Special Issue - 2015 International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
NCICCT-2015 Conference Proceedings

Object Recognition using Adaptive Threshold Based DRLBP for Feature Extraction

Gargi Vijayan
M-Tech Student ,Department of ECE
Jawaharlal College of Engineering and Technology
India

Lincy K
Assistant Professor,Department of ECE Palakkad, Kerala,
Jawaharlal College of Engineering and Technology
Palakkad, Kerala, India

***Abstract*—Feature extraction is a vital step in object recognition. Two new adaptive threshold based feature extraction method is used. Discriminative robust local binary and ternary pattern based on adaptive threshold differentiates background from the object and vice versa .It is also robust to rotation invariance. Detecting humans in images is a challenging task owing to their variable appearance and the wide range of poses that they can adopt. The first need is a robust feature set that allows the human form to be discriminated cleanly, even in cluttered backgrounds under difficult illumination**

***Index Terms*— Object recognition, local binary pattern, local ternary pattern, feature extraction, adaptive threshold.**

I. INTRODUCTION

Object recognition is the method of finding and identifying objects in an image or moving image sequences. Humans recognize a large number of objects in images with little effort, despite of the truth that the image of the objects may vary according to different viewpoints, in many different sizes and scales or even when they undergo various compression operations such as cropping ,translation or rotation. Objects can also be recognized when it is partially obstructed from view. This objective is still a challenge for computer vision systems. Many approaches t have been implemented over many decades. Perception of objects is different for humans and computers. In case of humans object recognition is perception of familiar items whereas for computers it is the perception of familiar patterns. For this reason object recognition is also called as pattern recognition. Arrangement of feature descriptors forms a pattern. Many forms are there to represent descriptors, but they are primarily vectors and strings. Object recognition is the process by which observers recognizes three-dimensional objects despite receiving only two-dimensional input which varies greatly depending on viewing conditions. Object detection is the final step in image processing. It includes: separate object detection, three dimensional descriptions of their geometry and positions, classification into different classes, and knowing spatial relationships within objects. An object recognition algorithm depends on matching, learning, or pattern recognition algorithms. These algorithms in turn rely on appearance-based and feature-based techniques. Common methods include Histogram of oriented gradients (HOG), Haar wavelets and linear binary patterns. Object recognition found its applications such as : image, video stabilization, automated vehicle parking systems and in counting in bio-imaging etc.

II. LOCAL BINARY PATTERN AND LOCAL TERNARY PATTERN

A. LOCAL BINARY PATTERN

LBP (Local Binary Pattern) is one of the feature descriptors used in computer vision for classification. LBP can be considered as a Texture Spectrum model. It acts as a powerful feature for texture classification. Furthermore, combining LBP with the Histogram of oriented gradients (HOG) descriptor results in improvement of the detection performance considerably on some datasets. The basic form of LBP is illustrated in figure below. Specifically, a local neighbourhood around each pixel as input and then threshold the neighbourhood pixels at the value of the central pixel.

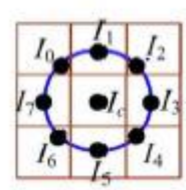

Fig. 1. A pixel and eight neighbours

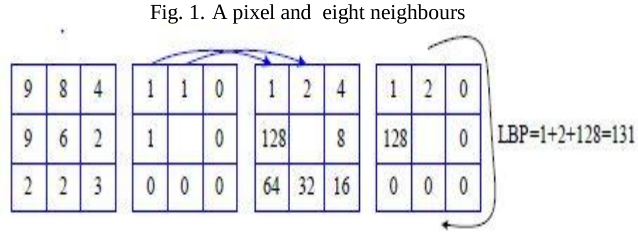

Fig. 2. Basic LBP

The resulting binary-valued string is weighted as follows:

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

where the parameter B varies over the eight neighbours of the central pixel value Pc. Pi and Pc are the gray scale values at positions i and c, and R(V) is 1 if V ≥ 0 and 0 otherwise. Uniform patterns are one of the extensions of LBP: an LBP is said to be 'uniform' if the maximum number of transitions from 0-1 or 1-0 is two when viewing it as a circular bit string (e.g., 10011111 is a uniform pattern). Histogram of the operator outputs (i.e., pattern labels) accumulated over a texture sample is the final texture sample used in the analysis. On comparing the histogram of uniform patterns with histogram of individual patterns, the latter will show better discrimination

Consider the above case for calculating LBP that B=8 and Radius R as 1, i.e., it is represented as LBP (8,1), where the quantization of the angular space is controlled by the parameter Q , and the spatial resolution of the operator is determined by R. The histogram of LBP (8, 1) of an image P is to be H. Before mapping in to a uniform pattern the histogram of LBP (8,1) has 256 bins . The histogram of uniform pattern is represented by Hu and the mapping function is given by:

$$H_u = F(H)$$

B. LOCAL TERNARY PATTERN

LTP (Local Ternary Pattern) is one of the extensions of LBP. In case of LTP, the pixel value into three values 0,1and -1. After thresholding these neighboring pixels are combined to form ternary pattern. Since large range of values are formed as a result of computation of these ternary values, so the ternary pattern is splitted into two binary patterns. Resulting Histograms are concatenated to form a descriptor of double the size of LBP. Let T be the threshold constant, c be the center pixel value and the neighboring pixel be n, then the result of threshold is given by:

$$LTPx,y = \sum_{b=0}^{B-1} s'(Z_b - Z_c)2^b \qquad (2)$$

In this way, each pixel has one of the three threshold values. These neighboring pixels are then combined to form ternary pattern after thresholding.

III. ROBUST LBP AND ROBUST LTP

A. ROBUST LBP

(RLBP) Robust Local Binary Pattern found its application in many domains, such as texture classification, human detection and face recognition. A disadvantage of LBP is that it is not robust to the presence of noise in the image. The robustness of LBP is acquired by its ability to change the coding bit. RLBP outperforms all other descriptors.

Computation method of RLBP from LBP is shown in figure. Let Z_c represents the center pixel. The LBP pattern string given by its neighbouring pixel is (11010011). If, the pixel value of Z_2=124 .Here the probability of pixel being noisy is high since it results in a substring (101). If the corresponding bit in LBP string of Z_2 is changed from 0 to 1, the new LBP string of pixel is formed as (11110011).It denotes the local corner, and represents more meaningful pattern for the texture and for classification process. In case of LBP with Q=8 and R=1, i.e., LBP (8,1), any neighboring three-bit substring of these eight-bit LBP pattern string is one of the following sets $Z=\{Z_1=(000), Z_2=(001), Z_3=(010), Z_4=(011), Z_5=(100), Z_6=(101), Z_7=(110), Z_8=(111)\}$.Let us consider the case of Z_3 and Z_6 as noisy and they are changed to new sub-strings: Z'_3= (000), and Z'_6= (111). If an image is represented by p, its histogram of LBP (8,1) is given by H, and has 256 bins before mapping into uniform pattern. All of its neighboring three-bit substrings are searched for each bin Hi of H (i = 0,….255),, and map its Z_3 or Z_6 to Z'_3 or Z'_6, respectively. The mapping function is given by:

$$RHs = F(Hi),$$

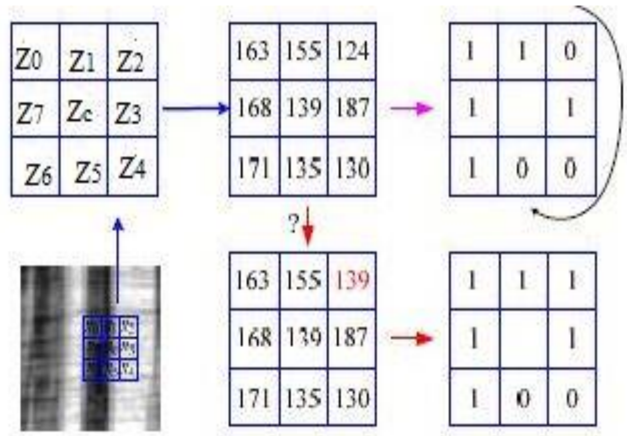

Fig. 3. Robust Local Binary Pattern

B. ROBUST LTP

Robust Local Ternary Pattern (RLTP) found its applications in large number of domains, such as texture classification, human detection and face recognition. An disadvantage of LTP is that it is not so robust to the noise present in the image which is lightly solved by RLTP.

IV. PROPOSED WORK

The project presents the robust object recognition using edge and texture feature extraction. The system proposes new approach in extension with local binary pattern and ternary pattern called discriminative local binary pattern (DRLBP) and discriminative local ternary pattern (DRLTP).The DRLBP is used for different object texture and edge contour feature extraction process. Since DRLBP and DRLTP considers only the signs of the pixel differences it is robust to illuminations and contrast variations. The proposed features retain the contrast information of image patterns. They contain both edge and texture information which is desirable for object recognition. Object surface texture and the object shape formed by its boundary are used by DRLBP to discriminates different objects. Much higher contrast between the object and the background are shown by the boundaries than the surface texture. Since the boundary contains the shape information an additional discriminatory information is brought by differentiating the boundary from the surface texture. Maximum number of samples are accurately distinguished by using these features and for similar category classification it is matched with already stored image samples. Two distinct cues are used to differentiate an object from other objects .It differentiates the object surface texture and the object shape formed by its boundary. Much higher contrast between the object and the background is shown by the boundary than that of the surface texture. An additional discriminatory information is shown by differentiating the surface from the boundary since the boundary contains the shape information. Using adaptive thresholded DRLBP and DRLTP improves feature extraction process taking more number of variations.

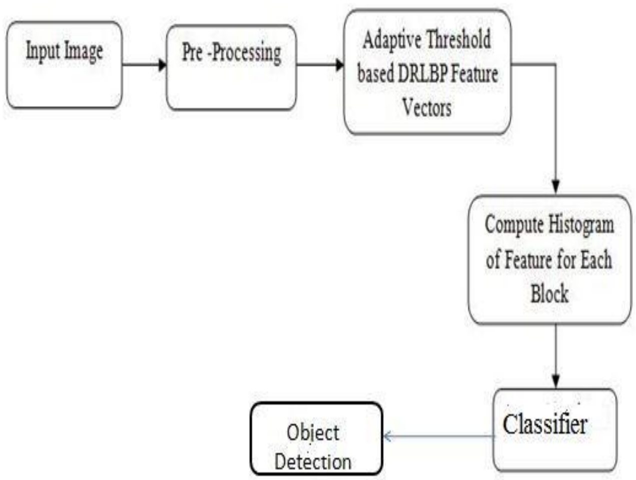

Fig. 4. Proposed System

LBP does not differentiate between a weak contrast local pattern and a strong contrast one because of this feature it is robust to illumination and contrast variations. The object texture information is mainly captured by it. only the frequencies of the codes are only considered for histogramming of LBP codes i.e. the weight for each code is the same. A difficulty is made due to this in differentiating a weak contrast local pattern and a strong contrast one.

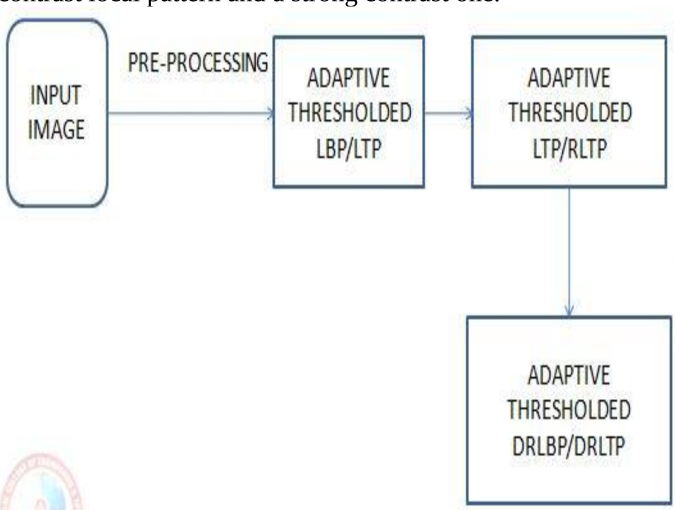

Fig. 5. Adaptive Thresholded DRLBP/DRLTP

The issues of LBP, LTP and RLBP are solved using DRLBP and DRLTP. The intensity reversal problem of object and background is also reduced by this .In additional DRLBP discriminates local structures that is not found in RLBP misrepresent. The proposed features retain the contrast information of image patterns. Both edge and texture information desirable for object recognition is contained in it. DLBP feature extracted using adaptive threshold method for an input image of size 259 *194 is shown below:

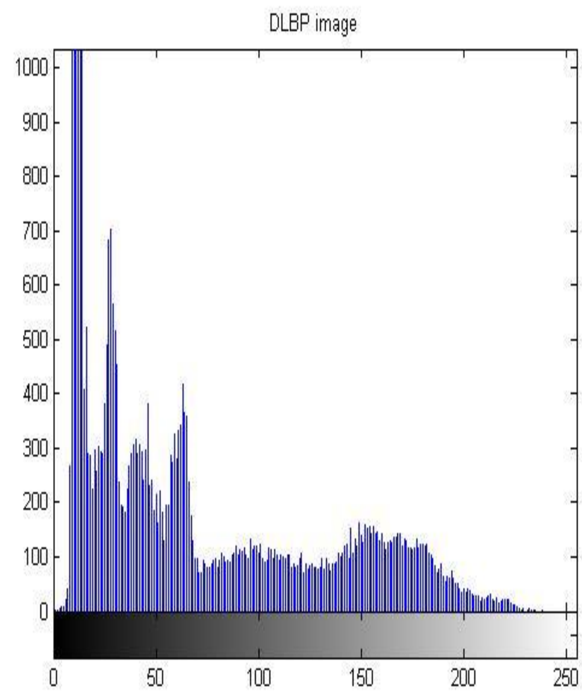

Fig. 6. DRLBP Feature Descriptors

A. *ADAPTIVE THRESHOLD*

Adaptive threshold takes a gray scale or color image as input and, provides binary image as output which represents the edge information. A threshold value is automatically calculated for each pixel in an image. After comparison if the pixel value is below the threshold, it is set to the background value; otherwise it is given foreground value.

In many applications of image processing, the gray levels of pixels of an object are quite different from the gray levels of the pixels belonging to the background. Thresholding is a useful method to differentiate objects from the background. Thresholding found its applications in many areas such as document image analysis ,here the function is to extract printed characters, logos, graphical content, musical scores, map processing in which lines, legends, characters are detected, scene processing where a target is to detected , inspection of quality of the materials . Other applications include cell images and knowledge representation, segmentation of various image modalities for non-destructive testing (NDT) applications, such as ultrasonic images in, eddy current images , thermal images , X-ray computed tomography (CAT) , laser scanning ,confocal microscopy , edge field extraction , general image segmentation , spatio-temporal segmentation of video images etc. The thresholding operation will results in a binary image whose gray level of 0 (black) will indicate a pixel belongs to foreground and the background is indicated by. gray level of 1 (white).

If the noise associated with an application is non-stationary, correlated and non-Gaussian the process of thresholding become difficult. Other factors which affects the thresholding process includes ambient illumination, variance of gray levels within the object and the background, inadequate contrast, object shape and size non-commensurate with the scene. Another negative effect is the lack of objective measures to assess the performance of thresholding algorithms. Thresholding algorithms depends on the exploitation of 1) Histogram entropy information, 2) Histogram shape information, 3) Image attribute information such as contours, 4) Clustering of gray-level information, 5) Locally adaptive characteristics, 6) Spatial information.

The foreground (object) and background probability mass function's will be expressed as $m_f(g),\ 0 \le g \le T$, and $m_b(g), T+1 \le g \le G,$ respectively, where T is the threshold value. The foreground and background area probabilities are calculated as:

$$m_f(T) = m_f = \sum_{g=0}^{T} m(g) \tag{3}$$

$$m_b(T) = m_b = \sum_{g=T+1}^{G} m(g) \tag{4}$$

The fuzzy measures attributed to the background and foreground events, that is the degree to which the gray level; g, belongs to the background and object.

V. CONCLUSION

Drawback of the existing texture features, such as Local Binary Pattern, Local Ternary Pattern and Robust LBP are led to extraction of new features adaptive threshold based DRLBP and DRLTP. Adaptive threshold based DRLBP and DRLTP are proposed by analyzing the weakness of LBP, LTP and RLBP. The weighted sum and absolute difference of the bins of LBP code and LTP code with their complement codes are considered to solve the problem of others. The objects in the image can be further analyzed for the exact location of the object in the given image by this proposed feature.

VI. IMPLEMENTATION

The tool used for the implementation of the work is MATLAB. MATLAB (matrix laboratory) is a multi-paradigm numerical computing environment. Developed by MathWorks, MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C++, Java, and Fortran . MATLAB is widely used in academic and research institutions as well as industrial enterprises. The implementation of this project is divided in to two parts. The first part of the work includes pattern based object recognition and in second phase implementation is based on classifier.

VII. SCOPE OF WORK

The concept of using patterns for object recognition using edge-texture features can be effectively extended to the fields such as Image water marking, Face detection ,Object counting and monitoring ,Content-Based Image Indexing ,Visual Positioning and tracking etc.

ACKNOWLEDGEMENT

I would like to thank my guide Ms. Lincy k, assistant professor, department of electronics and communication engineering Jawaharlal college of engineering and technology Palakkad for her unwavering support and valuable suggestions for successful completion of this first phase of the project

REFERENCES

[1] A. Fernández, M. Álvarez, and F. Bianconi, “Texture description through histograms of equivalent patterns,” J. Math.Image. Vis., vol. 45, no. 1, pp. 1–27, 2012

[2] Gustaf Kylberg and Ida-Maria Sintorn ,“Evaluation of noise robustness for local binary pattern descriptors in texture classification”, EURASIP Journal on Image and Video Processing 2013 .

[3] 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.

[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] J. Mutch and D. Lowe, “Multiclass object recognition with sparse,localized features,” in *Proc. IEEE Int. Conf.* Comput. Vis. Pattern Recognit., vol. 1. Jun. 2006, pp. 11–18

[6] J. Chen et al., “WLD: A robust local image descriptor,” IEEE Trans.Pattern Anal. Mach. Intell., vol. 32, no. 9, pp. 1705–1720, Sep. 2010.

[7] J. Maver, “Self-similarity and points of interest,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 32, no. 7, pp. 1211–1226, Jul. 2010.

[8] Pooja Kamavisdar, Sonam Saluja,and Sonu Agrawal" A Survey on Image Classification Approaches and Techniques ", International Journal of Advanced Research in Computer and Communication Engineering Vol. 2, Issue 1, January 2013,.