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OBJECT RECOGNITION BASED ON LOCAL BINARY AND TERNARY PATTERNS

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Abstract

This paper proposes four sets of edge-texture features, those are; Local Binary Pattern (LBP), Local Ternary Pattern (LTP), Discriminative Robust Local Binary Pattern (DRLBP) and Ternary Pattern (DRLTP), for object recognition. By investigating the limitations of Local Binary Pattern (LBP), and Local Ternary Pattern (LTP) DRLBP and DRLTP are proposed as new features. They solve the problem of discrimination between a bright object against a dark background and vice-versa inherent in LBP and LTP. DRLBP also resolves the problem of RLBP whereby LBP codes and their complements in the same block are mapped to the same code. Furthermore, the proposed features retain contrast information necessary for proper representation of object contours that LBP, LTP, and RLBP discard.

Keywords—*Object recognition, local binary pattern, local ternary pattern, feature extraction, texture, DRLBP, DRLTP.*

I. INTRODUCTION

CATEGORY recognition and detection are 2 parts of object recognition. The objective of category recognition is to classify an object into one of several predefined categories. The goal of detection is to distinguish objects from the background. There are various object recognition challenges. Typically, objects have to be detected against cluttered, noisy backgrounds and other objects under different illumination and contrast environments. Proper 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. Furthermore, a good feature also simplifies the Classification framework. The features are essential for recognition of objects. Features used in this project are Local Binary Pattern (LBP) and Local Ternary Pattern (LTP). The patterns are the binary bits either zero or one for the Local Binary pattern. For Local Ternary Pattern it may be either zero or ±1. The patterns generated are converted to decimal values. Those decimal values are called as bins. Bins are plotted in a graphical representation to generate the histograms.

II. DISCRIMINATIVE ROBUST LOCAL BINARY PATTERN

The LBP [1] code at location *(x, y)* is computed as follows:

$$LBP_{x,y} = \sum_{b=0}^{B-1} S(P_b - P_c)2^b$$

Where,

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

where p_c is the pixel value at *(x, y)*, 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 p_c and *B* is the total number of neighboring pixels. A 2^B-bin block histogram is computed.

An issue with LBP is that they differentiate a bright object against a dark background and vice-versa. This differentiation makes the object intra-class variation larger. To solve the above mentioned problem of LBP, the authors in [2] propose mapping a LBP code and its complement to the minimum of the two. For instance, "1101 0101" and its complement, "0010 1010", become the same code "0010 1010" in the mapping. The states are changed from 0 to 1 or 1 to 0 during this mapping. By doing so, the code is ***robust*** to the reversal in intensity between the background and the objects. Based on this, we name this code as *Robust* LBP (RLBP). RLBP is computed as follows:

$$RLBP_{x,y} = min\{LBP_{x,y}, 2^B - 1 - LBP_{x,y}\}$$

An object has 2 distinct cues 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. However, in order to be robust to illumination and contrast variations, LBP does not differentiate between a weak contrast local pattern and a strong contrast one. 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 differentiate a weak contrast local pattern and a strong contrast one. To mitigate this, we propose to fuse edge and texture information in a single representation by modifying the way the codes are histogrammed. Instead of considering the code frequencies, we assign a weight, $\omega_{x,y}$, to each code which is then voted into the bin that represents the code. The weight we choose is the pixel gradient magnitude which is computed as follows. Following [3], the square root of the pixels is taken. Then, the first order gradients are computed. The gradient magnitude at each pixel is then computed as

$$W_{x,y} = \sqrt{I_x^2 + I_y^2}$$

where *Ix* and *Iy* are the first-order derivatives in the *x* and *y* directions. *ωx,y* is then used to weigh the LBP code.
The stronger the pixel contrast, the larger the weight assigned to the pixel LBP code. 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:

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

Where,

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

The RLBP histogram is created from above as

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

where *hrlbp(i)* is the *ith* RLBP bin value. To mitigate the RLBP issue in consider the absolute difference between the bins of a LBP code and its complement to form Difference of LBP (DLBP) histogram as follows:

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

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

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

For *B* = 8, the number of bins is 256 (128 + 128). Using uniform codes, it is reduced to 60 (30 + 30). DRLBP contains *both* edge and texture information.

III. DISCRIMINATIVE ROBUST LOCAL TERNARY PATTERN

LBP is invariant to monotonic intensity changes. Hence, it is robust to illumination and contrast variations. However, it is sensitive to noise and small pixel value fluctuations. Therefore, LTP [4] has been proposed to handle this situation. The LTP code at location *(x, y)* is computed as follows:

$$LTP_{x,y} = \sum_{b=0}^{B-1} S'(P_b - P_c)3^b$$

Where,

$$S'(z) = \begin{cases}1, & z \ge t\\ 0 & -t < z < t\\ -1, & z \le -t\end{cases}$$

where *T* is a user-defined threshold. As defined by *s'(z)*, LTP has 3 states while LBP has two. A 3*B*-bin block histogram is computed. For *B* = 8, the histogram has 6561 bins which is very high-dimensional. Hence, in [4], the authors propose to split the LTP code into its “upper” and “lower” LBP codes.

LBP is sensitive to noise and small pixel value fluctuations [4]. LTP solves this using 2 thresholds to generate codes. It is more resistant to small pixel value variations and noise compared to LBP. However, it also has the same problem as LBP whereby it differentiates a bright object against a dark background and vice-versa. RLBP [5] solves this problem for LBP by mapping a LBP code and its complement to the minimum of the two.

In this paper, the maximum of a LTP code and its inverted representation is chosen. We name it as *Robust* LTP (RLTP). Mathematically, RLTP is formulated as follows:

$$RLTP_{x,y} = max\{LTP_{x,y} - LTP'_{x,y}\}$$

The RLTP code can then be split into “upper” and “lower” LBP codes. The “upper” code, *URLBP*, is expressed as follows:

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

Where,

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

where *RLBPx,y,b* represents the RLTP state value at the *b*-th location. The “lower” code, *LRLBP*, is computed as follows:

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

Where,

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

The most significant bit of *LRLBP* is 0 as the state at *(B*−1*)*th location of RLTP is either 0 or 1.

LTP and RLTP are also robust to illumination and contrast variations and only capture texture information. Hence, the weighting scheme is also used. The *kth* weighted LTP bin value of a *M* × *N* image block is as follows:

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

The RLTP histogram is created from above equation,

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

where *hrltp(k)* is the *kth* RLTP bin value.

The absolute difference between the bins of a LTP code and its inverted representation is taken to form Difference of LTP (DLTP) histogram as follows:

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

Where *hrltp(k)* is the *kth* DLTP bin value. The Discriminative Robust Local Ternary Pattern (DRLTP) can be calculated as follows

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

The “upper” and “lower” LBP histograms of DRLTP can be computed. Similar to DRLBP, DRLTP contains both edge and texture information.

All these histograms are generated for input object and also for all objects present in the database. After generating match the histograms of input object with that of database using Euclidean distance algorithm.

IV. EXPERIMENTAL RESULTS

The whole project is conducted on MATLAB platform and also implemented on Graphical User Interface. Here comparison of LBP, DRLBP, LTP and DRLTP is done. The object recognition is done from the database. Database contains 3 categories of 9 objects those are 3-apple, 3-car and 3-orange. For LBP, orange is the input and it recognizes only one orange out of 3 it is as shown in fig 1. For DRLBP the second orange is taken as input and it recognizes two objects out of 3 it is as shown in fig 2. Here compared to LBP, DRLBP recognizes more objects than LBP. For LTP, the input is a car and it recognizes one car from the database having three cars it is as shown in fig 3. For DRLTP technique the input is also a car and it recognizes two cars out of three it is as shown in fig 4.

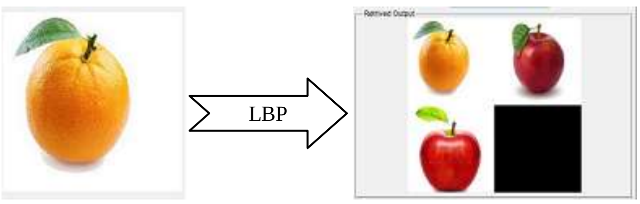

Fig: 1: Recovered Objet using LBP

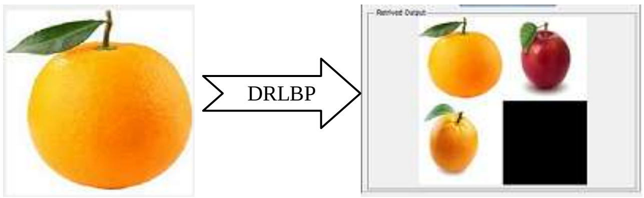

Fig: 2: Recovered Objet using DRLBP

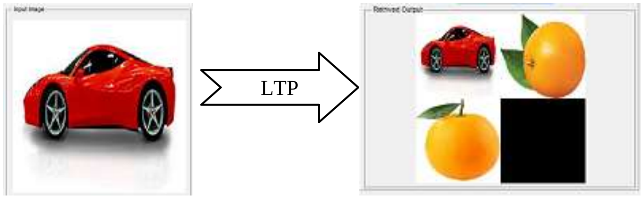

Fig: 3: Recovered Objet using LTP

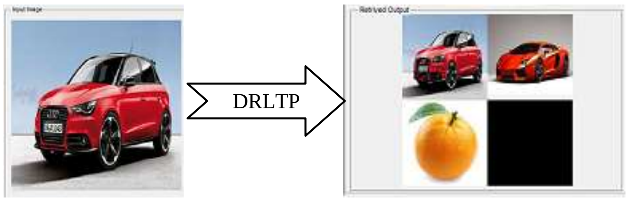

Fig: 4: Recovered Objet using DRLTP

Here compared to LTP, DRLTP recognizes more objects than LTP. The performance table is as shown below.

Table: I: Performance table.

SI. No.	Technique used	Object recognition (Out of 3)	Efficiency in %
1.	LBP	1	33.3%
2.	DRLBP	2	66.6%
3.	LTP	2	33.3%
4.	DRLTP	3	66.6%

V. CONCLUSION

This paper proposes 2 sets of novel edge-texture features, Discriminative Robust Local Binary Pattern (DRLBP) and Ternary Pattern (DRLTP), for object recognition. The limitations of existing texture features, Local Binary Pattern (LBP), Local Ternary Pattern (LTP) and Robust LBP (RLBP), for object recognition are analyzed. LBP and LTP differentiate a bright object against a dark background and vice versa. This differentiation makes the object intra-class variations larger. RLBP solves the LBP problem by choosing the minimum of a LBP code and its complement. However, RLBP maps LBP codes and their complement in the same block to the same value. This causes some structures to be misrepresented. Furthermore, LBP, LTP and RLBP discard contrast information. This is not desired as object texture and contour both contain discriminative information. By capturing only the texture information, the contour is not effectively represented. 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 with their respective complement/ inverted codes. The new features are robust to image variations caused by the intensity inversion and are discriminative to the image structures within the histogram block.

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