantic Analysis (LSA)

Here the image clusters are formed from the various derivatives of the image, the content of the images are explored and all possible derivatives of the image is calculated and with this information relative images are linked in the form of graphs. The original content of the image forms the root of the graph and its relative derivatives form the other nodes of the graph.

B. Image Retrieval and Query Matching

For each query image the distance of it from each database image is calculated using a distance equation. If the distance is null then the images are exactly the same. As the distance increases it means that the similarity between the query image and the corresponding database image is less. With this we can rank the similar images accordingly and retrieve the top matching images.

The distance equation that was used is as follows:

$$D(Q,DB) = \sum_{i=1}^{Lg} \frac{f_{DB_{ji}} - f_{Q_i}}{1 + f_{DB_{ji}} + f_{Q_i}}$$

Where Q is the query image, DB is the Database image, and $f_{DB_{ji}}$ is the jth feature of the ith image in the database.

5 EXPERIMENTAL RESULTS AND DISCUSSION

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The proposed CBIR system was tested using a Corel database of 1000 images that has 100 images in each category. Performance was calculated on the basis of precision and recall.

Precision = (Number of relevant images retrieved)/ (No of images retrieved)

Recall= (Number of relevant images retrieved)/ (Total number of relevant images in database)

The output and the performance measures are shown in figs (ii,iii,iv,v&vi) respectively

Fig. ii. Sample Images from the Database

Fig. iii. Query Image

Fig. iv. Retrieved Images

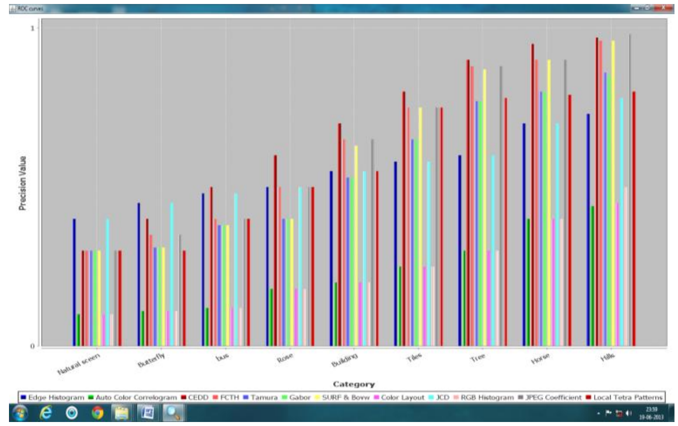

Fig. v. Precision graph

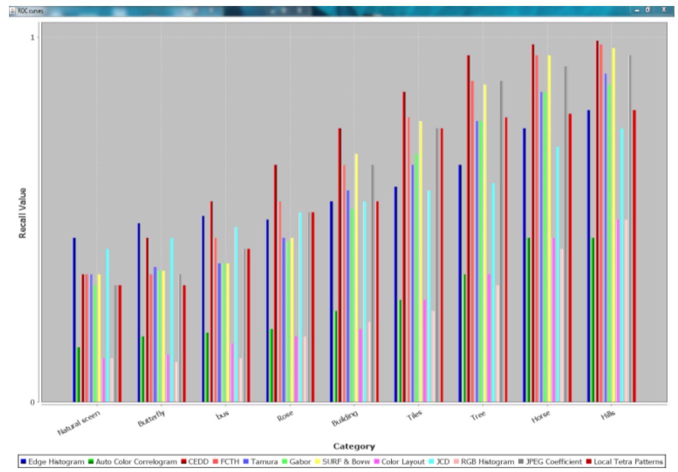

Fig. vi. Recall graph

6 CONCLUSION AND FUTURE WORK

The process is about image search engine not only by text annotated to the image by an end user, but also by the visual contents available in the image. The proposed system reduced the number of required iterations and improves overall retrieval performance and time consumed will be very less. Thus, we can guarantee that intended target related images can be retrieved. The data stored and retrieved is accurate and gives enough information whenever the data is required in required format. All modules consist of necessary reports to help the users of the project to work easily in a user-friendly way. Thus I conclude that the software is best to my knowledge. An automation of annotation is required. Based on the already defined MPEG-7 based visual descriptors some of the work is needed for annotation. This should be done automatically in the future program, like detecting visually similar images and proposing that they have similar semantics or object tracking through a sequence of images. An Internet or intranet based retrieval engine is requested..

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J. Divya received her Bachelor of technology degree in Information Technology from Anna University, Master of Engineering degree in computer Science and Engineering from Anna University. Currently she is serving for AIAIE's editorial board and her major fields of interests are content-based image retrieval and biomedical imaging.