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Object Recognition Using DRLTP for Image Retrieval Systems

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Abstract: With many potential practical applications, Object Recognition has attracted substantial attention during the past few years. A variety of relevance feedback (RF) schemes have been developed as a powerful tool to bridge the semantic gap between low-level visual features and high-level semantic concepts, and thus to improve the performance of IR systems. The project presents the robust object recognition using edge and texture feature extraction. The system proposes new approach in extension with local ternary pattern called DRLTP. By using these methods, the category recognition system will be developed for application to image retrieval. The category recognition is to classify an object into one of several predefined categories. The discriminative robust local ternary pattern (DRLTP) is used for different object texture and edge contour feature extraction process. we discuss the fundamental aspects, visual features and techniques for fast searching and retrieval of images from the database. These features are useful to distinguish the maximum number of samples accurately and it is matched with already stored image samples for similar category classification. The simulated results will be shown that used discriminative robust local ternary pattern has better discriminatory power and recognition accuracy compared with prior approaches.

Keywords: Test image, Preprocessing, Feature Extraction, Database Training, Classification, Parameter analysis.

1. INTRODUCTION

During the past few years, content-based image retrieval has gained much attention for its potential applications in multimedia management. Content-based image retrieval, a technique which uses visual contents to search images from large scale image databases according to user interests, has been an active and fast advancing research area since the 1990s. Content-based image retrieval, also known as query by image content. It is motivated by the explosive growth of image records and the online accessibility of remotely stored images. An effective search scheme is urgently required to manage the huge image database. Different from the traditional search engine, in IR, an image query is described by using one or more example images, and low-level visual features (e.g., color [4]-[5], texture [5]-[7], shape [8]-[10], etc.) are automatically extracted to represent the images in the database. However, the low-level features captured from the images may not accurately characterize the high-level semantic concepts. To reduce the inconsistency problem, the image retrieval is carried out according to the image contents; such strategy is called content-based image retrieval. In Content-Based Approach, Images can be search based on visual features, such as color, texture, and edge information shown in fig 1.

Text based image retrieval system also known as concept based image retrieval system. In concept based image retrieval user poses the query using natural language text, subject heading, keywords or annotations of the image. These systems do not actually understand the actual content of the images. Metadata is used for image indexing in concept based system. There is various limitation of concept based image retrieval system. There are number of ways to say the same thing. Annotation of images is never complete and is time consuming process because human perceptivity can lead to a number of errors. A new method for image retrieval is needed where the human factor would be relieved from the annotation task and doing it automatically. Most web based image search engines rely only on metadata and this produces a lot of garbage in the results. In these search engines, humans have to enter the keywords manually and it is inefficient and expensive way to find images in a large database. The basic fundamentals of content based image retrieval are divided into three parts feature extraction; multidimensional indexing and retrieval systems design. They discussed about the use of digital images and rapid increase in the size of digital image collections. The proper organization of the generated large amount of images by both military and civilian is needed, so as efficient browsing, searching and retrieval takes place. The two ways of image retrieval, text based image retrieval and visual based image retrieval. There exist two major difficulties. The first difficulty is when the size of image collections is large then vast amount of labour required in manual image annotation. The other difficulty is resulted from the rich content in the images and the subjectivity of human perception. That is, for the same image content different people may perceive it differently.

However, for object recognition, LTP present two issues. They differentiate a bright object against a dark background and vice versa. This increases the object intra-class variations which is undesirable for most object recognitions. Nguyen et al. Propose Robust LTP (RLTP) to map a LTP code and its complement to the minimum of both to solve the problem. However, in the same block, RLBP also maps to the same value. For some different local structures, a similar feature is obtained. Hence, it is unable to differentiate them.

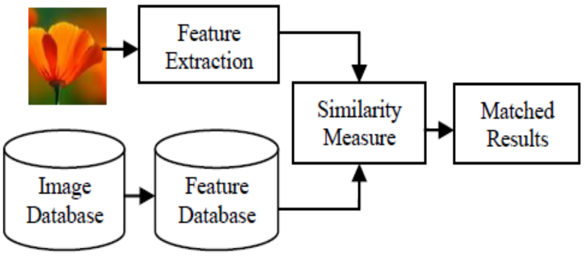

Figure 1 Content-based Image Retrieval System

II. APPLICATIONS

1) The advantage of such systems ranges from simple users searching a particular image on the web
2) Various types of professionals like police force for picture recognition in crime prevention.
3) Geographical information and remote sensing systems
4) Medicine Diagnosis
5) Architectural & Engineering Design
6) Fashion & Publishing
7) Home Entertainment
8) Retail Catalogues

III. LITERATURE SURVEY

1. International Journal of Computer Applications (0975 – 8887) Volume 18– No.6, March 2011 "Content based Image Retrieval System based on Dominant Color and Texture Features" The proposed system uses three image features namely MCM, DBPSP and DDC to characterize a color image for image retrieval. MCM and DBPSP can describe texture distribution, while DDC can describe color features of the pixels in an image. DDC is invariant to translation and rotation. Since these features can describe different properties of an image, the CTDCIRS system integrates these three features to retrieve the images. The experimental results show that the proposed system outperforms Hung's and Jhanwar's methods.

2. DAGM'03, 25th Pattern Recognition Symposium September 10-12, 2003, Magdeburg, Germany c Springer-Verlag "Image Retrieval Using Local Compact DCT-based Representation" In this paper, an image retrieval system based on local affine frames (object-centered coordinate systems) was presented. The system is robust to object occlusion and background clutter, and allows retrieval of objects in images taken from significantly different viewpoints. Normalised image patches are extracted, and photometrically and geometrically normalised according to the detected frames. Local matches are formed both by direct comparison of photometrically normalised colour intensities in the normalized patches, and by comparison of DCT (discrete cosine transform) coefficients of the patches. Both representations allow for robust and selective matching, providing excellent retrieval performance. Experimental results obtained on a publicly available image dataset of buildings were superior to other published results. Retrieval performance of 100% in rank one was achieved when the local image patches were represented by 15 DCT coefficients in every colour channel. The DCT representation performed better in terms of recall rate and required about 5 times less memory storage than representation by the intensities of the normalised patches.

3. "Content Based Image Retrieval Using Curvelet Transform" In this paper, a new texture feature based on curvelet transform is presented. The first contribution of the paper is the systematic description, implementation, analysis and evaluation of the curvelet transform which represents the latest research progress on multi-resolution image analysis. The second contribution is the application of curvelet transform on content based image retrieval and has produced a new texture feature. Results show the curvelet texture feature is very promising for image retrieval, and significantly outperforms the best texture features in literature such as the wavelet feature and the Gabor filter feature. In future, rotation and scale invariance will be investigated to further improve curvelet retrieval performance. Application of curvelet feature in color image retrieval and semantic learning will also be investigated.

IV. PROPOSED METHOD

We have proposed a novel edge-texture feature for recognition that provides discrimination which is Discriminative Robust Local Ternary Pattern which helps in discrimination of the local structures that Robust Local Ternary Pattern seems to misrepresent. Also, the proposed features tend to retain the contrast information of the image patterns. They comprises of both edge and texture information which seem desirable for object recognition. Euclidian Distance Classifier is been used to provide image classification.

An object has 2 distinct states for differentiation from other objects - the object surface texture and the object shape formed by its boundary. The boundary often shows much higher contrast between the object and the background than the surface texture. Differentiating the boundary from the surface texture brings additional discriminatory information because the boundary contains the shape information. Local Ternary Pattern does not provide differentiation between a weak contrast local pattern and a strong contrast pattern. It mainly captures the object texture information. The histogramming of LTP codes only considers the frequencies of the codes i.e. the weight for each code is the same. This makes it difficult to provide differentiation between a weak contrast and a strong contrast local pattern. To mitigate this, we propose to fuse edge and texture information together in a single representation by further modifying the way the codes can be histogrammed. Figure 2 shows Block Diagram representation.

$$LBP_{x,y} = \sum_{b=0}^{B-1} s(p_b - p_c)2^b, \qquad (1)$$

$$s(z) = \begin{cases} 1, & z \geq 0 \\ 0, & z < 0 \end{cases}$$

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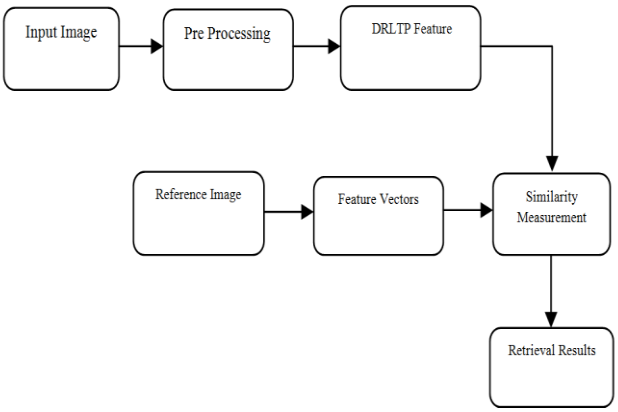

Figure 2. Proposed System

Where pc is the pixel value at (x, y), pb is the pixel value estimated using bilinear interpolation from neighbouring pixels in the b-th location on the circle of radius R around pc and B is the total number of neighbouring pixels.

$$h_{lbp}(i) = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} \omega_{x,y}\delta(LBP_{x,y}, i), \quad (2)$$

$$\delta(m,n) = \begin{cases} 1, & m = n \\ 0, & \text{otherwise} \end{cases}$$

In this way, if a LBP code covers both sides of a strong edge, its gradient magnitude will be much larger and by voting this into the bin of the LBP code, we take into account if the pattern in the local area is of a strong contrast. Thus, the resulting feature will contain both edge and texture information in a single representation. The value of the i th weighted LBP bin of a M × N block is as follows:

The RLBP histogram is created from (6) as follows:

$$h_{rlbp}(i) = h_{lbp}(i) + h_{lbp}(2^B - 1 - i), \quad 0 \le i < 2^{B-1} \quad (3)$$

where hdlbp (i) is the i th DLBP bin value. The number of DLBP bins is 128 for B = 8. Using uniform codes, it is reduced to 30. For blocks that contain structures with both LBP codes and their complements, DLBP assigns small values to the mapped bins. It differentiates these structures from those having no complement codes within the block.

$$h_{dlbp}(i) = |h_{lbp}(i) - h_{lbp}(2^B - 1 - i)|, \quad 0 \le i < 2^{B-1} \quad (4)$$

The 2 histogram features, RLBP and DLBP, concatenated to form Discriminative Robust LBP (DRLBP) as follows:

$$h_{drlbp}(j) = \begin{cases} h_{rlbp}(j), & 0 \le j < 2^{B-1} \\ h_{dlbp}(j - 2^{B-1}), & 2^{B-1} \le j < 2^B \end{cases} \quad (5)$$

LBP is invariant to monotonic intensity changes. Hence, it is vigorous to lighting and contrast variations. However, it is responsive to noise and small pixel value fluctuations. Therefore, LTP has been introduced to solve this situation.

The LTP code at (x, y) is calculated as follows:

$$LTP_{x,y} = \sum_{b=0}^{B-1} s'(p_b - p_c)3^b,$$
$$s'(z) = \begin{cases} 1, & z \ge T \\ 0, & -T < z < T \\ -1, & z \le -T \end{cases} \quad (6)$$

LTP code is divided into “upper” and “lower” LBP codes. The ULBP and LLBP is calculated as follows:

$$ULBP = \sum_{b=0}^{B-1} f(p_b - p_c)2^b,$$
$$f(z) = \begin{cases} 1, & z \ge T \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

$$LLBP = \sum_{b=0}^{B-1} f'(p_b - p_c)2^b,$$
$$f'(z) = \begin{cases} 1, & z \le -T \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

The RLTP code is divided into “upper” and “lower” LBP codes. The URLBP is calculated as follows:

$$URLBP = \sum_{b=0}^{B-1} h(RLTP_{x,y,b})2^b,$$
$$h(z) = \begin{cases} 1, & z = 1 \\ 0, & \text{otherwise} \end{cases} \quad (9)$$

Where RLTPx,y,b represents the RLTP state value at the bth location. The “lower” code, LRLBP, is computed as follows:

$$LRLBP = \sum_{b=0}^{B-1} h'(RLTP_{x,y,b})2^b,$$
$$h'(z) = \begin{cases} 1, & z = -1 \\ 0, & \text{otherwise} \end{cases} \quad (10)$$

Euclidean Distance Classifier: Here the Euclidean distance classifier is used to classify the different facial expressions. It is a minimum distance classifier. The minimum distance classifier is used to classify unknown image data to classes which minimize the distance between the image data and the class in multi-feature space. The distance is defined as an index of similarity so that the minimum distance is identical to the maximum similarity. Euclidean distance based classifier is used which is obtained by calculating of distance between image to test and available images that are taken as training images. Using the given set of values minimum distance can be found. In testing, for every expression computation of Euclidean distance (ED) is done between new image (testing) Eigenvector and Eigen subspaces, to find the input image expression classification based on minimum Euclidean distance is done the formula for the Euclidean distance is given by

$$\text{ED} = \sqrt{\sum (x_2 - x_1)^2}$$

Consider, the immediate consequence of this is that the squared length of a vector $x = [x_1 x_2]$ is the sum of the squares of its coordinates and the squared distance

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between two vectors $x = [x_1 x_2]$ and $y = [y_1 y_2]$is the sum of squared differences in their coordinates. Furthermore, we can carry on like this into 4 or more dimensions, in general J dimensions, where J is the number of variables. we can express the distance between two J-dimensional vectors x and y as: This is called the Euclidean distance.

V. PARAMETER ANALYSIS

The System saves and presents a sequence of images ranked in decreasing order of similarity or with the minimum distances is returned to the user.
To evaluate the efficiency of the proposed system precision and recall rates are to be calculated where,

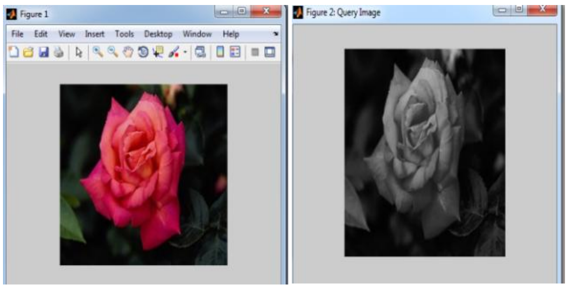
$$\text{Precision} = (IR / IT) \quad (1)$$

IR=No Of Relevance Images Retrieved
IT=Total Number of Images Retrieved on the screen

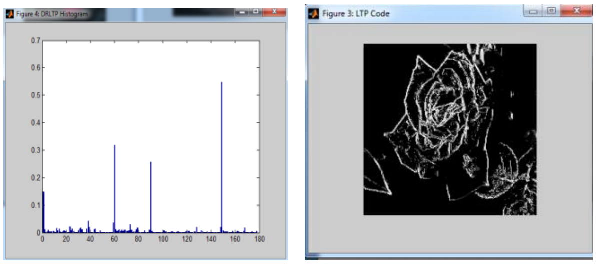
$$\text{Recall} = IR / IRB \quad (2)$$

IR=No Of Relevance Images Retrieved
IRB=Total Number of relevant Images in the database

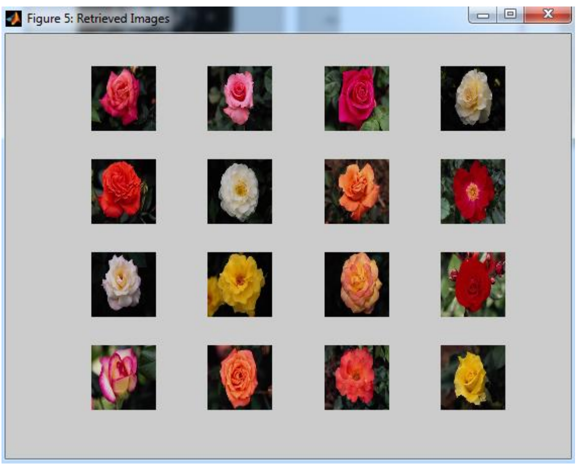
VI. RESULT & DISCUSSION



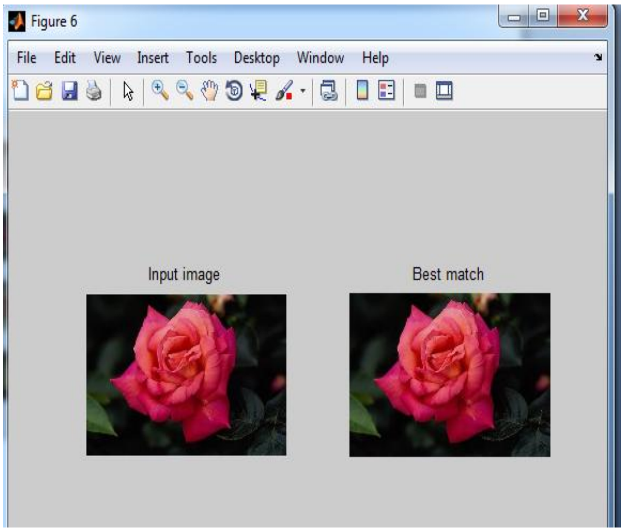
a) input image b) pre-processed image



c) DRLTP histogram d) LTP



e) DRLTP Retrieved images



VII. CONCLUSION

We have proposed an object recognition system which is used for image retrieval application. In this system features extracted are found robust to image variations that are caused due to the intensity inversion and they also provide discrimination to the image structures which are within the histogram block. The Interclass variations are also reduced. The Proposed system provides efficient recognition and helps to alleviate the issues of Local Ternary Pattern, Robust Local Ternary pattern. And our system is giving more relevant image extraction accuracy then existing system.

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