ISSN: 2278 – 909X
International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)
Volume 4, Issue 7, July 2015

A Robust Object Recognition Using Edge Texture Analysis for Image Retrieval Application

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***Abstract*— It is a new approach in which the performance of DRLBP and DRLTP is compared with that of the Curvelet transform. For the application to image retrieval in these techniques, the category recognition system is used. The category recognition enable Computers to Recognize Different Categories of Objects in Images also it classifies an object into one of several predefined categories. For different object texture and edge contour feature extraction process, The discriminative robust local binary pattern (DRLBP) and discriminative robust local ternary pattern (DRLTP) are used. As it only considers the signs of the pixel differences, it is robust to illumination and contrast variations. The DRLBP particularly discriminates an object. Like the object shape and the object surface texture formed by its boundary. The boundary is inevitable because it shows higher contrast between the object and the background than the surface texture. This is compared with already stored image samples for similar category classification. Curvelet is also used for image recognition and the simulated results shows that even though DRLBP and DRLTP has better discriminatory power and recognition accuracy compared with prior approaches, the curvelet transform gives better performance compared with all other techniques**

***Index Terms*— Histograms of equivalent patterns, Local binary pattern, Local ternary pattern , Robust Local binary pattern , Robust Local ternary pattern.**

I.INTRODUCTION

The method of finding and identifying objects in an image or video sequence is called as the object recognition. There will be multitude of objects in images and it can be recognized by a normal human eye with little effort, still the image of the objects may vary somewhat in different viewpoints. It is a fact that it varies in different sizes and scales or even when they are translated or rotated. If the objects are partially obstructed, it can be easily recognized. It is a risky task when it comes to computer vision. Different approaches to the idea have been implemented over several decades. Category recognition and detection are the two parts of the object recognition. The function of category recognition is to classify an object into one of several categories which are already defined. The necessity of detection is that it differentiates objects from the background. There are various object recognition difficulties. Basically, the objects have to be recognized against cluttered, noisy environments or backgrounds and also it has to detect other objects various contrast and illumination environments. Accurate feature representation is an important stage in an object recognition system as it improves performance by differentiating the object from the background or other objects in various lightings and scenarios.

II. SYSTEM DESIGN

In the proposed system, it is mentioned about the edge-texture feature, Discriminative Robust Local Binary Pattern (DRLBP) and Discriminative Robust Local ternary Pattern (DRLTP) for detection. These techniques are compared with the old binary and ternary patterns. Later the performance of DRLBP and DRLTP is evaluated comparing with the curvelet tansform. DRLBP alleviates the drawbacks of LBP in certain areas .Mainly considering the weighted sum and absolute difference of a LBP code and its complement, the problem can be nullified. DRLTP is formed by the absolute difference between a LTP code and its inverted representation. Later a comparison is made between the features in the reference images and the extracted features. And hence it enables to find similar set of images from the reference samples. Euclidean distance measurement is the method used to measure the similarity.

DRLBP and DRLTP solve the problem of differentiation between a bright object against a dark background and vice-versa inherent in binary patterns. It also maintain contrast information necessary for best representation of object contours. Contourlets, [12], form a discrete filter bank structure that can deal effectively with piecewise smooth images with smooth contours. This discrete transform can be connected to curvelet-like structures in the continuous domain. Curvelet constructions require a rotation operation and correspond to a partition of the 2-D frequency plane based on polar coordinates.So the curvelet transform can be also used for image recognition, for extracting the features for the performance comparison two parameters are used. They are precision rate and recall rate.

Manuscript received July, 2015.
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III. Previous Work

Object recognition features are classified into two mainly as sparse and dense representations. In the case of sparse feature representations, the interest-point detectors are used to locate corners and blobs on the object. Around each point A feature is created for the image patch. The Scale-Invariant Feature Transform (SIFT) [6], Speeded Up Robust Feature [3], Region Self-Similarity features [8], Sparse Color and the sparse parts-based representation [4] Principal Curvature-Based Regions[9], and A comprehensive evaluation of sparse features[7] are the major feature representations.

Dense feature representations are gaining significance as they explain objects richly compared to sparse feature representations. In the case of dense feature extraction, it is from the detection window that the features are extracted at fixed locations. Wavelet[4], Histogram of Oriented Gradients (HOG), Haar-like features [9], [8], Extended Histogram of Gradients, Local Ternary Pattern[1] ,Feature Context and Local Binary Pattern (LBP) are the important dense feature representations.

Geometric-blur and Local Edge Orientation Histograms [10] are the other major representations that have been proposed over latest years. To alleviate the sparse representation problems [11] Dense SIFT has also been proposed, LBP is the most significant texture classification feature. LBP provide excellent face detection performance .It is robust to illumination and contrast variations since it only considers pixel differences. The descriptor is resistant to translations within the histogramming neighborhood. Because of the histogramming of LBP code However, it is not that resistant to noise and small fluctuations of pixel values. Due to this sensitive behavior Local Ternary Pattern (LTP) was proposed. LTP mainly has three different states with two thresholds as compared to two states in LBP. LTP is more resistant to noise and small pixel value variations,while comparing with LBP. Same as LBP, it can be used for both texture classification and face detection. However there are mainly two issues concerned with the object recognition. One is that they will differentiate a bright object against a dark background and vice versa. Which will lead to the increase in the object intra-class variations and those variations are undesirable for most object recognitions.

In the case of Robust LBP (RLBP), a LBP code and its complement is mapped from the LBP code. To solve the problem, minimum of both is taken .Sometimes RLBP maps to the same value in the same block, and it is undesirable. Hence for some different local structures, a similar feature is obtained. Hence, it is difficult to differentiate them. It is better to represent objects using both texture and edge information for different objects have various shapes and textures. LBP, LTP and RLBP do not have the capacity to discriminate between a weak contrast local pattern and a similar strong one instead they only capture texture information. If the contrast information is discarded, then contours may not be effectively represented. The reason is that the object contours, which also have the discriminatory information, tend to be located in strong contrast regions. In this paper, it is mainly said about two sets of novel edge-texture features and they are the main , Discriminative Robust LBP (DRLBP) and DRLTP. The described features solve the limitations of LBP, LTP and RLBP. Which in turn compensate the intensity reversal problem of object and background. Furthermore, DRLBP differentiates local structures that RLBP fail to represent. Along with that, the described features maintain the contrast information of image patterns. They contain both edge and texture information which is supporting for object recognition. And later it is used image retrieval application.

Discreet wavelet transform has established an attractive reputation as a tool for mathematical analysis and signal processing, but it has the limitation of poor directionality, which has affected its usage in many applications. In the recent years there was significant progress in the development of wavelets. To improve directional selectivity complex wavelet transform can be used. But in the past, the complex wavelet transform has not been widely used. This is because it was difficult to design complex wavelets with absolute reconstruction properties and good properties [13]. One significant technique is the dual-tree complex wavelet transform (DT CWT) proposed, which added almost all absolute reconstructions to the other attractive characteristics of complex wavelets.Tensor-product one-dimensional (1-D) wavelets are essentially used to construct The 2-D complex wavelets. The directional selectivity provided by complex wavelets in six directions are much better than that obtained by the typical or classical DWTs in three directions, still it is limited.

Later, an anisotropic geometric wavelet transform, called ridgelet transform, was proposed [15]. The ridgelet transform is best at indicating straight-line singularities. But the fact is that global straight-line singularities are rarely observed in real situations. To understand local line or curve singularities, a basic idea is to consider the partition of the image , and then ridgelet transform is applied to the sub images. This block ridgelet-based transform, is finally named as curvelet transform, Other than the blocking effects, the applications of first generation curvelet transform is limited for the geometry of ridgelets. As time passed, a considerably easy second-generation curvelet transform was proposed and that was based on frequency partition. The second-generation curvelet transform is a very efficient technique for many applications such as seismic data exploration, image processing, fluid mechanics, and solving partial different equations (PDEs).

IV. Proposed Methodology

An object has mainly two separate cues for discriminating from other objects. And the two cues are namely the object surface texture and the object shape. The object shape is formed by its boundary. Since the boundary provide higher contrast between the object and the background than the surface texture, the boundary is very essential. Additional discriminatory information can be bought by differentiating the boundary from the surface texture, this is because the shape information is contained in the boundary. The histogramming of LBP codes only checks the frequencies of the codes instead of the weight of the code. Also all the codes have same weight. This makes it very difficult to discriminate a weak contrast local pattern and a strong contrast one. To compensate this, edge and texture information is fused and represented as a single by modifying the way the codes are histogrammed. Here by

ISSN: 2278 – 909X
International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)
Volume 4, Issue 7, July 2015

using the histogramming method the image is divided into different ranges. Each such range is called as bins [3]. They are independent of code frequencies, a weight, $\omega_{x,y}$ is computed as follows

$$\omega_{x,y} = \sqrt{I_x^{\,2} + I_y^{\,2}} \tag{1}$$

Here I_x and I_y are the first-order derivatives in the x and y directions.

The Discriminative Robust LBP (DRLBP) is formed by the concatenation of RLBP and DLBP .The DRLBP can be computed as follows:

$$h_{drlbp(j)} = \begin{cases} h_{rlbp(j)} & 0 \le i \le 2^{B-1} \\ h_{dlbp(j-2^{B-1})} & 2^{B-1} \le j \le 2^{B} \end{cases} \tag{2}$$

The i th weighted LBP bin of a M × N block can be computed as follows:

$$h_{lbp(i)} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \omega_{x,y} \delta(LBP_{x,y}, i) \tag{3}$$

$$\delta(m,n) = \begin{cases} 1 & m = n \\ 0 & others \end{cases} \tag{4}$$

The equation for LBP can also be found as follows

$$LBP_{X,Y} = \sum_{b=0}^{B-1} s(P_b - P_c) 2^b \tag{5}$$

$$s(z) = \begin{cases} 1 & z \ge 0 \\ 0 & z < 0 \end{cases} \tag{6}$$

Here p_b is the pixel value and it is estimated by using bilinear interpolation from neighboring pixels in the b-th location on the circle of radius R around p_c . B is the total number of neighboring pixels. p_c is the pixel value at (x, y), A 2^B-bin block histogram is found out and the. The RLBP histogram is computed from (5) as follows:

$$h_{rlbp(i)} = h_{lbp(i)} + h_{lbp}(2^B - 1 - i), \quad 0 \le i \le 2^{B-1} \tag{7}$$

Here hrlbp(i) is the i th RLBP bin value. Also the perfect or absolute difference between the bins of a LBP code and its complement form difference of LBP (DLBP) histogram as follows:

$$h_{dlbp(i)} = \left| h_{lbp(i)} - h_{lbp}(2^B - 1 - i) \right|, \quad 0 \le i \le 2^{B-1} \tag{8}$$

Regarding the case of DRLTP, LTP can be used to find RLTP.DLTP and DRLTP requires a large storage requirement and so it is computationally very intensive.Hence a simpler method is used known as ULBP and LLBP.The expression for URLBP and URLTP is as follows

$$URLBP = \max\{ULBP, LLBP\} \tag{9}$$

$$LRLBP = \min\{ULBP, LLBP\} \tag{10}$$

By finding URLBP and LRLBP codes for any LTP code, RLTP is found out in the split LBP code representation.
Expression for ULBP and LLBP can be computed as follows:

$$ULBP = \sum_{b=0}^{B-1} f(p_b - p_c) 2^b \tag{11}$$

$$f(z) = \begin{cases} 1 & z \ge T \\ 0 & others \end{cases} \tag{12}$$

$$LLBP = \sum_{b=0}^{B-1} f'(p_b - p_c) 2^b \tag{13}$$

$$f'(z) = \begin{cases} 1 & z \le T \\ 0 & others \end{cases} \tag{14}$$

From this the URLBP and LRLBP can be easily found. The parameters, s th URLBP bin value, 0 < s < 2B, is calculated for a M × N block from ULBP and LLBP codes. It can be represented as follows:

$$h_{urlbp(s)} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \omega_{x,y} \delta(\max(ULBP, LLBP, s) \tag{15}$$

The t th LRLBP bin value, 0 ≤ t < 2B−1, is computed as:

$$h_{lrlbp(t)} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \omega_{x,y} \delta(\min(ULBP, LLBP, t) \tag{16}$$

The s th UDLBP bin value can be represented as follows:

$$h_{udlbp(s)} = \left| \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \omega_{x,y} \delta'(\lambda(ULBP, LLBP, s) \right| \tag{17}$$

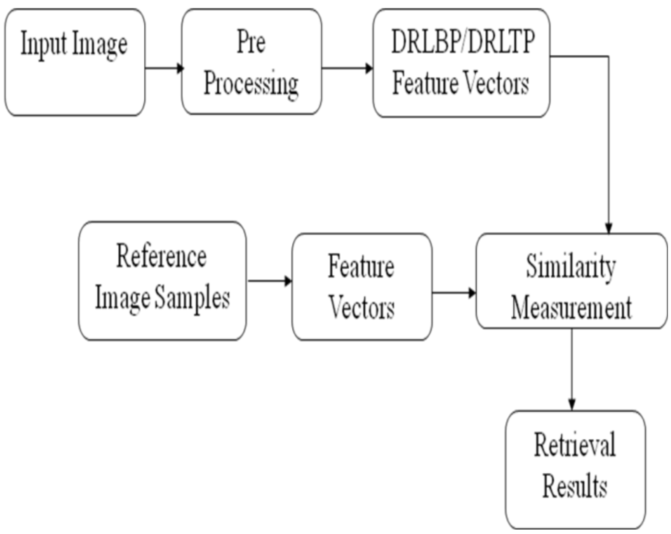

Fig.1. Block diagram of the DRLBP/DRLTP image retrieval system

$$\lambda(p,q) = \begin{cases} p & p \ge q \\ -q & p < q \end{cases} \tag{18}$$

$$\delta'(m,n) = \begin{cases} 1 & m = n, m > 0 \\ -1 & |m| = n, m < 0 \\ 0 & other \end{cases} \tag{19}$$

Also The t[th] LDLBP bin value is as follows:

$$h_{ldlbp(t)} = \left| \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \omega_{x,y} \delta''(\lambda'(ULBP, LLBP, t) \right| \tag{20}$$

$$\lambda'(p,q) = \begin{cases} q & p \geq q \\ -p & p < q \end{cases} \tag{21}$$

$$\delta''(m,n) = \begin{cases} 1 & m = n, m > 0 \\ -1 & |m| = n, m < 0 \\ 0 & other \end{cases} \tag{22}$$

λ'(.) shows whether the ULBP and LLBP codes are being swapped. The negative minimum code is assigned to the result, at the time of swap. Thus the features can be effectively extracted by DRLBP and DRLTP techniques. Finally the extracted features are compared with the features of the images in reference samples .Fig 1 shows the block diagram of the system while using the DRLBP and the DRLTP.As shown in the fig1, the extracted features are compared with the features of the images in the reference images Euclidean Distance method is used to find the similar images. It is found that by using DRLBP and DRLTP techniques better performance is obtained, compared to old techniques. Also more similar images are obtained in the case of DRLTP. Fig 2 shows the block diagram. of the system using curvelet transform. Fig 2 explains that the image undergoes entropy measurement soon after the curvelet decomposition. Instead of intensity values here the frequency

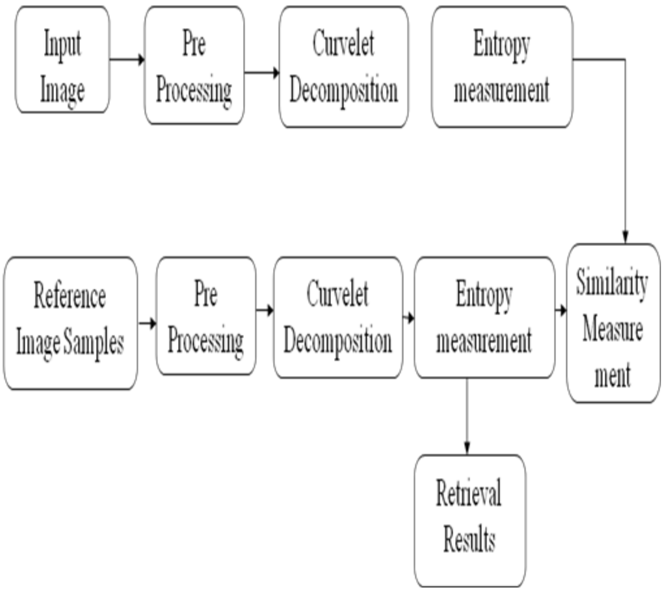

Fig.2. Block diagram of the curvelet transform image retrieval system

values are considered. So before extracting features the entropy is found out and there by the steps are followed. In the case of curvelet transform the steps are as same that of DRLBP and DRLTP.

V. Simulation Results

Mathlab 7 is used to find out the features extracted by using the techniques DRLBP, DRLTP and Curvelet transform. Performance of the system is evaluated by using two parameters. They are namely precision rate and recall rate. The number of relevant images retrieved to that of the total images retrieved is defined as the precision rate [3]. Similarly recall rate can also be defined. It is the total number of relevant images retrieved to that of the total number of relevant images. The findings of the proposed method is as follows.Fig 3 shows the query image.It is this image which is considered for feature extraction.The techiques are carried out and their corresponding histograms are plotted.

Figure 4 and figure 5 shows the DRLBP and DRLTP histograms respectively.It is observed that different images are obtained at the time of retrieval. The number of images retrieved is shown in table 1. Analyzing table 1 it is clear that the LBP, LTP, RLBP, RLTP shows comparatively less number of images retrieved. Whereas in the case of DRLBP and DRLTP much more similar images are obtained. 11 to 12 images are retrieved from the group of images. Fig 6 shows the output obtained while using curvelet transform. The advantages of curvelet transform can be justified by fig 6. From the number of retrieved images the performance parameters, precision rate and the recall ate can be calculated. These parameters are displayed on the command window. The performance of the curvelet transform is shown in command window and that is displayed in Fig 6.

Fig.3. The query image

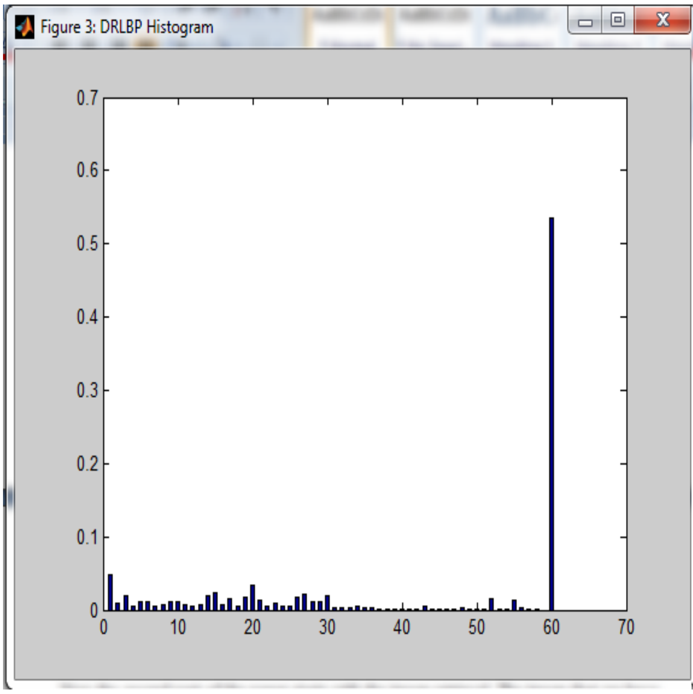

Fig. 4. The DRLBP histogram

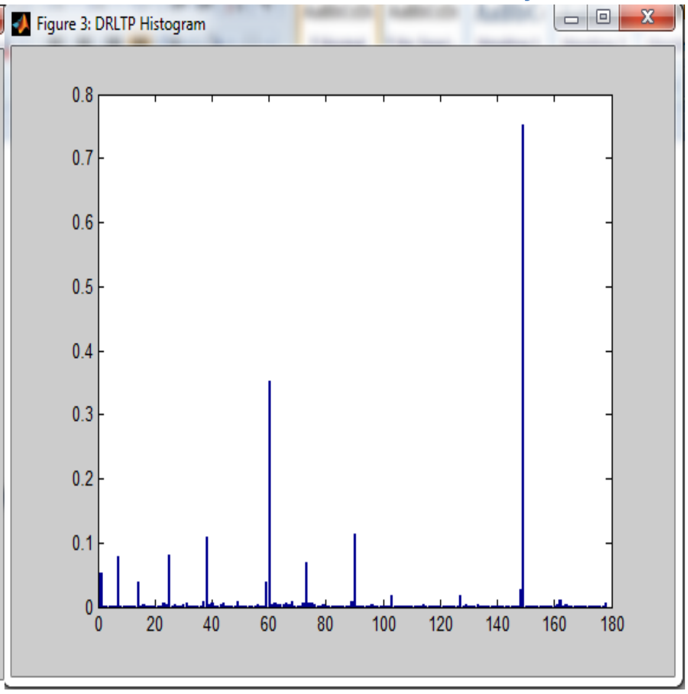

Fig. 5. The DRLTP histogram

Table 1 shows the comparison of all techniques.Table displays the total number similar images obtained ,presicion rate and recall rate.DRLBP and DRLTP techniques shows 11 and 12 images retrieved from reference images.In the case of curvelet transform ,13 similar images are obtained indicating better efficiency.The performance parameters are obtained by manually entering the number of retrieved images.And hence the output is obtained in commend window.The outputs in command window is plotted in the table 1.

Table I:Comparison Of The Techniques

Techniques	No of images retrieved	Precision rate	Recall rate
LBP	5	.3125	.2500
LTP	7	.4375	.3500
RLBP	8	.5000	.4000
RLTP	10	.6250	.5000
DRLBP	11	.6875	.5500
DRLTP	12	.7500	.6000
Curvelet transform	13	.8125	.6500

VI CONCLUSION

This paper describes two sets of novel edge-texture features for object recognition, along with the curvelet transform. The novel edge texture features are Discriminative Robust Local Binary Pattern (DRLBP) and Discriminative Robust Local Ternary Pattern (DRLTP).Texture information alone will not support for the effective representation of the contour. By analyzing the weaknesses of LBP, LTP and RLBP, the new techniques are proposed. By considering both the weighted sum and absolute difference of the bins of the LBP and LTP codes, the problems of LBP, LTP and RLBP can be solved. These extracted features are robust to image variations that are caused by the intensity inversion. They are also differentiative to the image structures within the histogram block. A better performance is exhibited by curvelet transform when compared to the novel edge texture features. Which in turn indicate better efficiency.

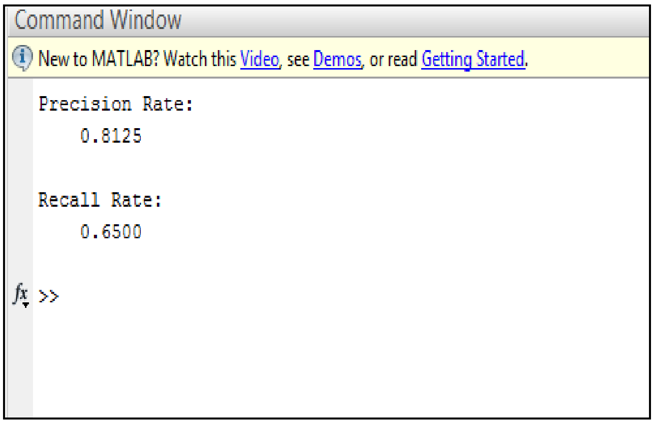

Fig. 6.Output of curvelet transform obtained in command window

VII FUTURE SCOPES

As future work the image recognition and retrieval can be performed using other transforms which may give a bit more accuracy. In the case of curvelet transform frequency is the parameter chosen instead of intensity. Similarly other factors can be choosed..Using frequency as parameter, the accuracy is increased and for the comparison entropy measurements are adopted.

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ACKNOWLEDGEMENT

We express our deep and sincere thanks to god for the completion of the work. We would also like to thank our parents teachers and friends for the support given to us .

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