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Object Recognition Is Acchived Through LBP, LTP and RLBP

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Abstract:
In this paper two sets of edge-texture features are proposed such as Discriminative Robust Local Binary Pattern (DRLBP) and Discriminative Robust Local Ternary Pattern (DRLTP) for object recognition. The proposed DLBP and DRLTP are derived from the drawback of the Local Binary Pattern (LBP), Local Ternary Pattern (LTP) and Robust LBP (RLBP). It solves the problem of the bright object against dark background vice-versa which LBP and LTP fail to detect. DRLBP resolves the problem of the LBP code and their complement of RLBP code in the same block are mapped to the same. The proposed feature retains contrast information for representation of object contours the LBP, LTP and RLBP fail to identify. By this proposed features the objects in the image can be further analyzed for the exact location of the object in the given image.

Keywords: *Object recognition, Local Binary pattern, Local Ternary Pattern, Face recognition, Texture, feature extraction*

1. Introduction

The two part of the object recognition are category recognition and detection. The objective of the category recognition is to order object in to one of several predefined categories. The key plan of the detection is to differentiate objects from the background. Objects are detected from the noisy background, disordered and other object from different background. Object recognition system improves the performance by discriminating the object from the background.

Object recognition features are represented in two groups-Spare representation and dense representation. Spare feature representation means interest-point detectors to indentify the structures like corners and disk-shaped mass on the objects. Some of the spare feature representations are Scale-Invariant Feature (SIFT), Speed up Robust Feature, Local Steering Kernel, Principal Curvature-Based Regions, Region Self-Similarity Feature, Spare color, Spare parts-Based representation.

Dense feature representation means extract occurs at a permanent location with density at the detection windows. Some of the dense feature representations are Wavelet, Haar- Feature, and Histogram like of Oriented Gradients, Extended Histogram of Gradients, Feature Context, Local Binary Pattern, Local Ternary Pattern, Geometric-Blur, and Local Edge Orientation Histogram.

However in texture analysis face recognition problem has not been associated. Face recognition application is widely used by LBP. When LBP operation is applied to the image the face can be seen as a composition of micro-patterns. Local binary pattern (LBP) operator transforms an image into an array or image of integer labels describing micro-pattern, i.e. pattern formed by a pixel and its immediate neighbours.

LBP is a type of feature used for arrangement in computer vision. It is the most powerful features for texture classification. It show brilliant face recognition or texture analysis. Robust illustration and Contrast variation are considering only the signs of the pixel differences.

LBP has set procedure for the image to be recognized. At initial stage, divide the examined window in to cells (e.g., 16x16 pixels for each cell). For each pixel in a cell, compare the pixel to each of its 8 neighbours. Follow the pixel along a circle, i.e., clockwise or counter-clockwise.

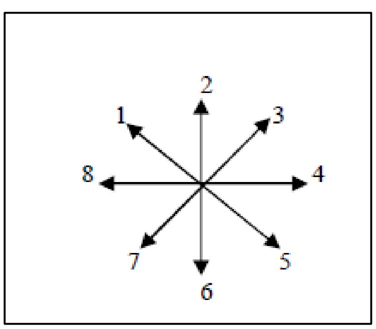

Figure 1: Neighbouring coordinates of an image

Where the center pixel's values is greater than neighbour's value, write "1" otherwise write "0". This gives eight digit binary numbers. Now compute the histogram, over the cell of the frequency of each number occurring. Then concatenate histogram of all cells.
LBP has gained much popularity because of its simplicity and robustness to illumination variations, its sensitivity to noise limits its performance. The LBP codes are defined as uniform patterns if they have at most two circularly bitwise transitions from 0 to 1 or vice versa, and non-uniform patterns if otherwise.
In uniform LBP mapping, one separate histogram bin is used for each uniform pattern and all non-uniform patterns are accumulated in a single bin. In contrast, non-uniform patterns are statistically insignificant, and hence noise-prone and unreliable. By grouping the non uniform patterns into one label, the noise in non-uniform patterns is suppressed. The number of patterns is reduced significantly at the same time.
Histogramming LBP is opposed to translation, since it is sensitive to noise and small fluctuations of pixel values. To overcome the problem LTP has been introduced. LTP has two threshold1's that create three different states. It is resistant to noise and small variation in pixel values. It partially solves the problem of the LBP. Likewise LBP, LTP also used for texture classification and face detection. LTP is more resistant to noise. However, the dimensionality of LTP histogram is very large.

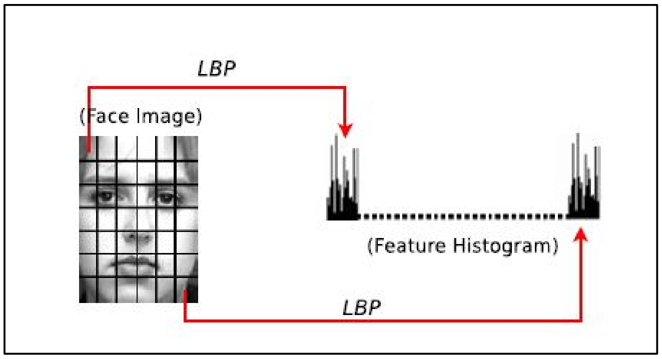

Figure 2: LBP Histogram representation

LBP and LTP are used to differentiate a bright object against dark background and vice-versa. This increases the object intra-class difference for some object recognition. Robust LBP is proposed to map a LBP system and its complement to minimum of both to solve the problem. Like LBP system, RLBP also maps to the same value. RLBP is not capable to show the dissimilarity for different local structures. Objects have dissimilar shapes and texture, which are represented by means of texture and edge information. Robust and contrast variation of LBP, LTP and RLBP does not offer difference between weak and strong contrast local pattern. For strong contrast regions object contour is required. Removing the contrast information does not provide a successful contour representation.
The proposed two set of edge-texture features like Discriminative Robust LBP and Discriminative Robust LTP are used for Object recognition. They crack the problem of discrimination between a bright object against dark background and vice-versa. It also retains the contrast information of image patterns. Edge and texture information are require for Object recognition.

2. Proposed Discriminative Robust Local Binary Pattern and Ternary Patterns

2.1. Drawback of LBP, LTP and Robust LBP

For LBP code in case for (x,y) is as follows:

$$LBPx,y = \sum_{b=0}^{B-1} s(Pb - Pc)2{\wedge}b \qquad (1)$$

where Pc is the pixel values of (x,y), Pb is the pixel values for bilinear interruption from neighbouring pixels and B is the total number of adjoining pixels. There are two patterns for Object recognition. Uniform pattern is indentifying by the number of state transitions between 0 and 1 and the rest are non Uniform pattern. Bin is reduced from 256 to 59.
Rotation-invariant LBP is designed for Object classification. It retains the inter-class variation to model the Objects. Rotation-invariant reduce the inter-class variation and simplifies the Object model. So rotation-invariant is not used in the paper. LBP is invariant to intensity changes, so it is robust and contrast variation. Since LBP is sensitive to noise and small pixel value fluctuation, this lead to the formation of the LTP to solve the problem of LBP.
The LTP code for (x,y) is as follows:

$$LTPx,y = \sum_{b=0}^{B-1} s'(Pb - Pc)3{\wedge}b \qquad (2)$$

LTP has two thresholds so it under go three state when compared with the LBP which has two state. It proposes 3^B bin blocks of histogram for B=8 and has 6561 bins. So LTP is split in to "UPPER" and "LOWER" LBP codes.
The "UPPER" code (ULBP) is as follows:

$$ULBP = \sum_{b=0}^{B-1} f(Pb - Pc)2^{\wedge}b \quad (3)$$

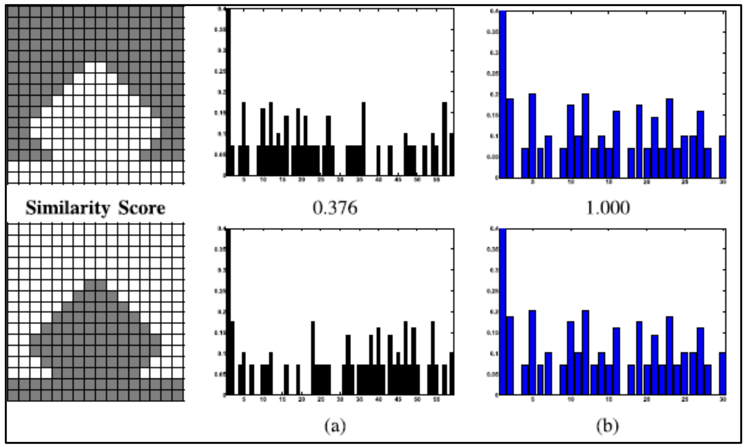

Figure 3: a) LBP and b) RLBP Histogram representation of image

The "LOWER" code (LLBP) is as follows:

$$LLBP = \sum_{b=0}^{B-1} f'(Pb - Pc)2^{\wedge}b \quad (4)$$

This reduces the bin number from 6561 to 512, and then by using Uniform pattern the LBP code is reduces to 118. Since it contain T user-defined threshold values.

LBP and LTP differentiate bright object against bark background and vice-versa. This makes the Object intra-class variation larger. By mapping LBP code and its complement are used to solve the problem of LBP. During this mapping the states are changed from 1 to 0 or 0 to 1. By doing this, the code is Robust between the background and the Objects.

The RLBP is as follows:

$$RLBPx, y = \min\{LBPx, y, 2^{B} - 1 - LBPx, y\} \quad (5)$$

where 2^B-1-LBPx, y is the complemented code. Then it produces the RLBP bin number is 128 for B=8. By using Uniform code the code is reduced to 30. It solves the problem of the intensity reversal for object and its background. This leads to solve the problem of the LBP and LTP. However this mapping is difficult to differentiate some dissimilar local structures.

2.2. The Proposed Discriminative Robust Local Binary Pattern

The object has two distinct ideas for differentiation of the object, such as Objet surface texture and object shape formed by its boundary. Boundary shows higher contrast between the object and its background. Since the boundary contains the shape information that is discriminated from the surface texture for additional discriminative information.

LBP do not differentiate between a weak contrast local pattern and a strong contrast local pattern. Histogram of LBP provides frequencies of the code (i.e.) weight for each code is the same. By combining the edge and texture information into a single representation we get expected histogram.

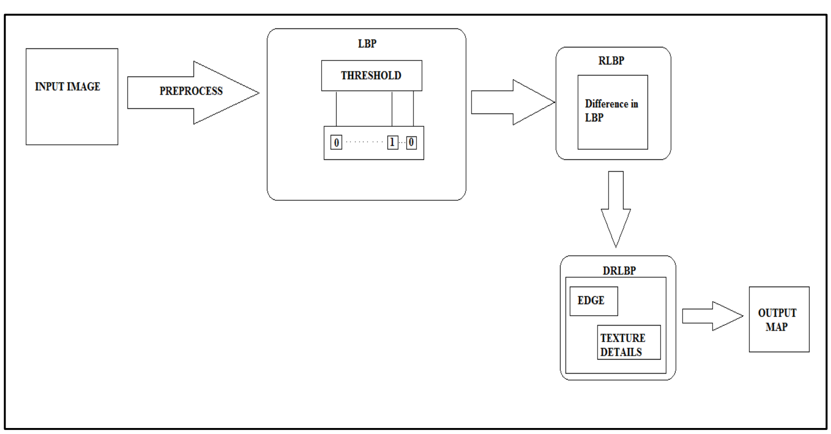

Figure 4: Architecture Diagram for Discriminative Robust Local Binary Pattern (DRLBP)

LBP system covers both side of a strong edge to generate larger magnitude. The result feature contains both edge and texture information in a single representation. The number of Difference LBP (DLBP) bin is128 for B=8. Using Uniform code it is reduced to 30. Since DLBP assigns small values to the mapped bins. So to show the difference in the map of the given object Discriminative Robust LBP are derived. For DRLBP the value of B=8 which has the bin number 256(128+128).Then by using Uniform code the value is been reduced to 60(30+30). DRLBP has edge and texture information. It resolves the issue of the intensity reversal of object and background.

2.3. The Proposed Discriminative Robust Local Ternary Patter

2.3.1. Robust Local Ternary Pattern

LBP is sensitive to noise and small pixel value fluctuations. LTP solves this problem by using two thresholds that create three different states. It is more resistant to noise and small pixel variations. To solve the problem of LBP and show the difference in bright object against a dark background and vice-versa RLBP is used. RLBP is not applicable to ULBP and LLBP of LTP. To solve the problem of LTP we need to analyze the three-state of the LTP definition in equitation (2): 1, 0 and-1. The state 0 represent the region of small variations, noise and Uniform regions.

The Robust LTP (RLTP) is as follows:

$$\mathrm{RLTPx,y} = \max\{\mathrm{LTPx,y} - \mathrm{LTPx,y}\} \quad (6)$$

For a pair of brightness inverted object/background pattern, only the state os-1 is inverted to 1 and vice-versa. The RLTP is split into "UPPER" and "LOWER" LBP codes.

The "UPPER" code (URLBP) is as follows:

$$\mathrm{URLBP} = \sum_{b=0}^{B-1} h(\mathrm{RLBPx,y,b})2\,\hat{}\,b \quad (7)$$

Where RLBPx, y, b represents the RLTP state value at the b-th location.

The "LOWER" code (LRLBP) is as follows:

$$\mathrm{LRLBP} = \sum_{b=0}^{B-1} h'(\mathrm{RLBPx,y,b})2\,\hat{}\,b \quad (8)$$

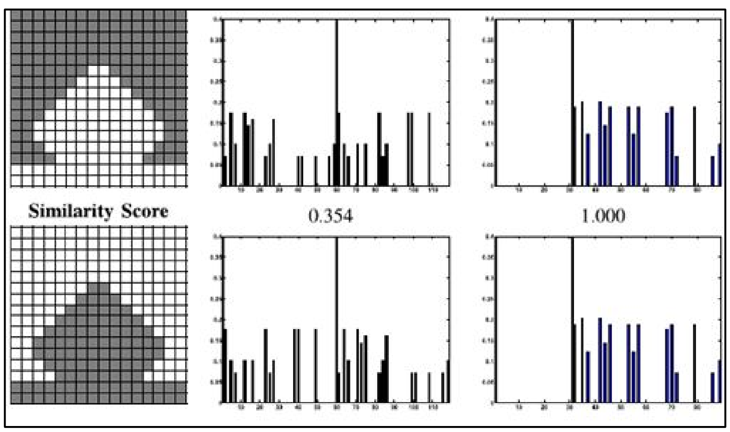

Figure 5: a) LBP and b) RLBP Histogram representation of image

Hence the LRLBP bit is 0 as the state has (B-1)-th location of RLTP is either 0 or 1. Similar to RLBP the RLTP also maps a LTP code and its complement are in the same block to the same value.

2.3.2. Discriminative Robust Ternary Pattern

LTP and RLTP also strong and contrast variations which confine the texture information. The difference between the bin values of a LTP code and its inverted representation is taken to form Difference of LTP (DLTP). The RLTP and DLTP are concatenated to form Discriminative Robust LTP (DRLTP).

The DRLBP and DRLTP contains both edge and texture information. It resolves the issue of brightness reversal of object and background. DLTP uses UDLBP and LDLBP that gives total bin number of 88 and overall DRLTP bin number is 176.

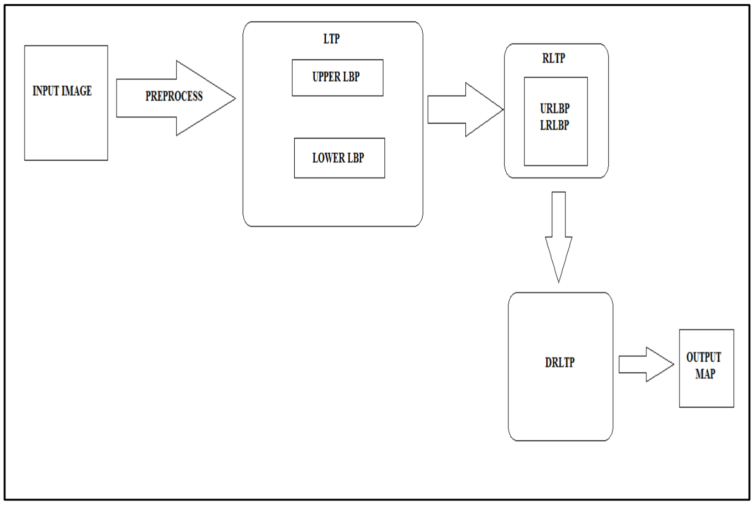

Figure 6: Architecture Diagram for Discriminative Robust Local Ternary Pattern (DRLTP)

3. Conclusion

This paper proposed two set of edge texture features such as Discriminative Robust Local Binary Pattern and Discriminative Robust Local Ternary Pattern for object recognition. Disadvantage of the existing texture features, Local Binary Pattern, Local Ternary Pattern and Robust LBP are used to derive the DRLBP and DRLTP. The discrimination makes the object intra-class variations is bigger. RLBP solves the problem of LBP system and its complement in the same block to the same value. Due to this misrepresentation occurs. Since capture of the texture information do not offer proper representation of the contour. DRLBP and DRLTP are proposed by analyzing the weakness of LBP, LTP and RLBP. They solve the problem by considering the weighted sum and absolute difference of the bins of LBP system and LTP system with their complement codes. The proposed features are strong to the image variation caused by the intensity inversion and are discriminative to the image structure with in the histogram block. By the proposed features the objects in the image can be further analyzed for the exact location of the object in the given image.

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