Dominant Local Binary Pattern Based Face Feature Selection And Detection

Anusha Bamini.A.M[#1], Kavitha.T[#2]
[#1] *Computer Science and Engineering, Anna University Tirunelveli, India*
[#2] *Lecturer, Computer Science and Engineering, Anna University Tirunelveli, India*

***Abstract* - Face Detection plays a major role in Biometrics. Feature selection is a problem of formidable complexity. This paper proposes a novel approach to extract face features for face detection. The LBP features can be extracted faster in a single scan through the raw image and lie in a lower dimensional space, whilst still retaining facial information efficiently. The LBP features are robust to low-resolution images. The dominant local binary pattern (DLBP) is used to extract features accurately. A number of trainable methods are emerging in the empirical practice due to their effectiveness. The proposed method is a trainable system for selecting face features from over-completes dictionaries of image measurements. After the feature selection procedure is completed the SVM classifier is used for face detection. The main advantage of this proposal is that it is trained on a very small training set. The classifier is used to increase the selection accuracy. This is not only advantageous to facilitate the data-gathering stage, but, more importantly, to limit the training time. CBCL frontal faces dataset is used for training and validation.**

Keywords:
Face features, feature selection, dominant local binary pattern, Support Vector Machine.

I. INTRODUCTION

The face detection plays a major role in biometrics. Various methods involved in biometrics. But some method will be efficient. Acceptable by all and have the uniqueness. Used in all area for perfect authentication purpose, such as ports, airports, criminal identification, employee identification, etc. Extracting features from the face and train the dataset with face employee identification, etc. Extracting features from the face and train the dataset with face features. By comparing these features with the given input picture the face detection is performed. The input may be photo, picture, or video, anything. Train dataset with face and non-face examples.

LBP was proposed originally for texture analysis [3, 4]. The face images can be seen as a composition of micro-patterns which can be well described by LBP. A facial image is divided into a set of small regions from which LBP histograms are extracted and concatenated into a single, spatially enhanced feature histogram. The simple LBP features can be fast derived in a single scan through the raw image, whilst still retaining enough facial information in a compact representation.

The number of trainable methods present in the paper [3]. Lasso is least absolute shrinkage and selection tool used to select features. It will set the wanted pixels to one and the unwanted pixels to zero. One drawback of this paper is select background pixels with the face features. Support Vector Machine (SVM) is a classifier used to classify the face and non-face images. One of the best classifier compared to other techniques.

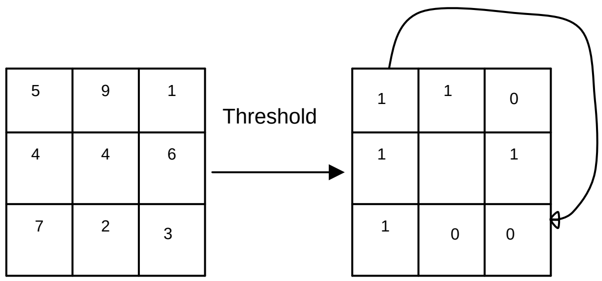
Features extracted using rectangle features [4]. The sub-window is resized by 24x24. But in this the size of the sub-window is 19x19. We decrease the size of the dataset because of increasing the performance and reduce the training time. In Adaboost based face detector paper the boosting method is presented for face detection.

First train dataset with number of face and non-face examples. When the number of training rate increases the accuracy of result also increases. The training faces are taken from the CBCL dataset. It contains only pictures. From that cut the face with 19x19 window and train the dataset. After train our dataset the input image is given by picture, photo, video, or by digital camera.

The paper is organized as follows. In Section II, we describe the local binary pattern which will be the main ingredient of our feature selection method. In Section III, we introduce the dominant local binary pattern scenario. The face detection method using SVM classifier is illustrated in Section IV, whereas the experimental analysis described in Section V. Section VI contains our conclusions and future work.

II. LOCAL BINARY PATTERNS

The original LBP operator was introduced by Ojala et al [8]. The operator labels the pixels of an image by thresholding the 3 X 3 neighbourhood of each pixel with the center value and considering the result as a binary number. Then the histogram of the labels can be used as a texture descriptor.



Binary: 11010011

Fig 1.The basic LBP operator

The limitation of the basic LBP operator is its small 3 X 3 neighbourhood can not capture dominant features with large scale structures. Hence the operator was extended to use neighbourhood of different sizes [9]. Using circular neighbourhoods and bilinearly interpolating the pixel values allow any radius and number of pixels in the neighbourhood.

At a center pixel t_c, each neighboring pixel is assigned with a binary label, which can be either "0" or "1," depending on whether the center pixel has higher intensity value than the neighboring pixel (see Fig. 1 for an illustration). The neighboring pixels are the angularly evenly distributed sample points over a circle with radius R centered at the center pixel. The LBP label for that center pixel is given by,

$$LBPm,R = \min_{0 \le n < m} \left\{ \sum_{i=0}^{m-1} u(ti - tc) 2 \left[(i+n) \bmod m \right] \right\} \qquad (1)$$

Where t_c represents the center pixel, t_i is the ith neighboring pixel, $i = 0,\ldots,m-1$, m is the total number of neighboring pixels, R is the circle radius which determines how far the neighboring pixels are located away from the center pixel, and $u(x) = 1$ if $x \ge 0$ else $u(x) = 0$. The value of m is assigned according to the value of R as suggested in [19]. In our implementation, $m = 8$ when $R = 1$; $m = 16$ when $R = 2$; and $m = 24$ when $R = 3$. It is noted that computing LBP based on (1) is a rotation invariant operation. Rotating an image causes the circular shifting of the binary labels at locations t_o, $t_1, \ldots,$ and t_{m-1}. This shifting effect can be eliminated by finding the minimum value among all possible values of in (1). This minimum value denotes the rotation invariant LBP at the center pixel. Furthermore, the absolute pixel intensity information at t_c and t_i is discarded by using the step function $u(ti - tc)$ in (1) when calculating LBP. Therefore, the LBP operator is not sensitive to histogram equalization.

III. DOMINANT LOCAL BINARY PATTERNS

In the conventional LBP method proposed by Ojala *et al.* [19], only the uniform LBPs are considered. At a pixel, it gives a uniform LBP if the corresponding binary label sequence has no more than two transitions between "0" and "1" among all pairs of the adjacent binary labels. For example, the binary label sequences "10001111" and "00011000" are uniform LBPs. But the sequence "01001111" is not a uniform LBP because it has four transitions. Therefore, we propose to use dominant local binary patterns (DLBPs) which consider the most frequently occurred patterns in a face image. It avoids the aforementioned problems encountered by merely using the uniform LBPs or making use of all the possible patterns, as the DLBPs are defined to be the most frequently occurred patterns. In this paper, it will be demonstrated that a minimum set of pattern labels that represents around 80% of the total pattern occurrences in an image can effectively captures the image feature information for classification tasks. The given algorithm used to determine the highest dominant LBP patterns in the image. Based on the center pixel value and the neighbourhood pixel values the LBP will be determined.

Algorithm: Determining the number of Dominant LBP patterns

Input: Training image set
Output: Number of DLBP patterns occurred

1. Initialize *temp = 0*
2. FOR each image I in the training image set
3. Initialize the pattern histogram, *H = 0*
4. FOR each center pixel *tc Є I*
5. Compute the pattern label of *tc*, LBP(1)
6. Increase the corresponding bin by 1
7. END FOR
8. Find the highest DLBP feature for each face and non-face for SVM training.

Without encapsulating the pattern type information, the DLBP features also possess surpassing robustness against image noise, as compared to the conventional LBP features. Under the effect of image noise, the binary label of a neighboring pixel is possible to be flipped by the intensity distortion induced by noise. Flipped binary labels alter the extracted LBPs. As a result, even though some LBPs are computed on the same type of image structures, the extracted LBP type can vary significantly. In the conventional LBP framework, the pattern types are categorized as uniform patterns or nonuniform patterns. In which, under the effect of image noise, a large amount of useful patterns turns into nonuniform ones that are unconsidered in the conventional LBP method. On the contrary, the DLBP approach processes all 80% dominant patterns disregarding the pattern types. DLBP is capable of encoding the pixel-wise information in the face images.

However, it does not take into account the long range pixel interaction that takes place outside the coverage of its circular neighborhood system, which normally has a radius of 2 or 3 pixels of 2 or 3 pixels.

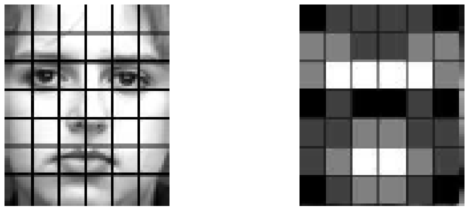


Fig 2.Example result of DLBP. Left: A face image divided into 6X7 sub-region. Right: The weights set for weighted dissimilarity measure. Black squares indicate weight 0.0, dark gray 1.0, light gray 2.0 and white 4.0.

IV. SUPPORT VECTOR MACHINE

Support Vector Machine is a popular technique for classification. SVM performs an implicit mapping of data into a higher dimensional feature space, where linear algebra and geometry can be used to separate data that is only separable with nonlinear rules in the input space. SVM can be used to separate face and non-face images accurately.

Given a training set of labeled examples T = {(x_i; y_i); i = 1,…, l} where $x_i \in R^n$ and $y_i \in$ {1, -1}, the new test data x is classified by the following function:

$$f(x) = \mathrm{sgn}\left(\sum_{i=1}^{l} \alpha i y i K(xi, x) + b\right) \quad \textbf{(2)}$$

where α_i are Lagrange multipliers of a dual optimization problem, and K(x_i, x) is a kernel function. Given a nonlinear mapping Φ that embeds input data into feature space, kernels have the form of K(x_i , x_j) = Φ(x_i).Φ(x_j). SVM finds a linear separating hyperplane with the maximal margin to separate the training data in feature space b is the parameter of the optimal hyperplane.

SVM allows domain-specific selection of the kernel function. Though new kernels are being proposed, the most frequently used kernel functions are the linear, polynomial, and RBF kernels. SVM makes binary decisions. Multi-class classification here is accomplished by a cascade of binary classifiers together with a voting scheme. It will classify face and non-face in the form of,

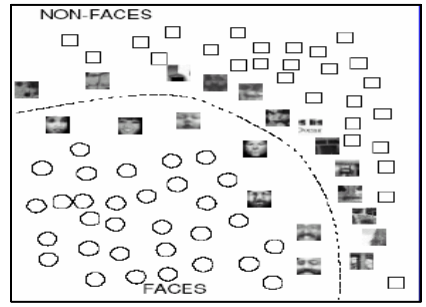


Fig 3.Classification of face and non-face using SVM classifier.

V. EXPERIMENTS

We tested our system on the MIT+CMU frontal face test set [Rowley et al. 1994] and own database. There are more than 2,500 faces in total. To train the detector, a set of face and non-face training images were used. The pairwise recognition framework is evaluated on a compound face database with 2000 face images hand labeled faces scaled and aligned to a base resolution 32 by 32 pixels by the centre point of the two eyes and the horizontal distance between the two eyes. For non-face training set, an initial 10,000 non-face samples were selected randomly from 15,000 large images which contain no face.

The flow of this face detection system is in the form of,

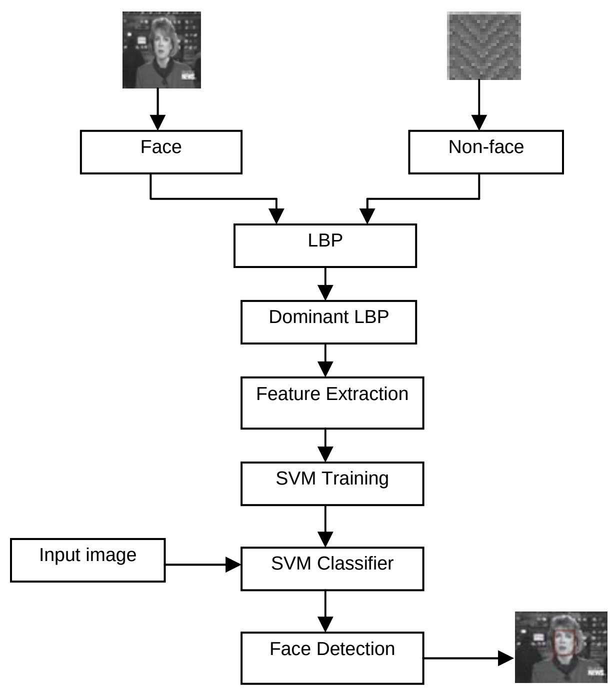


Fig 4.Flow diagram of whole system

The detected faces will be marked by a rectangular region.

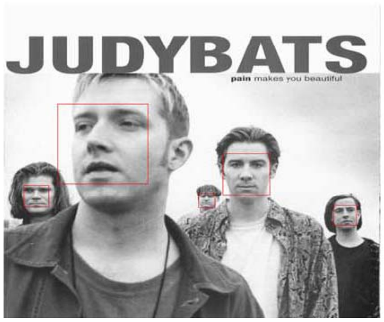


Fig 5.Face detection result

A. Experimental Analysis

We now report on the experiments we performed using the feature selection process described above. We consider 200 subproblems built each time by extracting 10% of the total set of features. We represented the dataset images according to the selected features and defined a training set, a validation set and a test set. Then we trained the DLBP on the training data, tuned the DLBP regularization parameter on the validation set and, finally, evaluated the classification performance on the test set. To this purpose, we built a ROC curve over the test set, varying the offset. In particular we analyzed two points of the ROC curve: the classical equal error rate (e.e.r.), corresponding to an equal percentage of false positives and false negatives, and the error rate corresponding to a small false positive rate, useful for the particular case of object detection in which the ratio between positive and negative examples on a random image is small.

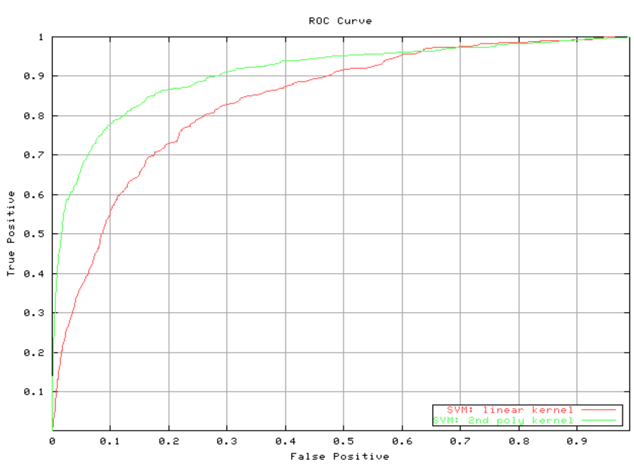


Fig 6.ROC curve

VI. CONCLUSION AND FUTURE WORK

This paper presented a new method for face detection using Dominant Local Binary Patterns. Compared with Sparsity enforcing method, the simple DLBP features save much computational resource whilst retaining facial information efficiently. Extensive experiments demonstrate that the DLBP features are discriminative and robust over a range of facial image resolutions, which is critical in real-world applications where only low-resolution video input is available. Compared to Sparsity enforcing method the DLBP method gives the time and speed efficiency. By using the SVM classifier the detection accuracy is increased, and the false detection rate will be reduced.

The future work of this will be the face authentication (Recognition) process. Face Recognition is one of the main process after the detected face. This is used for criminal identification, gender classification, company monitoring system, facial expression recognition, authentication in bank.

REFERENCES

[1] Augusto Destrero, Christine De Mol, “A Sparsity-Enforcing Method for Learning Face Features”, VOL. 18, No.1, January 2009.
[2] S. Liao, Max W. K. Law, and Albert C. S. Chung “Dominant Local Binary Patterns for Texture Classification”, IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 18, NO. 5, MAY 2009
[3] T. Ojala, M Pietikinen, and D. Harwood,”A comparative study of texture measures with classification based on featured distribution”,. *Pattern Recognition*, vol. 29, no. 1, 1996.
[4] T. Ojala, M. Pietikinen, and T. Menp, “Multiresolution grayscale and rotation invariant texture classi_cation with local binary patterns”,. *IEEE PAMI*, vol. 24, no. 7, July 2002.
[5] M.S. Bartlett, G. Littlewort, I. Fasel, and R. Movellan, “Real time face detection and facial expression recognition: Development and application to human computer interaction”,. In *CVPR Workshop on CVPR for HCI*, 2003.
[6] F. Fleuret and D. Geman, “Coarse-to-fine face detection,” *Int. J. Comput. Vis.*, vol. 41, pp. 85–107, 2001.
[7] I. Guyon and E. Elisseeff, “An introduction to variable and feature selection,” *J. Mach. Learn. Res.*, vol. 3, pp. 1157–1182, 2003.
[8] B. Heisele, T. Serre, M. Pontil, and T. Poggio, “Component-based face detection,” presented at the CVPR, 2001.
[9] B. A. Olshauser and D. J. Field, “Sparse coding with an overcomplete basis set: A strategy employed by V1?,” *Vis. Res.*, vol. 37, no. 23, pp. 3311–3325, 1997.
[10] D. Roth, M. Yang, and N. Ahuja, “A snowbased face detector,” *Neur. Inf. Process.*, vol. 12, 2000.
[11] K. Sung and T. Poggio, “Example-based learning for view-based human face detection,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 20, no. 1, pp. 39–51, Jan. 1998.
[12] R. Tibshirani, “Regression shrinkage and selection via the lasso,” *J Roy. Statist. Soc. B*, vol. 58, no. 1, pp. 267–288, 1996.
[13] P. Viola and M. J. Jones, “Robust real-time face detection,” *Int. J. Comput. Vis.*, vol. 57, no. 2, pp. 137–154, 2004.