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A Discriminative Robust Local Binary Patter for Object Recognition

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***Abstract*— Object recognition is very important process in computer vision. Texture and edge information is mainly used for object recognition. Local Binary Pattern (LBP) and Local Ternary Pattern (LTP) are mainly used for object recognition. But these two techniques suffer from noise and intra-class variations due to small pixel fluctuations. To solve this problem a new algorithm called Robust Local Binary Pattern (RLBP) and Discriminative Robust Local Binary Pattern (DRLBP) are used for object recognition. Comparative analysis is done between RLBP and DRLBP using Caltech 101 dataset.**

***Index Terms*— Object recognition, intra-class variations, pixel fluctuations.**

I. INTRODUCTION

Object recognition is very important process. Object recognition is mainly used in face detection and pedestrian detection. Object recognition is a process of identifying and classifying the objects in digital images and videos. Object recognition consists of two steps, object identification and object classification. Object identification is process of identifying the object and object classification is classifying the detect object to specific class. Detecting the objects for human is very easy but for machines it is difficult. For this purpose algorithmic model is developed. Surface texture of the object is one of important feature for object recognition. Many techniques are used to extract the texture information of the object.

Local Binary Pattern (LBP) is commonly used to extract the texture information. From [2], LBP has two states 1 and 0 and one threshold state. LBP is also used for face detection in many applications. But LBP has small pixel fluctuations these fluctuations results in noise. Hence it is more sensitive to noise. To reduce the noise in the image, X. Tan and B. Triggs [3] introduces new technique called Local Ternary Pattern (LTP). LTP consist of two threshold states and three states represented by 1, 0 and -1. It reduces the noise completely. Both LBP and LTP have intra-class variations. If the intensity of the image changes during different illumination condition

There are no changes in the LBP and LTP pattern. This condition is undesirable for object recognition.

To avoid this condition [4] D. T. Nguyen, Z. Zong, P. Ogunbona introduced new technique Non-redundant local binary pattern (NRLBP). In NRLBP uncertain bit is used to represent the small pixel fluctuations. LBP, LTP and RLBP provide only the texture information of the object but object recognition requires edge information along with texture information. Edge is the outer boundary of the object and it provides the shape of the object. To obtain both edge and texture information Discriminative Robust Local Binary Pattern (DRLBP) is introduced [1]. It provides both edge and texture information of the object.

II. OVERVIEW OF THE PROPOSED WORK

A. Block Diagram

The block diagram is shown in figure 1.

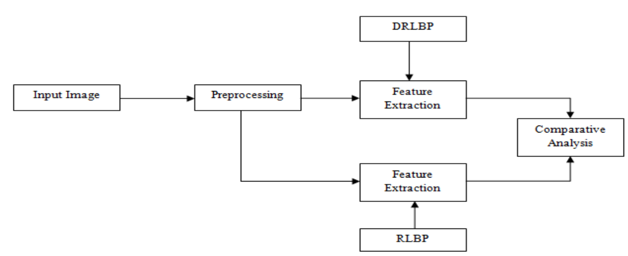

Figure 1: Block Diagram

Input image: Input image is a color image taken from the dataset. Here Caltech 101 dataset is used.

Preprocessing Step: The color image is converted into gray scale image. DRLBP is applicable only for the gray images.

Feature Extraction: Edge and texture information of object is considered has the features for object recognition. Edge information is gives the boundary of the object and texture information gives the type of object. To extract both the information Robust Local Binary Pattern (RLBP) and Discriminative Robust Local Binary Pattern (DRLBP) are used.

Comparative Analysis**:** The output from RLBP and DRLBP are compared to know which technique is more robust for edge and texture extraction.

III. ALGORITHM USED

A. Robust Local Binary Pattern (RLBP)

D. T. Nguyen, Z. Zong, P. Ogunbona introduced RLBP. To reduce noise obtained in LBP an uncertain bit is introduced to represent the pixel fluctuations. This uncertain bit is either 1 or 0 based on threshold value.
The threshold level is represented by [4],

$$s(z) = \begin{cases} 1 & u \geq i_c + t \\ X & i_c - t < u < i_c + t \\ 0 & u \leq i_c + t \end{cases} \quad (1)$$

Where i_c is intensity of center pixel and t is used defined value.

To avoid intra-class variation instead of average image threshold average local gray level is taken. Average local gray level is calculated by [5].

$$ALG = \frac{\sum_{i=1}^{8} g_i + g_c}{9} \quad (2)$$

Where g_i is gray value of neighbor pixel. g_c is center pixel value. RLBP is calculated by [5]

$$RLBP = \sum_{b=0}^{8} s(g_i - ALC_c)2^b \quad (3)$$

Where g_i is gray value of neighbor pixel and ALG_c is ALG value of center pixel.

B. Discriminative Robust Local Binary Pattern (DRLBP)

In DRLBP pixel gradient magnitude is calculated for image and this gradient magnitude is used to weigh the LBP codes. The pixel gradient magnitude is calculated by [1],

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

Where, I_x and I_y are the first order derivatives in x and y direction.

After calculating the gradient magnitude, h_{lbp} is calculated and it is given by [1],

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

By using this h_{lbp} values, histogram of robust local binary pattern (h_{rlbp}) and histogram of difference local binary pattern (h_{dlbp}) is calculated [1],

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

And

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

DRLBP histogram is calculated by concatenating h_{rlbp} and h_{dlbp}[1].

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

$h_{drlbp}(i)$ is the DRLBP value at i^{th} position.

DRLBP is calculated for 256 bins. h_{rlbp} is calculated for 128 bins and h_{dlbp} is calculated for 128 bins. When concatenated it will becomes 256(128+128) bins.

IV. EXPERIMENTAL RESULTS

For comparative analysis Caltech 101 dataset is used. Both RLBP and DRLBP techniques are applied for this dataset image and output are compared. Both techniques provide texture information but the histograms are analyzed to know which technique gives better edge information.

The original image is shown in figure 2;

Figure 2: Original Image

DRLBP has following steps:

1. Pixel gradient magnitude of image is calculated, the gradient image is shown in figure 3.

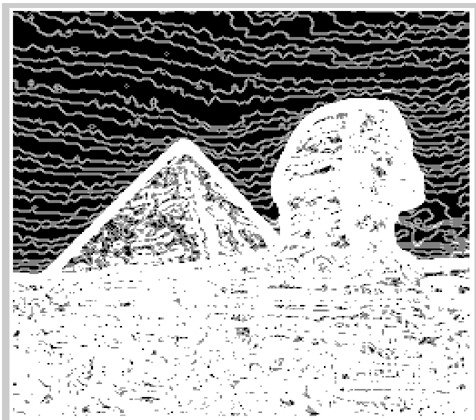

Figure 3: Gradient Image

2. h_{rlbp} and h_{dlbp} of image is given in figure 4 and 5.

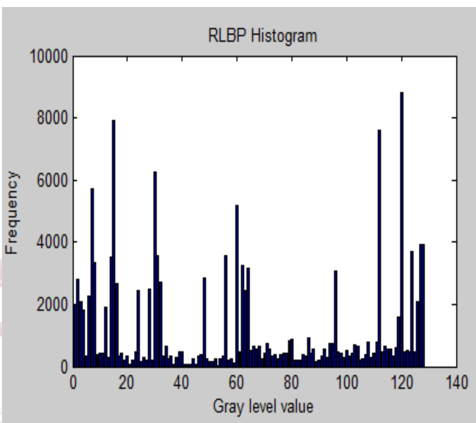

Figure 4: h_{rlbp} histogram

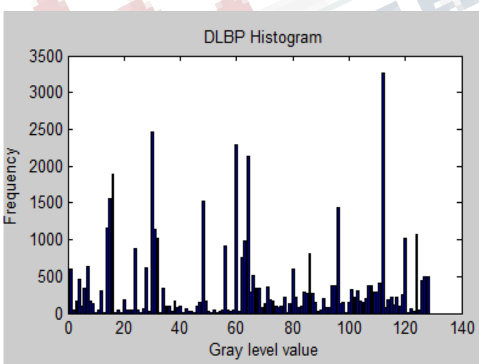

Figure 5: h_{dlbp} histogram

3. h_{drlbp} is given figure 6,

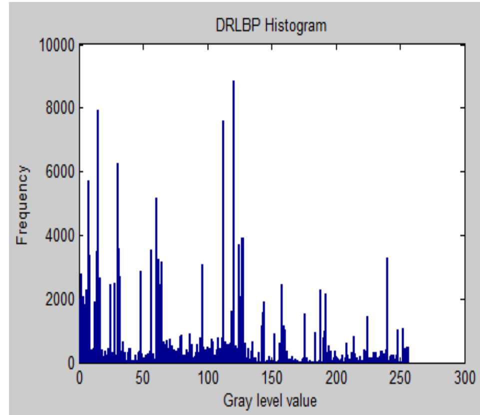

Figure 5: DRLBP histogram

Histogram is plotted by taking frequency versus pixel values. In the histogram, if sudden change in the frequency in respective pixel value is represented as edge of the image. By analyzing the DRLBP histogram, it shows that more frequency changes occur in the different pixel values. Thus DRLBP provides clear information about the edges of the image.

The RLBP histogram of image is shown in figure 6;

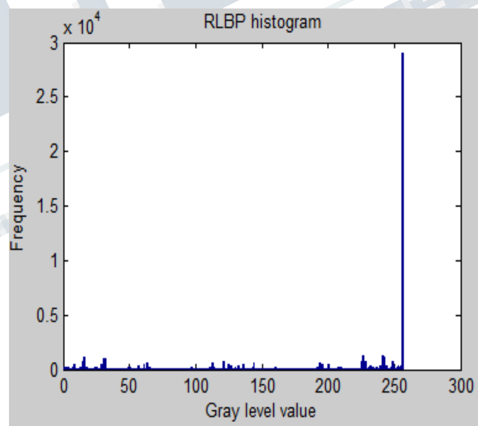

Figure 6: RLBP histogram

By analyzing the RLBP histogram it shows that there is only some part of pixel value there is a sudden change in the frequency. This gives RLBP provides some edge information of the image. It does not provide the clear edge information like DRLBP technique.

V. CONCLUSION

Both RLBP and DRLBP provides texture and edge information for object recognition. But from histogram analysis it shows that DRLBP provides more edge information of the object than RLBP. Thus DRLBP is more robust for object recognition.

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