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Object Recognition Using DRLBP for Image Retrieval Systems

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Abstract: The project presents the robust object recognition using edge and texture feature extraction. The system proposes new approach in extension with local binary pattern called DRLBP. 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 binary pattern (DRLBP) is used for different object texture and edge contour feature extraction process. It is robust to illumination and contrast variations as it only considers the signs of the pixel differences. The proposed features retain the contrast information of image patterns. They contain both edge and texture information which is desirable for object recognition. The DRLBP discriminates an object like 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. 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 binary 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

Now days, CBIR (Content based image retrieval) is a hotspot of digital image processing techniques. CBIR research started in early 1990's and is likely to continue during the first two decades of 21st century [1].The growing demands for image retrieval in multimedia field such as crime prevention, Fashion and grapic design and biometrics has pushed application developers to search ways to manage and retrieve images more efficiently. Manual browsing the database to search for identical images would be impractical since it takes a lot of time and requires human intervention. A more practical way is to use Content based image retrieval (CBIR) technology.

The two part of the object recognition are category recognition and detection. The goal of the category recognition is to classify object in to one of several predefined categories. The main aim of the detection is to distinguish objects from the background. Objects are detected from the noisy background, cluttered and other object from different background. Object recognition system improves the performance by discriminating the object from the background.

Object recognition features are represented in two groups- Spare representation and dense representation. Spare feature representation uses the interest-point detectors to indentify the structures like corners and roundish mass on the objects. Some of the spare feature representations are Scale-Invariant Feature (SIFT), Speed up Robust Feature, Local Steering Kernel, Principal Curvature-Based Regions, Region Self-Similarity Feature, Spare color, Spare parts-Based representation.

Dense feature representation, which are extracted at fixed locations density in a detection windows. Some of the dense feature representations are Wavelet, Haar- Feature, and Histogram like of Oriented Gradients, Extended Histogram of Gradients, Feature Context, Local Binary Pattern, Local Ternary Pattern, Geometric-Blur, and Local Edge Orientation Histogram.

LBP is a type of feature used for classification in computer vision. It is the most powerful features for texture classification. It show excellent face recognition or texture analysis. Robust illustration and Contrast variation are considering only the signs of the pixel differences.

Histogramming LBP is resistant to translation, since it is sensitive to noise and small fluctuations of pixel values. To overcome this problem LTP has been proposed. LTP has two thresholds that create three different states. It is resistant to noise and small variation in pixel values. It partially solves the problem of the LBP. Likewise LBP, LTP also used for texture classification and face detection.

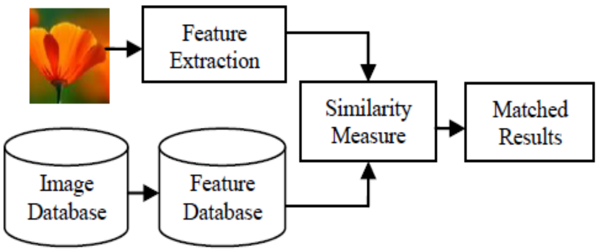

Figure1. Content-based Image Retrieval System

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

According to, J. Yuan, J. Ren and X. Jiang have proposed a noise-resistant LBP (NRLBP) that preserves the image local structures in presence of noise. The small pixel difference is vulnerable to noise. Thus, it is been encoded as an uncertain state first, and then to determine its value based on the other bits of the Local Binary Pattern code. Most of the image local structures are represented by uniform codes and noise patterns and it is widely accepted and most likely fall into the non-uniform codes. Thus, here the value of an uncertain bit is assigned so as to form possible uniform codes. They develop an error correction mechanism in order to recover the distorted image patterns. In addition, we could find that some of the image patterns such as lines are not captured in uniform codes. The line patterns may seem to appear less frequently than uniform codes, but they also tend to represent a set of important local primitives for appropriate pattern recognition. Thus the author proposed an extended noise-resistant Local Binary Pattern (ENRLBP) to capture the line patterns. The proposed noise-resistant Local Binary Pattern and an extended noise-resistant Local Binary Pattern seem to be more resistant to noise as compared with the LBP, and many other variants. On various other applications, superior performance is demonstrated by the proposed NRLBP and ENRLB to LBP variants.

In, despite of the excellent performance by Local Binary Pattern (LBP) in the texture classification as well as in face detection, its performance parameter in human detection has been limited for mostly two reasons. Local Binary Pattern differentiates a bright human that considers as object from a dark background and vice-versa. Due to this there is increase in the intra-class variation of humans.

However, LBP provides contrast and illumination invariance. It does not tend to discriminate between a weak contrast local region and a similar strong contrast region, thus providing a similar feature representation. Non-Redundant Local Binary Pattern (NRLBP) was proposed in order to solve the first issue of Local Binary Pattern. However, an inherent limitation of Non-Redundant Local Binary Pattern is that LBP codes and the complements of LBP in the same block area been mapped to the same code. Non-Redundant Local Binary Pattern, like Local binary pattern, is also illumination and contrast invariant. In this paper, it proposes a novel edge-texture feature Discriminative Robust Local Binary Pattern, for the human detection. It alleviates the problems of Local Binary Pattern and Non-Redundant Local Binary Pattern since it considers the weighted sum and also absolute difference of the LBP code and its complement.

In the field of image processing and computer vision the Interest point detection is concluded as an important research area. In particular, object categorization and image retrieval tend to heavily rely on the interest point detection from which the particular local image descriptors are computed for further image matching. The interest points are seemed to be based on luminance, and color is ignored. The distinctiveness of interest points and the use of color increases. The selective search is provided by the use of color by reducing the total number of interest points that are used for image matching. In this paper sparse image representation is provided by color interest points. The light-invariant interest points are introduced to reduce the sensitivity in varying imaging conditions. Saliency-based feature selection provides Color statistics that are based on the occurrence probability tend to provide color boosted points. Furthermore, a selection method is proposed that is principal component analysis-based scale, which provides robust scale estimation per interest point. It has been shown through large scale experiments that the proposed color interest point detectors provide high repeatability as compared to the Luminance based detector. Predictable and a reduced and number of color features in the context of image retrieval, tend to show an increase in the performance when compared to the state-of-the-art interest points. However, in the context of object recognition this method provides comparable performance for the state-of-the-art methods for the Pascal VOC 2007 challenge using only a small fraction of the particular features, further reducing the computing time.

IV. PROPOSED METHOD

We have proposed a novel edge-texture feature for recognition that provides discrimination which is Discriminative Robust Local Binary Pattern and Local Ternary Pattern. Discriminative Robust Local Binary Pattern and Local Ternary Pattern help in discrimination of the local structures that Robust Local Binary 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. K Nearest Neighborhood 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 Binary 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 LBP 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

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representation by further modifying the way the codes can be histogrammed. Figure 2 shows Block Diagram representation.

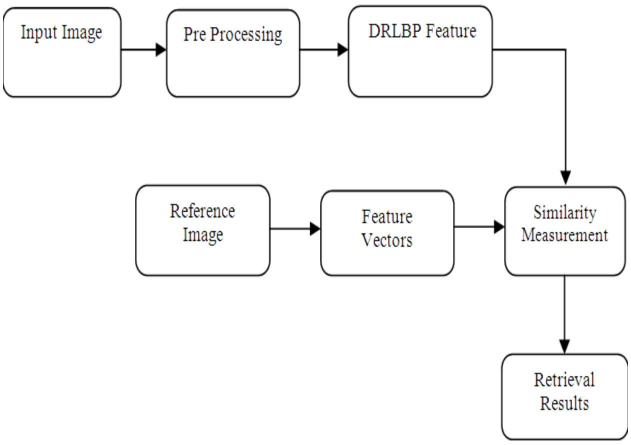

Figure2. Proposed System

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

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

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.

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

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

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:

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

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.

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

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

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

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

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

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 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 xand yas: 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,

Precision = (IR / IT) (1)

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

Recall = IR / IRB (2)

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

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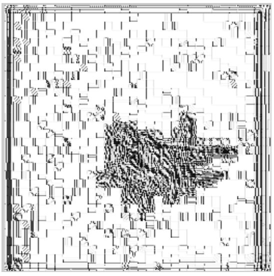
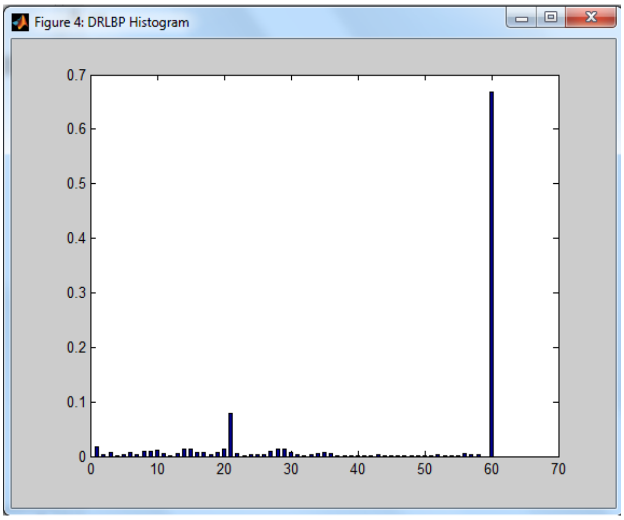
VI. RESULT & DISCUSSION

a) Input image

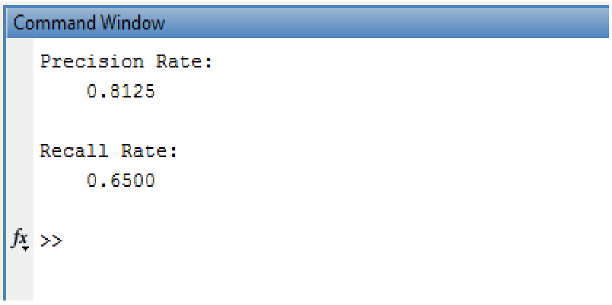


b) LBP



c) DRLBP Histogram feature

d) Retrieved result



e) Validation

VII. CONCLUSION

We had proposed a 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 Binary Pattern, Robust Local Binary pattern. And our system is giving more relevant image extraction accuracy then existing system.

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