ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

IJESRT

INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

LOCAL BINARY PATTERN BASED EDGE- TEXTURE FEATURES FOR OBJECT RECOGNITION

Abhijeet S. Tayde*
* Electronics and Tele-communication (Signal Processing), University of Pune
JSPM's Imperial College of Engineering and Research, Wagholi, Pune, Maharashtra (412207), India

ABSTRACT
In object recognition, there are two sets of edge-texture features and discriminative Robust Local Binary Pattern (DRLBP) and Ternary Pattern (DRLTP). By knowing the limitations of Local Binary Pattern (LBP), Local Ternary Pattern (LTP) and Robust LBP (RLBP). DRLBP and DRLTP are proposed with new features to solve the problem of discrimination between a bright object against a dark background and vice-versa inherent in LBP and LTP. DRLBP also solves the problem of RLBP whereby LBP codes and complements in the specific block are mapped to the same code. Furthermore, the proposed features maintain contrast information for representation of object contours discard by LBP, LTP, and RLBP. These features are tested on seven data sets like INRIA Human, Caltech Pedestrian, UIUC Car, Caltech 101, Caltech256 and Brodatz, with KTH-TIPS2. Results shows that the proposed features outperform the compared approaches on most data sets.

KEYWORDS: Object recognition, local binary pattern, local ternary pattern, feature extraction, texture, Ternary Pattern (DRLTP), DRLBP.

INTRODUCTION
Object recognition has two main parts: recognition and detection. The objective of recognition is to classify an object into predefined categories. The aim of detection is to distinguish objects from the background. There are various object recognition challenges, like objects 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 scene, a feature also simplifies the classification. The object recognition features are categorized into two groups - sparse and dense representations. In sparse feature representations the interest-point detectors used to identify structures like corners and blob. A feature created for the image patch around each point, the popular feature representations include Scale-Invariant Feature Transform (SIFT), Speeded Up Robust Feature, local steering kernel and principal curvature-based regions, region self-similarity features, sparse color and the sparse parts based presentation. A comprehensive evaluation of sparse features can be found. Dense feature representations extracted at fixed locations in a detection window which is gaining popularity as they describe objects richly compared to sparse feature representations. Different feature representations such as Wavelet, Haar-features, Histogram of Oriented Gradients (HOG), Extended Histogram of Gradients, Feature Context, Local Binary Pattern (LBP), Local Ternary Pattern (LTP), Geometric-blur and Local Edge Orientation Histograms have been proposed over recent years.

LBP is the most popular texture classification feature. It has also shown excellent face detection performance. It is robust to illumination and contrast variations as it only considers the signs of the pixel differences. A Histogramming LBP code makes the descriptor 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) has been proposed. Comparison to LBP it has 2 thresholds which create 3 different states as compared to 2 in LBP. It is more resistant to noise and small pixel value variations compared to LBP and it also used for texture classification and face detection. However, for object recognition, LBP and LTP present two issues. They differentiate a bright object against a dark background. This increases the object intra-class variations which

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

is undesirable for most object recognitions. Robust LBP (RLBP) to map a LBP code and its complement to the minimum of both to solve the problem.

DISCRIMINATIVE ROBUST LOCAL BINARY PATTERN

An object has 2 distinct cues for differentiation, the object surface texture and the object shape formed by its boundary. The boundary often shows higher contrast between the object and the background than the texture of surface and differentiating the boundary with respect to the surface texture brings additional discriminatory information because the boundary contains the shape information. In order to be robust to illumination and contrast variations, LBP does not differentiate between a weak contrast local pattern and a strong contrast. It 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, it proposes to fuse edge and texture information in a single representation by modifying the way the codes are histogrammed. Instead of considering the code frequencies, it assign a weight, Wx,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. The square root of the pixels is taken and after that 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 while Wx,y is used to weighing LBP code. The stronger the pixel contrast, the larger the weight assigned to the pixel LBP code. By this way, if a LBP code covers both sides of a strong edge and its gradient magnitude is 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, therefore the resulting feature will contain both edge and texture information in a single representation. The value of the ith weighted LBP bin of a M × N block is as follows:

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

The RLBP histogram is created from (1) as follows:

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

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

$$h_{dlbp}(i) = \left|h_{rlbp}(i) + h_{lbp}(2^B - 1 - i)\right|, \quad 0 < i < 2^{B-1} \qquad (3)$$

Where *hdlbp (i)* is the *ith* DLBP bin value. The number of DLBP bins is 128 for B = 8. Using uniform codes, it is reduced upto 30. Also for blocks that containing structures with both LBP codes and their complements, DLBP assigns small values to the mapped bins to differentiate 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:

$$h_{drlbp}(j) = \begin{cases} h_{rlbp}(j), & 0 < j < 2^{B-1} \\ h_{dlbp}(j - 2^{B-1}), & 2^{B-1} < j < 2^B \end{cases} \qquad (4)$$

For *B* = 8, the number of bins is 256 (128 + 128). Using uniform codes, it is reduced to 60 (30 + 30).

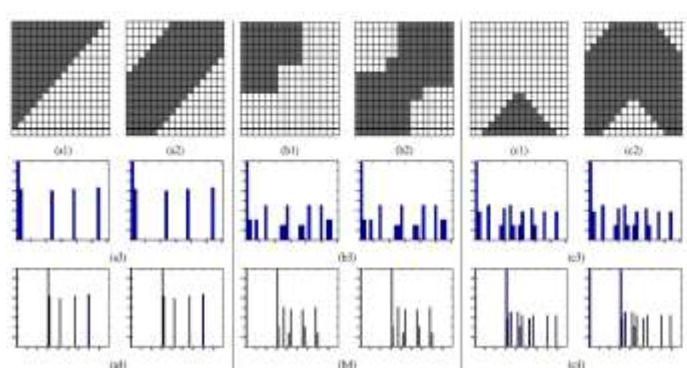


Fig.1: Problem of Robust LBP (RLBP) and Robust LTP (RLTP). 6 local structures are shown in the first row and second row shows the RLBP features for each structure. In third row, RLTP features for each structure. RLBP and RLTP create the different structures in (a1) and (a2) similar as shown in (a3) and in (a4) and different structures in (b1) and (b2) similar as shown in (b3) and (b4). A similar situation can be observed in (c).

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

The PROPOESD DISCRIMINATIVE ROBUST LOCAL TERNARY PATTERN

Robust Local Ternary Pattern

LBP is sensitive to noise and small pixel value fluctuations. 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 solves this problem for LBP by mapping a LBP code and its complement to the minimum of the two.

However, RLBP cannot be applied to ULBP and LLBP of LTP. For a pair of object/background intensity inverted patterns, their ULBP codes are decomplements. Likewise their LLBP codes are also not complements. This is illustrated where 2 different cases of object/background inverted intensity patterns are shown in fig.(1). In Fig. 1(a1) and (a2), a case illustrating a neighborhood, where all 3 LTP states occur, is shown. From the two LTP codes, it is observed that the 2 patterns are simply intensity inverted also their corresponding ULBP codes are not complements. Thus their corresponding LLBP codes are also not complements. A similar situation is observed in (b1) and (b2) where only 2 LTP states are present and the ULBP and LLBP codes are not complements of each other. Hence, RLBP cannot be applied to ULBP and LLBP to obtain a feature that is robust to the reversal intensity between the objects and background.

In order to alleviate this problem of LTP, need to analyze the 3-state LTP definition in (2): 1, 0 and −1. The state of 0 represents regions of small variations, noise and uniform regions. It will not change when there is an inversion of brightness between the background and objects as the variations remain the same. Hence for a pair of brightness inverted object/background patterns, only the state of −1 is inverted to 1 and vice-versa. Hence, for every LTP code, we can find its corresponding inverted code, for instance, −1-100 1100 has an inverted code 1100 −1-100. If both codes are mapped to a one bin then a feature is robust to the reversal in intensity between the objects and background can be obtained

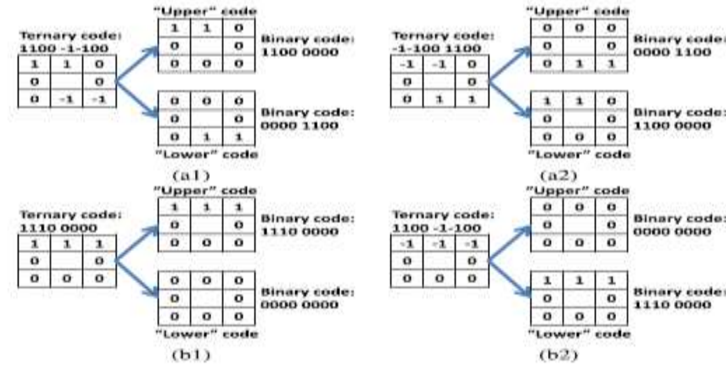


Fig.2: Illustration of ULBP and LLBP codes of LTP for 2 situations where the intensities are reversed. It can be seen that the ULBP and LLBP codes are reversed for the 2 situations.

The maximum of a LTP code and its inverted representation is chosen. It name as *Robust* LTP (RLTP). Mathematically, RLTP is formulated as follows:

$$RLTPxy = \max\{LTPx,y - LTPx,y\} \tag{5}$$

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

$$URPLBP = \sum_{b=0}^{B-1} h(RLTPx,y,b)2^b \tag{6}$$

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

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

$$LRPLBP = \sum_{b=0}^{B-1} h'(RLTPx,y,b)2^b \tag{7}$$

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

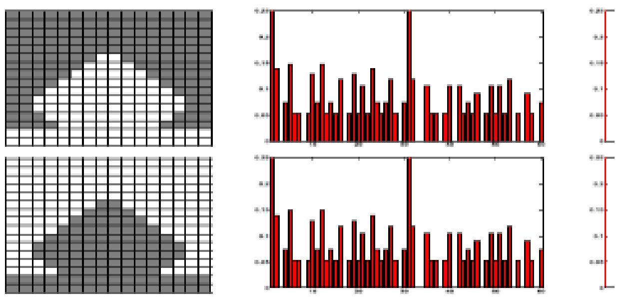
The most significant bit of LRLBP is 0 as the state at (B−1)th location of RLTP is either 0 or 1. Fig. 1(d) illustrates how RLTP alleviates the brightness reversal problem of object and background and observing that for the two situations, the RLTP features are the same.

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

Discriminative Robust Local Ternary Patterns(DRLTP)

LTP and RLTP are also robust to illumination and contrast variations and only capture texture information. The *kth* weighted LTP bin value of a $M \times N$ image block is as follows:

$$h_{ltp}(k) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} w_{x,y}\delta(LTP_{x,y}) \qquad (8)$$



DRLBP

Fig. 3: Same DRLBPs and DRLTPs are produced for the two intensity reversed patterns in Fig. 1. The similarity values using histogram intersection is 1 for both features.

EFFICIENT COMPUTATION OF DRLTP USING ULBP AND LLBPP

Using LTP to find RLTP, DLTP and DRLTP is computationally intensive and requires a large storage requirement. For B = 8, the number of LTP codes is 6561. To generate the RLTP and DLTP histograms from the LTP histogram, there are 3280 addition and subtraction operations respectively. This is followed by 8 addition operations for each RLTP and DLTP code to find the "upper" LBP code and 8 addition operations to find the "lower" LBP code. If the "upper" and "lower" LBP codes of RLTP and DLTP can be produced directly from the split LBP codes of LTP, the computational complexity and storage requirements will be greatly reduced.

The behaviors of ULBP (3) and LLBP (4) for object/background intensity inverted situations are analyzed as follows. Suppose there is a bright object against a dark background. Consider a neighborhood with an object boundary. Assume that the centre pixel resides in the background and differences between the object pixel values and the centre pixel value are larger than the threshold, T. The differences between the background pixel values and the centre pixel value are in between T and −T. The ULBP bits corresponding to the object are 1 while others are 0. Also the LLBP bits are all 0. When the brightness is now inverted for the situation, all ULBP bits are 0 and the LLBP bits corresponding to the object are 1 while the rest are 0. The brightness inversion turns LLBP into ULBP and ULBP into LLBP.

Now, assume that the centre pixel does not belong to the background or object. Instead, it has a value between the bright object and dark background pixel values. The absolute differences of the object and the centre pixel and the background and the centre pixel are larger than T. The ULBP bits corresponding to the object are 1 while the rest are 0. The LLBP bits corresponding to the background are 1 while others are 0, when the intensity is now inverted in the situation the ULBP bits corresponding to the background are all 1 and remain are 0. Similarly, the LLBP bits corresponding to the object are 1 while the rest are 0. Again, the intensity inversion turns LLBP into ULBP and ULBP into LLBP. Because of this analysis, we find that the ULBP and LLBP codes for object/background intensity inverted situations are exchanged. If they are rearranged such that the "upper" and "lower" codes for both situations are same and RLTP is achieved. For any LTP code, the URLBP code is defined as follows:

$$URLBP = \max\{ULBP, LLBP\} \qquad (9)$$

The *LRPBP* code is defined as follows:

$$LRLBP = \min\{ULBP, LLBP\} \qquad (10)$$

By producing *URLBP* and *LRLBP* codes for any LTP code. As RLTP is obtained in the split LBP code representation. For the situation where *ULBP* = 0 and *LLBP* = 0, only 1 LBP result is considered and assigned to *LRLBP*. In Fig.1 (a) and (b), for each case, the LBP codes of the 2 intensity inverted LTP codes are reversed. For instance, in Fig. 1(a1), the *ULBP* code is the *LLBP* code in (a2). Similarly, the *LLBP* code is the *ULBP* code in (a2). By following (8) and (9), we can obtain the *URLBP* and *LRLBP* easily from *ULBP* and *LLBP* for both cases.

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

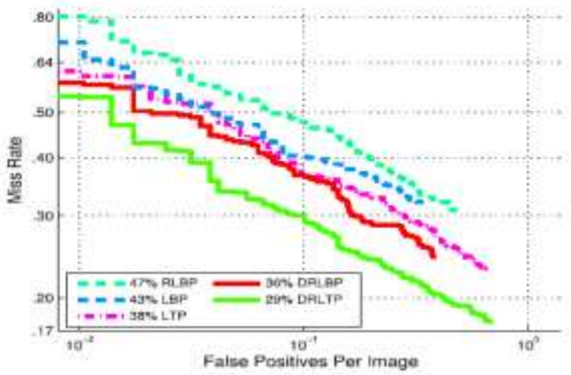


Fig. 4: Performance of DRLBP and DRLTP against LBP, LTP and RLBP. DRLTP outperforms all other methods.

PERFORMANCE COMPARISON OF DRLBP AND DRLTP AGAINST LBP, LTP AND RLBP

We compare the performance of DRLBP; DRLTP opposite to LBP, LTP and RLBP on INRIA for detection and on Caltech 101 for classification, INRIA training set contains 2416 cropped positive images and 1218 uncropped negative images. The sliding image window size is 128 × 64 pixels. By randomly take 10 samples from each negative image to obtain a total of 12180 negative samples for training the linear SVM classifier. Bootstrapping is then performed across multiple scales at a scale step of 1.05 to obtain hard negatives which are added to the original training set for retraining. The INRIA test set consist of 288 images and scanned over multiple scales at a scale step of 1.05, after that window stride is 8 pixels in the x and y directions. The miss rate (MR) against false positives per image (FPPI) (using log-log plots) is plotted to compare between different detectors. The log-average miss rate (LAMR) is used to summarize the detector performance which is computed by averaging the miss rates at nine evenly spaced FPPI rates in the range 10−2 to 100. If any of the curves end before reaching 100, the minimum miss rate achieved is used.

CONCLUSION

Here, the 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 and LBP and LTP differentiate a bright object against a dark background and vice-versa. Because of this, the object intra-class variations larger. By choosing the minimum of a LBP code and its complement RLBP solves the LBP problem. However, RLBP detect LBP codes and respective complement in the same block to the same value.

Furthermore, LBP, LTP and RLBP discard contrast information. This is not require for object texture and contour both contain discriminative information and capturing only the texture information, so the representation of contour is not effective. The new features, DRLBP and DRLTP proposed by analyzing the weaknesses of LBP, LTP and RLBP and they alleviate the problems of LBP, LTP and RLBP considering both the weighted sum and absolute difference of the bins of the LBP and LTP codes with their respective complement codes. New features are robust to image variations caused by the intensity inversion and are discriminative to the image structures within the histogram block. The results of the proposed features on 7 data set and compare them with several methods for object recognition. Results shows that the proposed features outperform the compared recognition approaches on most data sets.

REFERENCES

1. S. Agarwal, A. Awan, and D. Roth, "Learning to detect objects in images via a sparse, part-based representation," IEEE Trans. Pattern Anal. Mach. Intell., vol. 26, no. 11, pp. 1475–1490, Nov. 2004.
2. T. Ahonen, A. Hadid, and M. Pietikainen, "Face description with local binary patterns: Application to face recognition," IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 12, pp. 2037–2041, Dec. 2006.
3. H. Bay, A. Ess, T. Tuytelaars, and L. J. V. Gool, "Speeded-up robust features (surf)," Comput. Vis. Image Understand., vol. 110, no. 3, pp. 346–359, 2008.
4. O. Boiman, E. Shechtman, and M. Irani, "In defense of nearest-neighbor based image classification," in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., Jun. 2008, pp. 1–8.
5. B. Caputo, E. Hayman, and P. Mallikarjuna, "Class-specific material categorisation," in Proc. IEEE Int. Conf. Comput. Vis., vol. 2. Oct. 2005, pp. 1597–1604.
6. J. Chen et al., "WLD: A robust local image descriptor," IEEE Trans. Pattern Anal. Mach.

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

Intell., vol. 32, no. 9, pp. 1705–1720, Sep. 2010.

7. 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.
8. H. Deng, W. Zhang, E. Mortensen, T. Dietterich, and L. Shapiro, “Principal curvature-based region detector for object recognition,” in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., Jun. 2007, pp. 1–8.
9. P. Dollar, C. Wojek, B. Schiele, and P. Perona, “Pedestrian detection: An evaluation of the state of the art,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 34, no. 4, pp. 743–761, Apr. 2012.
10. L. Fei-fei, R. Fergus, and P. Perona, “One-shot learning of object categories,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 4, pp. 594–611, Apr. 2006.
11. R. Fergus, P. Perona, and A. Zisserman, “Object class recognition by unsupervised scale-invariant learning,” in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., vol. 2. Jun. 2003, pp. 264–271.
12. A. Fernández, M. Álvarez, and F. Bianconi, “Texture description through histograms of equivalent patterns,” J. Math. Imag. Vis., vol. 45, no. 1, pp. 1–27, 2012.
13. J. Gall and V. Lempitsky, “Class-specific hough forests for object detection,” in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., Jun. 2009, pp. 1022–1029.
14. P. Gehler and S. Nowozin, “On feature combination for multiclass object classification,” in Proc. IEEE Int. Conf. Comput. Vis., Oct. 2009, pp. 221–228.
15. C. Geng and X. Jiang, “Face recognition based on the multi-scale local image structures,” Pattern Recognit., vol. 44, nos. 10–11, pp. 2565–2575, 2011.