IJARCCE
ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 9, September 2016

DRLBP and DRLTP Based Object Recognition for Image Retrieval Systems

Ms. Rajashri. A. Kolhe[1], Prof. A. S. Deshpande[2]

JSPM's Imperial College of Engineering and Research, Wagholi, Pune[1, 2]

Abstract: This paper presents the robust object recognition using Discriminative Robust Local Binary Pattern (DRLBP) and Discriminative Robust Local Ternary Pattern (DRLTP) methods for feature extraction. The system proposes new approach in extension with local ternary pattern called DRLTP and 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. DRLTP & DRLBP is used for different object texture, edge contour and shape 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 & DRLTP 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. Our proposed features are compared with two classifiers and results are tested on five datasets: WANG, Caltech 101, Caltech 256, VOC 2005, and UIUC.

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

1. INTRODUCTION

Texture classification [5] has become an active research topic in the computer vision and pattern recognition. Early texture classification methods were also focused on the statistical analysis of texture images. Interest-point detectors are been used in sparse feature representations. It helps to identify the structures like corners and blobs on the particular object.

A feature is created which is necessary for the image patch that tends to be around each point. Various feature representations that include Principal Curvature-Based Regions, Scale Invariant Feature Transform, Local Steering Kernel , Speeded Up Robust Feature, Region Self-Similarity features, sparse parts-based and Sparse Color representation.

At fixed locations, dense feature representations are extracted densely in a detection window, which are gaining popularity as they tend to describe objects richly when they are compared to the sparse feature representations.

Other feature representations Such as Local Ternary Pattern (LTP), Wavelet, Local Binary Pattern (LBP), Extended Histogram of Gradients, Local Edge Orientation Histograms, Geometric-blur and Feature Context have been proposed over recent years. Dense Scale-Invariant Feature Transform has also been proposed to help alleviate the problems in sparse representation. A similar feature is obtained for some different local structures. Hence, it becomes difficult to differentiate these local structures.

Various different objects are of different shapes and textures [1]. Hence, it becomes desirable to represent objects using both edge and texture information. Further, in order to be robust to the contrast variations and illumination, LBP, LTP and Robust Local Binary Pattern do not tend to provide discrimination between a weak contrast local pattern and strong pattern. There are various object recognition challenges. The objects are to be detected against the cluttered and noisy backgrounds along with the other objects under contrast environments and different illumination. It tends to be a crucial step in the object recognition system to obtain proper feature representation as it improves performance by providing discrimination.

In reference [5], the paper describes a general framework for the texture analysis which we refer as the Histograms of equivalent patterns. The histogram of equivalent pattern provides a clear and unambiguous mathematical definition that it is based on the partition of the feature space which is also associated to image patches which consist of a predefined size and shape. In order to achieve this task the local or global functions are defined of the pixels intensities.

In this correspondence [6], a modeling of the (LBP) local binary pattern operator is been proposed and a complete Local Binary Pattern (CLBP) scheme is been developed for the texture classification. Center pixel is used to represent a local region and a local difference sign-magnitude transform.

IJARCCE
ISSN (Online) 2278-1021
ISSN (Print) 2319 5940
International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 9, September 2016

II. LITERATURE SURVEY

Scale Invariant Feature Transform (SIFT) is an image descriptor for image-based matching and recognition developed by David Lowe [7] This descriptor as well as related image descriptors is used for a large number of purposes in computer vision related to point matching between different views of a 3-D scene and view-based object recognition. The SIFT descriptor is invariant to translations, rotations and scaling transformations in the image domain and robust to moderate perspective transformations and illumination variations. Experimentally, the SIFT descriptor has been proven to be very useful in practice for image matching and object recognition under real-world conditions.
Viola and Jones [8] adapted the idea of using Haar wavelets and developed the so-called Haar-like features. A Haar-like feature considers adjacent rectangular regions at a specific location in a detection window, sums up the pixel intensities in each region and calculates the difference between these sums. This difference is then used to categorize subsections of an image. For example, let us say we have an image database with human faces. It is a common observation that among all faces the region of the eyes is darker than the region of the cheeks. Therefore a common Haar feature for face detection is a set of two adjacent rectangles that lie above the eye and the cheek region. The position of these rectangles is defined relative to a detection window that acts like a bounding box to the target object (the face in this case).
Navneet Dalal and Bill Triggs [9] researchers first described Histogram of Oriented Gradient descriptors in June 2005. In this work they focused their algorithm on the problem of pedestrian detection in static images, although since then they expanded their tests to include human detection in film and video, as well as to a variety of common animals and vehicles in static imagery.

Grey-Level Co-occurrence Matrix texture measurements have been the workhorse of image texture since they were proposed by Haralick [10] in the 1970s. To many image analysts, they are a button you push in the software that yields a band whose use improves classification or not. The original works are necessarily condensed and mathematical, making the process difficult to understand for the student or front-line image analyst.

III. PROPOSED METHOD

We have proposed novel edge-texture-shape features for object recognition that provides discrimination which is Discriminative Robust Local Ternary Pattern and Discriminative Robust Local Binary Pattern [1] which helps in discrimination of the local structures that Robust Local Ternary and 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.

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 LBP and 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 1 shows algorithm flow

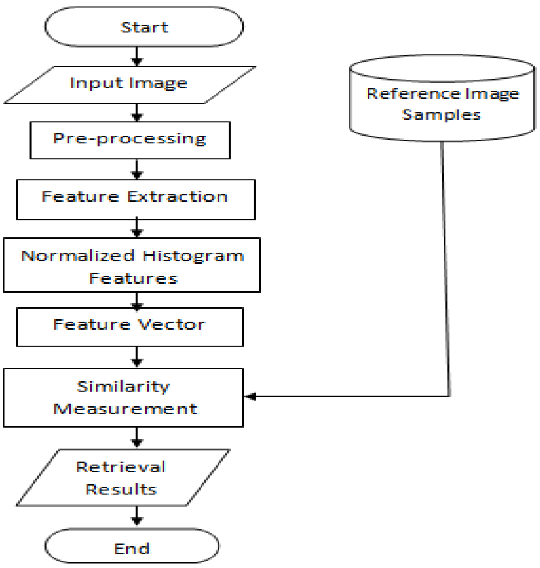

Fig. 1: algorithm flow of proposed System

Feature extraction process:

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

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

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 [1].

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

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

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 9, September 2016

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 [1] 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) [1] as follows:

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

The LTP code [1] at (x, y) is calculated as follows:

$$\mathrm{LTP}_{x,y} = \sum_{b=0}^{B-1} s'(p_b - p_c)3^b \quad (6)$$

$$s'(z) = \begin{cases} 1 & z \ge T \\ 0 & -T < z < T \\ -1 & z \le -T \end{cases}$$

LTP code is divided into "upper" and "lower" LBP codes. The ULBP [1] and LLBP [1] are calculated as follows:

$$ULBP = \sum_{b=0}^{B-1} f(p_b - p_c)\, 2^b \quad (7)$$

$$f(z) = \begin{cases} 1, & z \ge T \\ 0, & otherwise \end{cases}$$

$$LLBP = \sum_{b=0}^{B-1} f'(p_b - p_c)2^b \quad (8)$$

$$f(z) = \begin{cases} 1, & z \le -T \\ x, & otherwise \end{cases}$$

By doing so, the dimensionality of the feature is reduced from 6561 bins to 512 bins. Using uniform LBP code representation, the number of bins is further reduced to 118 bins.
The RLTP code is divided into "upper" and "lower" LBP codes. The URLBP [1] is calculated as follows:

$$URLBP = \sum_{b=0}^{B-1} h(RLTP_{x,y,b})\, 2^b \quad (9)$$

$$h(z) = \begin{cases} 1, & z = 0 \\ 0, & othrewise \end{cases}$$

Where RLTP x, y, b represents the RLTP state value at the bth location. The "lower" code, LRLBP [1] is computed as follows:

$$LRLBP = \sum_{b=0}^{B-1} h'(RLTP_{x,y,b})2^b \quad (10)$$

$$h'(z) = \begin{cases} 1, & z = -1 \\ 0, & otherwise \end{cases}$$

Here, LRLBP only has 7 bits as the state at $(B\text{-}1)^{th}$ location of RLTP is always 0 or 1.

Consider a LTP histogram for M×N image block. The value of the k^{th} bin of the weighted LTP histogram [1] is as follows:

$$h_{ltp}(k) = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} \omega_{x,y}\, \delta(LTP_{x,y}, k) \quad (11)$$

It is not difficult to see that the RLTP histogram [1] can be simply created from above equation as follows:

$$h_{rltp}(k) = \begin{cases} h_{ltp}(k), & k = 0 \\ h_{ltp}(k) + h_{ltp}(-k), & 0 < k < \frac{3^B + 1}{2} \end{cases} \quad (12)$$

Where $h_{rltp}(k)$ is the k^{th} bin value of RLTP.
We consider the absolute difference between the bins representing a LTP code and its inverted representation to form Difference of LTP [1] histogram as follows:

$$h_{dltp}(k) = |h_{ltp}(k) - h_{ltp}(-k)|, \quad 0 < k < \frac{3^B+1}{2} \quad (13)$$

Where $h_{dltp}(k)$ is the k^{th} bin value of DLTP.
RLTP and DLTP are concatenated to form Discriminative Robust LTP [1] as follows:

$$h_{drltp}(l) = \begin{cases} h_{rltp}(l), & 0 \le l < \frac{3^B + 1}{2} \\ h_{dltp}\left(l - \frac{3^B + 1}{2}\right), & \frac{3^B + 1}{2} \le l < 3^B \end{cases}$$

DRLTP produces different features for the structures. It also resolves the issue of brightness reversal of object and background.

Consider the ULBP and LLBP codes for an image block. The value of the s^{th} bin, $0 < s < 2^B$, of URLBP can be generated from ULBP [1] and LLBP [1] codes as follows:

 DOI 10.17148/IJARCCE.2016.5962

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 9, September 2016

$$h_{urlbp}(s) = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} \omega_{x,y}\delta(\max(ULBP, LLBP), s) \quad (14)$$

$$h_{lrltp}(t) = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} \omega_{x,y}\delta(\min(ULBP, LLBP), t) \quad (15)$$

The split LBP histograms, UDLBP and LDLBP, for DLTP can also be generated from the ULBP and LLBP codes. For every LTP code whose ULBP and LLBP representations are swapped, the corresponding values of UDLBP and LDLBP bins are decremented by 1 accordingly. Otherwise, the bins are incremented by 1. The s^{th} bin value, $0 < s < 2^B$, of UDLBP [1] is expressed as follows:

$$h_{udlbp}(s) = \left|\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} \omega_{x,y}\delta'(\lambda(ULBP, LLBP), s)\right| \quad (16)$$

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

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

The function λ (•) determines whether the ULBP and LLBP codes are being swapped. If a swap occurs, the negative maximum code is assigned to the result. The function $\delta'(\bullet)$ checks the value output from λ with s. If the value is positive and matches s, the s^{th} bin value is incremented. Otherwise, it is decremented. The t^{th} bin value of LDLBP [1] is determined as follows:

$$h_{ldlbp}(t) = \left|\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} \omega_{x,y}(\lambda'(ULBP, LLBP), t)\right| \quad (17)$$

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

$$\delta''(m,n) = \begin{cases} 1 & m = n, m \geq 0 \\ -1 & |m| = n, m, 0 \\ 0 & otherwise \end{cases}$$

The function $\lambda'(\bullet)$ determines whether the ULBP and LLBP codes are being swapped. If a swap occurs, the negative minimum code is assigned to the result. The function $\delta''(\bullet)$ checks the value output from λ' with t.

If the value is zero or positive and matches t, the t^{th} bin value is incremented. Otherwise, it is decremented. The URLBP, LRLBP, UDLBP and LDLB histograms are then concatenated to form DRLTP.

Similarity measurement:

The system computes the similarity between the query image and database images according to the aforementioned low level visual features. Here Euclidean Distance and Canberra Distance classifiers are used to measure the similarity between the input image and database images. The formula for calculating the similarity for Euclidean Distance [16] and Canberra Distance [16] are given bellow,

$$\mathrm{ED} = \sqrt{\sum(x_2 - x_1)^2} \quad (18)$$

Where, ED stands Euclidean Distance, x_2 stands for query image feature and x_1 stands for corrosponding feature vector database.

$$\mathrm{CD} = \frac{\sum_i |u_i - v_i|}{\sum_i |u_i + v_i|} \quad (19)$$

Where, CD stands Canberra Distance between two objects, u and v are both n- dimensional vectors. u and v are the feature vectors of database and query image respectively.

IV 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 [2] and recall [2] rates are to be calculated where,

$$\text{Precision} = (IR / IT) \quad (20)$$

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

$$\text{Recall} = IR / IRB \quad (21)$$

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

V. RESULT & DISCUSSION

With the help of given algorithm the results obtained by using Matlab are given below

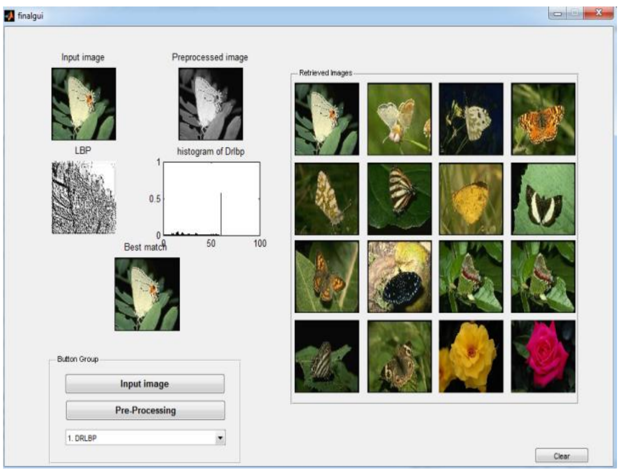

Fig.2: DRLBP feature extraction for image retrieval using ED

IJARCCE
ISSN (Online) 2278-1021
ISSN (Print) 2319 5940
International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 9, September 2016

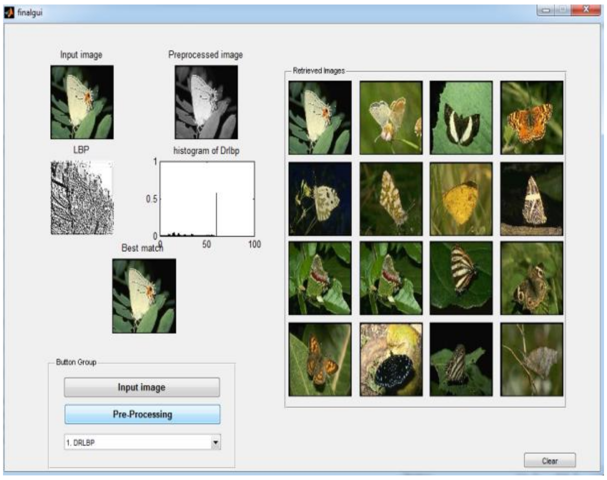

Fig. 3: DRLBP feature extraction for image retrieval using CD

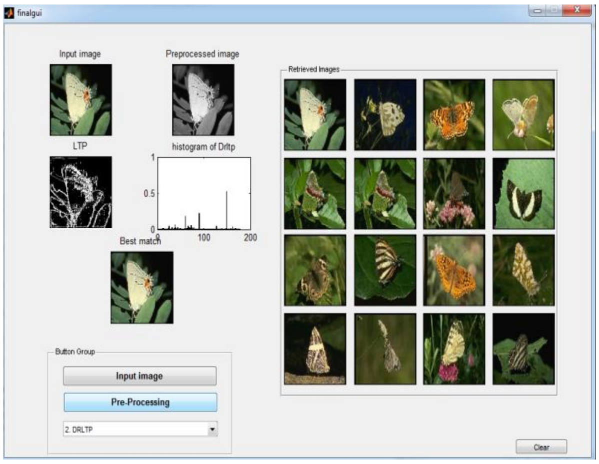

Fig. 4: DRLTP feature extraction for image retrieval using ED

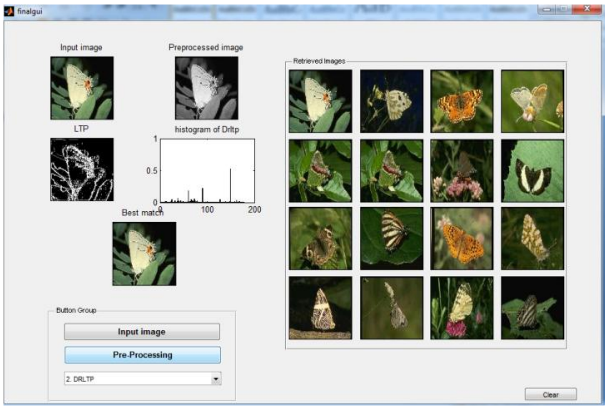

Fig. 5: DRLTP feature extraction for image retrieval using CD

We had applied various datasets to our proposed method and calculated accuracy, precision and recall below we had tabulated in detail.

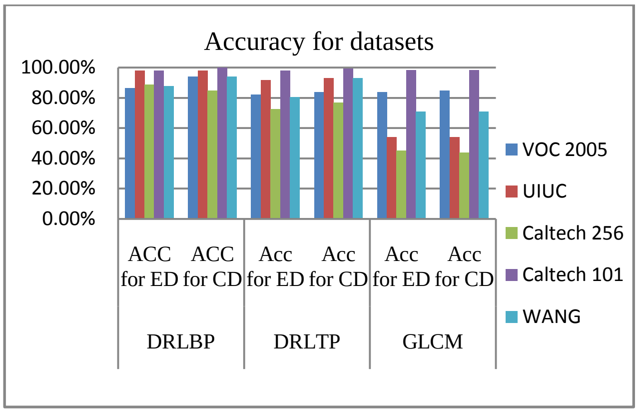

Fig.6: comparison graph of 5 datasets with ED and CD classifiers

TABLE I

Accuracy compared with 5 datasets							
S.N	Dataset	DRLBP		DRLTP		GLCM	
		ACC for ED	ACC for CD	Acc for ED	Acc for CD	Acc for ED	Acc for CD
1	VOC 2005	86.45%	94.04%	81.91%	83.65%	83.63%	84.72%
2	UIUC	97.91%	97.91%	91.64%	92.70%	54.08%	54.08%
3	Caltech 256	88.53%	84.72%	72.51%	76.71%	45.09%	43.71%
4	Caltech 101	97.91%	99.65%	97.91%	99.30%	98.26%	98.26%
5	WANG	87.49%	93.83%	80.43%	92.69%	70.79%	70.79%

TABLE II Precision for WANG dataset

Image	DRLBP	DRLTP	GLCM
17.jpg	0.93	0.81	0.68
11.jpg	1	0.93	0.37
107.jpg	0.81	0.62	0.43
102.jpg	0.81	0.56	0.68
110.jpg	0.93	0.62	0.68
105.jpg	0.8	0.68	0.37
60.jpg	0.8	0.75	0.37
57.jpg	0.75	0.25	0.68
64.jpg	0.75	0.56	0.51
56.jpg	1	0.56	0.8

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 9, September 2016

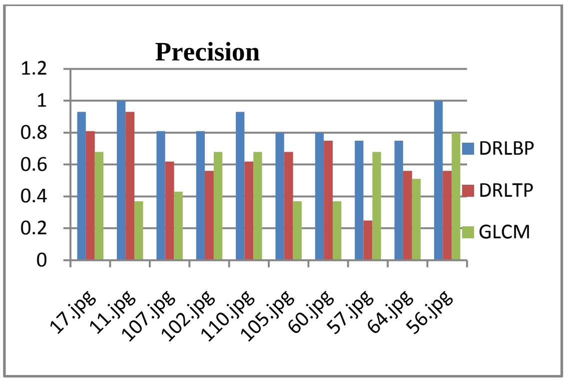

Fig. 7: Comparison bar graph for Precision

TABLE III Recall Rate for WANG dataset

Image	DRLBP	DRLTP	GLCM
17.jpg	0.6	0.52	0.44
11.jpg	0.64	0.6	0.24
107.jpg	0.52	0.4	0.28
102.jpg	0.52	0.36	0.44
110.jpg	0.6	0.4	0.44
105.jpg	0.56	0.44	0.24
60.jpg	0.56	0.48	0.24
57.jpg	0.48	0.19	0.44
64.jpg	0.48	0.36	0.38
56.jpg	0.64	0.36	0.56

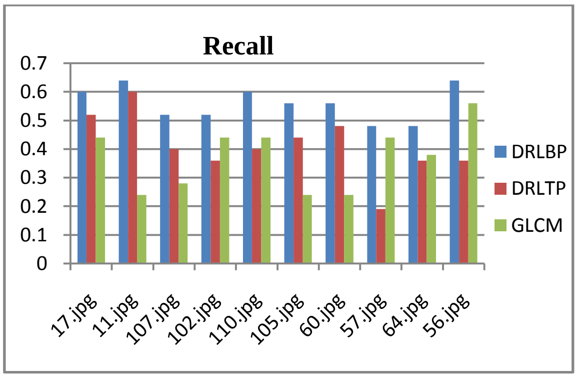

Fig. 8: Comparison bar graph for Recall rate

VI. CONCLUSION

We have present a robust object recognition using edge texture analysis for image retrieval application. In this dissertation we have implemented DRLBP, DRLTP and GLCM techniques for feature extraction. The query image features and database image features are compared with Euclidian Distance (ED) and Canberra Distance (CD) classifiers. It was observed that similarity measures not affect much on retrieval accuracy, but CD metric gives better results as compared to ED metrics. Experimental result indicates that the proposed method gives excellent retrieval accuracy of different image datasets. We present results of the proposed features on 5 datasets and compare them with 3 methods for object recognition. Results demonstrate that the proposed method achieves improvement in retrieval accuracy than using DRLTP and GLCM techniques. Finally, the performance factors such as precision, recall rate and accuracy are evaluated.

REFERENCES

[1] Amit Satpathy, Member, IEEE, Xudong Jiang, Senior Member, IEEE, and How-Lung Eng, Member, IEEE, "LBP-Based Edge-Texture Features for Object Recognition", IEEE Transactions on Image Processing, Vol. 23, No. 5, May 2014.

[2] R. A. Kolhe, and Prof. A. S. Deshpande "A Survey On: Object Recognition for Image Retrieval Systems" International Journal of Advanced Research in Computer Engineering & Technology (IJARCET) Volume 5, Issue 4, April 2016.

[3] R. A. Kolhe, and Prof. A. S. Deshpande "Object Recognition Using DRLBP for Image Retrieval Systems" International Journal Of Innovative Research In Electrical, Electronics, Instrumentation And Control Engineering Vol. 4, Issue 6, June 2016.

[4] Rajashri. A. Kolhe, and Prof. A. S. Deshpande "Object Recognition Using DRLTP for Image Retrieval Systems" International Journal Of Innovative Research In Electrical, Electronics, Instrumentation And Control Engineering Vol. 4, Issue 5, June 2016.

[5] M. Babu Rao et al, "Content Based Image Retrieval Using Dominant Color, Texture and Shape", International Journal of Engineering Science and Technology, vol.3, no.4, Apr 2011.

[6] S. Mangijao Singh et al, "Content Based Image Retrieval Using Color Moment and Gabor Texture Feature", International Journal of Computer Science, vol.9, Issue 5, no.1, Sep 2012.

[7] D. Lowe, "Distinctive image features from scale-invariant key points,"Int. J. Comput. Vis., vol. 60, no. 2, pp. 91–110, Nov. 2004.

[8] P. Viola, M. J. Jones, and D. Snow, "Detecting pedestrians using patterns of motion and appearance," Int. J. Comput.Vis., vol. 63, no. 2,pp. 153–161, 2005.

[9] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit.,Jun. 2005, pp. 886–893.

[10] A. Porebski, N. Vandenbroucke, and L. Macaire, "Haralick feature extraction from LBP images for color texture classification," inProc. 1st Workshops Image Process. Theory, Tools Appl., Nov. 2008,pp. 1–8.

DOI 10.17148/IJARCCE.2016.5962