International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-4 Issue-10, March 2015

Edge Texture Analysis for Image Retrieval Application with Aid of Robust Object Recognition

Anagha Sudhakaran, Manu Prasad

Abstract*— *It is a new approach in extension with local binary pattern and ternary pattern called DRLBP and 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 binary pattern (DRLBP) and discriminative robust local ternary pattern (DRLTP) are 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 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 DRLBP and DRLTP has better discriminatory power and recognition accuracy compared with prior approaches.

Index Terms*— *Histograms of equivalent patterns (HEP), Local binary pattern (LBP), Local ternary pattern (LTP), Robust Local binary pattern (RLBP), Robust Local ternary pattern (RLTP)

I. INTRODUCTION

The task of finding and identifying objects in an image or video sequence is defined as the object recognition. Multitude of objects in images can be recognized with little effort by a normal human eye, still it is a fact that the image of the objects may vary somewhat in different viewpoints, in different sizes and scales or even when they are translated or rotated. The objects can be recognized even if it is partially obstructed. It is a challenging task when it comes to computer vision. Different approaches to the task have been implemented over multiple decades. The object recognition has two parts namely Category recognition and detection. The aim of category recognition is to classify an object into one of several predefined categories. The significance of detection is that it distinguishes objects from the background.

Manuscript published on 30 March 2015.
*****Correspondence Author(s)
Ms. Anagha Sudhakaran, Pursuing MTech in Communication Engineering, Electronics & Communication Department, Vedavyasa Institute of Technology, Kozhikode, Kerala, India.
Mr. Manu Prasad, Assistant Professor, Department of Electronics & Communication, AWH Engineering College, Kozhikode, Kerala, India.

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There are various object recognition challenges. Basically, objects have to be detected against cluttered, noisy backgrounds and other objects under different contrast and illumination environments. Accurate feature representation is a crucial step in an object recognition system as it improves performance by discriminating the object from the background or other objects in different lightings and scenarios.

II. SYSTEM MODEL

In the proposed system, it is said about the edge-texture feature, Discriminative Robust Local Binary Pattern (DRLBP) and Discriminative Robust Local ternary Pattern (DRLTP) for detection. DRLBP alleviates the problems of LBP by considering the weighted sum and absolute difference of a LBP code and its complement. The absolute difference between a LTP code and its inverted representation is taken to form DRLTP. The extracted features of an image are compared with the features of the image in reference samples. And hence similar set of images of the image is found from the reference samples. To measure the similarity Euclidean distance measurement is adopted.

DRLBP and DRLTP solve the problem of discrimination between a bright object against a dark background and vice-versa inherent in LBP and LTP. It also retain contrast information necessary for proper representation of object contours. For the performance measurement two parameters are used. They are precision rate and recall rate.

III. PREVIOUS WORK

Object recognition features are categorized into two groups as sparse and dense representations. For sparse feature representations, to identify corners and blobs on the object the interest-point detectors are used. A feature is created for the image patch around each point. The Scale-Invariant Feature Transform (SIFT)[6], Speeded Up Robust Feature[3], Principal Curvature-Based Regions[9], Region Self-Similarity features[8], Sparse Color and the sparse parts-based representation[4] and A comprehensive evaluation of sparse features[7] are the popular feature representations. Dense feature representations are gaining popularity as they describe objects richly compared to sparse feature representations where in dense feature extraction features are extracted at fixed locations densely in a detection window. Wavelet[4], Haar-like features [9], Histogram of Oriented Gradients (HOG) [8], Extended Histogram of Gradients, Feature Context, Local Binary Pattern (LBP) and Local Ternary Pattern[1] are the major dense feature representations.

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Geometric-blur and Local Edge Orientation Histograms[10] are the other representations that have been proposed over recent years. Dense SIFT has also been proposed by other authors to alleviate the sparse representation problems[11], LBP is the most popular texture classification feature. Excellent face detection performance is the key feature of LBP. It only considers the signs of the pixel differences and hence it is robust to illumination and contrast variations. By the method of histogramming of LBP codes the descriptor is resistant to translations within the histogramming neighborhood. However, it is sensitive to noise and small fluctuations of pixel values. To handle this, Local Ternary Pattern (LTP) was proposed. LTP has three different states with two thresholds as compared to two in LBP. Comparing to LBP, LTP is more resistant to noise and small pixel value variations. Like LBP, it can be used for texture classification and face detection. However, LBP and LTP present two issues for object recognition. They differentiate a bright object against a dark background and vice versa. This will lead to increase in the object intra-class variations which is undesirable for most object recognitions. In Robust LBP (RLBP) the LBP code is mapped to a LBP code and its complement. The minimum of both is found out 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.

It is desirable to represent objects using both texture and edge information because different objects have different shapes and textures. LBP, LTP and RLBP do not differentiate between a weak contrast local pattern and a similar strong one but they only capture texture information. By discarding contrast information, contours may not be effectively represented. It is because object contours, which also contain discriminatory information, tend to be situated in strong contrast regions.

In this paper, it is said about two sets of novel edge-texture features, Discriminative Robust LBP (DRLBP) and DRLTP. The mentioned features solve the issues of LBP, LTP and RLBP. They alleviates the intensity reversal problem of object and background. Furthermore, DRLBP discriminates local structures that RLBP misrepresent. In addition, the mentioned features retain the contrast information of image patterns. They contain both edge and texture information which is desirable for object recognition. And it turn it is used image retrieval application.

IV. PROPOSED METHODOLOGY

An object has two distinct cues for differentiation from other objects. They are the object surface texture and the object shape formed by its boundary. The boundary is crucial since it provide 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. The histogramming of LBP codes only considers the frequencies of the codes rather than the weight of the code. In which all codes have the same weight. This makes it complicated to differentiate a weak contrast local pattern and a strong contrast one. To overcome this, edge and texture information is fused in a single representation by modifying the way the codes are histogrammed is proposed. Here in the method of histogramming the intensity of the images are distributed in different ranges, where each range is a bin Instead of considering the code frequencies, a weight, $\omega_{x,y}$ is computed as follows

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

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

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

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

The value of the i th weighted LBP bin of a M × N block is as follows:

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

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

The LBP can be found as follows

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

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

where P_b is the pixel value estimated using bilinear interpolation from neighboring pixels in the b-th location on the circle of radius R around pc and B is the total number of neighboring pixels. P_c is the pixel value at (x, y), A 2^B-bin block histogram is computed. The RLBP histogram is created from (5) as follows:

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

where $h_{rlbp(i)}$ is the i th RLBP bin value. consider the absolute difference between the bins of a LBP code and its complement to form Difference of LBP (DLBP) histogram as follows:

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

In the case of DRLTP, Using LTP to find RLTP, DLTP and DRLTP is computationally intensive and requires a large storage requirement. Hence we use a simpler method using ULBP and LLBP. We have the expression for URLBP and URLTP as follows

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

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

By producing URLBP and LRLBP codes for any LTP code, RLTP is obtained in the split LBP code representation. Expression for ULBP and LLBP is as follows.

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

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

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

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

The URLBP and LRLBP can be easily found from ULBP and LLBP. The parameters the s^{th} URLBP bin value, 0 < s < 2B, is generated for a M × N block from ULBP and LLBP codes are 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, $0 \leq t < 2B-1$, is as follows:

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

The s^{th} UDLBP bin value is as follows:

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

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

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

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'(.) Determines whether the ULBP and LLBP codes are being swapped. If a swap occurs, the negative minimum code is assigned to the result. Thus the features are extracted by DRLBP and DRLTP techniques.

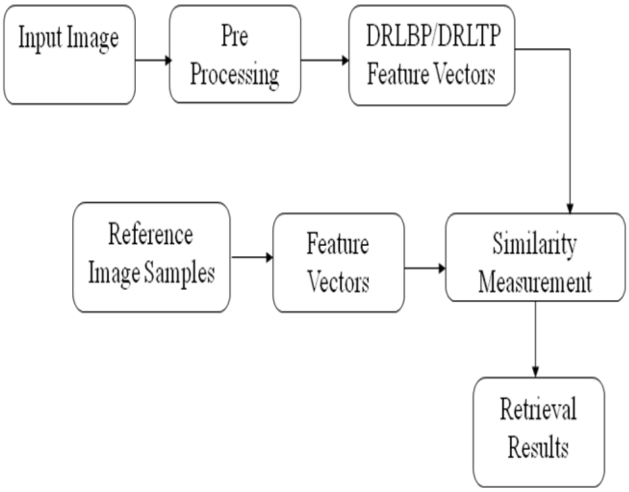

Fig 1: Block diagram of the image retrieval system

Now the extracted features are compared with the features of the images in reference samples. As shown in the fig1, the features are compared with the features of the images in the reference samples. Using the Euclidean distance method the similar images are found out. It is observed that by using DRLBP and DRLTP better performance is obtained. And more similar images are obtained in the case of DRLTP

V. Simulation Results

The image retrieval system using DRLBP and DRLTP is implemented with the help of the software MATLAB. Two parameters are used in the proposed system to measure the performance. They are precision rate and recall rate. The precision rate can be defined as the number of relevant images retrieved to that of the total images retrieved. Similarly recall rate is defined as the total number of relevant images retrieved to that of the total number of relevant images. The analysis of the proposed method is as follows:

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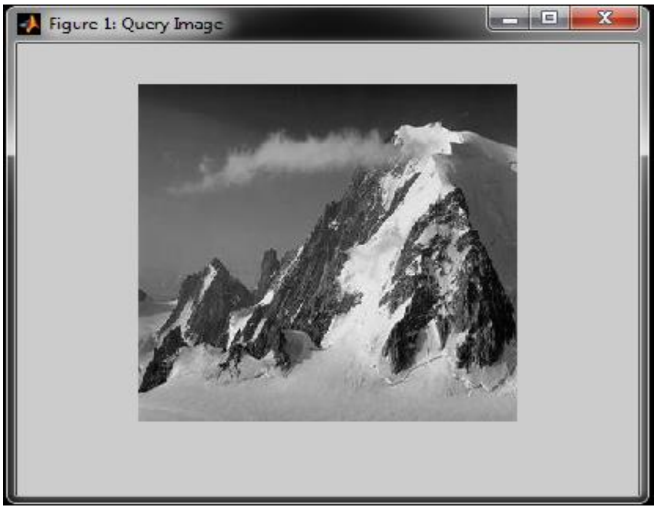

Fig 2: The query image

Fig 2 shows the image for which similar images has to be found out from the reference samplesInitially the feature is extracted and the DRLBP and DRLTP histograms are plottedThe histograms are followed by the similar images.Fig 3 and Fig 4 shows the DRLBP and DRLTP histograms respectively

It is found that about 9 similar images are recognized from the reference images in the case of DRLBP.The group consist of 20 similar images. From that group 16 are made to display and 9 similar images are obtained

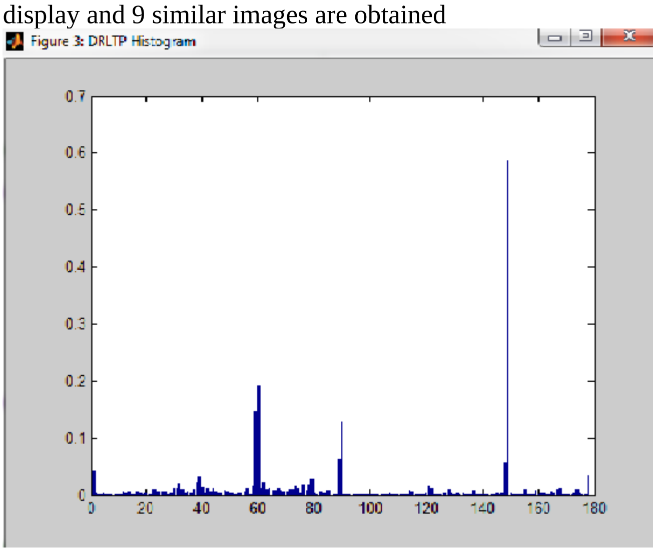

Fig3: The DRLBP histogram

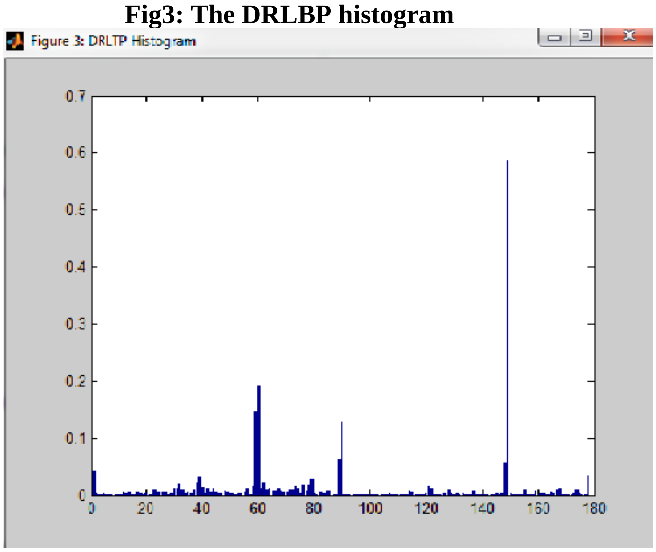

Fig 4: The DRLTP histogram

Similarly in the case of DRLTP 11 similar images were obtained. Manually pointing the number of retrieved images, the precision rate and the recall rate is displayed on the command window.

Table-1: Evaluation of DRLBP and DRLTP

	No. of similar images obtained	Precision rate	Recall rate
DRLBP	9	.5625	.4500
DRLTP	11	.6250	.5

From the table-1 it is clear that the DRLTP and DRLBP is having better performance in image texture analysis and image retrieval application. Also DRLTP is having better performance than DRLBP

VI. CONCLUSION

This paper proposes two sets of novel edge-texture features, for object recognition. They are Discriminative Robust Local Binary Pattern (DRLBP) and Ternary Pattern (DRLTP).Using texture information alone we cannot effectively represent the contour. Hence the new features, DRLBP and DRLTP, are proposed by analyzing the weaknesses of LBP, LTP and RLBP. They alleviate the problems of LBP, LTP and RLBP by considering both the weighted sum and absolute difference of the bins of the LBP and LTP codes, these new features are robust to image variations, which are generally caused by the intensity inversion. They are also discriminative to the image structures within the histogram block.

VII. FUTURE SCOPE

As future work the image recognition and retrieval can be done using curvelet transform. In the case of curvelet transform frequency is the parameter choose. While using frequency the accuracy is increased and for the comparison entropy measurements can be adopted.

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Anagha Sudhakaran has received her Bachelor of Technology degree in Electronics and Communication Engineering from Malabar College of Engineering and Technology in the year 2013. At present she is pursuing M.Tech in Communication Engineering in Vedavyasa Institute of Technology, Kozhikode. Her areas of interest include Signal

Manu Prasad has received his BE Degree in Electronics and Communication Engineering in the year 2007 from SCAD Engineering College, Thirunelveli and M.Tech Degree in VLSI & Embedded Systems from Rajagir School of Engineering, Kochi. At present he is working as an Assistant Professor in the Department of Electronics and Communication Engineering at AWH Engineering College, Kozhikode. His areas of interest are Image Processing, VLSI, and Signal Processing

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