An Efficient Face Detection and Recognition System

Vaidehi V[1], Annis Fathima A[2], Teena Mary Treesa[2], Rajasekar M[2], Balamurali P[3], Girish Chandra M[3]

***Abstract*-In this paper, an efficient Face recognition system based on Haar wavelet and Block Independent Component Analysis (BICA) algorithm is presented. The Adaptive boosting classifier is trained with Haar features to classify and to detect face. To recognize the detected face, the dimensionality reduced approach of Independent Component analysis; BICA is used. This system is capable of detecting the presence of faces in the field of view of camera in real time and verify the person's identity if the image of the person is already been trained by the system. The system is able to detect the face even with slight occlusions and under varying illumination conditions, improving the recognition significantly.**

***Index Terms*-Face detection, Face recognition, Haar-wavelet, BICA, Adaboost classifier.**

I. Introduction

The increased need of security in the state, both in constrained and unconstrained areas and the rapid development of the computer vision techniques paved the way for progress of the person detection and identification system. Such systems can be employed in surveillance and monitoring, biometrics, traffic assistance, health care, etc. Face detection is differentiating the face from any other objects (inter-class variability). Face recognition is differentiating one's face from the other (intra-class variability).

Detection and recognition of human face poses more challenges than detecting any other object as the skin color and facial expression varies dynamically. In the real time process illumination conditions, occlusion, background structure and camera positions adds on to the existing challenges.

Human detection techniques can be divided into two types sub-window based and part based approaches. Sub-window based approaches can be based on different types and combinations of features, such as histograms of oriented gradients (HOG) [8], covariance matrices [9], combination of several features [10] and multi-level versions of HOG [11]. Part-basedapproaches split the body into several parts that are detected separately and, finally, the results are combined.

The detection algorithm has two important processing steps: feature extraction and detection. Person detection techniques can be divided into various categories. View-based approaches can handle detecting faces in cluttered scenes, and have shown a reasonable degree of success when extended to handle non-frontal views.

For efficient face detection system, the system needs to be invariant to illumination conditions, skin color and occlusion (such as beard, mouth mask etc). There is no existing technique that addresses all the variations. The Haar based face detection system for person detection [6], implemented in this work, is a highly robust face detection technique for static images and overcomes these invariations. The motivation for using Haar face detection is that it is an easily trainable system for any object.

For face recognition systems, several holistic and feature based face recognition algorithms are available such as Principal Component Analysis (PCA), Fisher Linear Discriminant analysis, Image Principal Component Analysis (IMPCA), Independent Component Analysis (ICA) [4]. It is observed that these recognition algorithms work well in constrained environment. But face recognition is still an open and very challenging problem in real world applications. The holistic approach to face recognition has the advantage of distinctively capturing the most prominent features within the face image. However, disadvantages of holistic approaches are that the recognition performance could be significantly affected by illumination, orientation and scale.

On the other hand, feature based approaches have the advantage of automatic selection of facial features to uniquely identify individuals. These exhibit robustness in recognition performance despite of variations in lightning conditions, facial expressions, orientation. The BICA is an unsupervised statistical method based on higher-order statistics of data [4].

This paper proposes an integrated system for effective face detection and recognition by combining Haar based face detection with BICA. This proposed scheme provides an efficient solution for tailgating problem. Also the proposed scheme detects the face, recognize the face, checks for the

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[1] Head of the Department of Information Technology, MIT, Anna University, Chennai, India (vaidehi@annauniv.edu).

2 Department of Electronics Engineering, MIT, Anna University, Chennai, India (teenamarytreesa@yahoo.com, annisfathima@yahoo.com, rajamitcn@gmail.com,)

[3] Innovations lab, TCS Bangalore, India

availability of similar face in the database. This paper is organized as follows: section II describes the Haar wavelet based face detection using Adaboost classifier and recognition system using BICA with k-NN classifier; results are discussed in section III and section IV presents conclusion.

II. Face Recognition System

The face recognition system consists of modules for face detection, face recognition system shown in Figure.1. The initial face detection module scans the captured image and detects the human faces. In Face recognition module, for every detected face, BICA features are computed and minimum distance is calculated using KNN classifier.

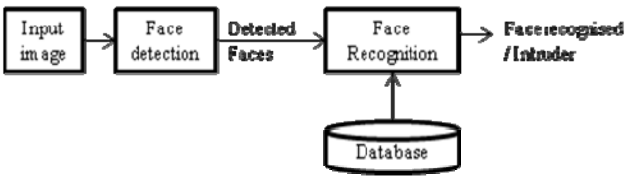


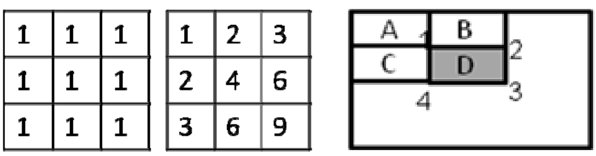
Figure1.Block diagram of Face recognition system

A. *Haar Face Detection*

Haar based face detection algorithm is a sub-window based algorithm with a dense or overcomplete feature set from which effective features are selected using Adaboost algorithm [5]. Haar wavelet features are suitable for rigid objects and are capable of extracting the structural content of an object [6]. Adaboost is the learning based algorithm; boost the performance of simple learning algorithm. The features obtained from a large set of face and non-face samples are trained and classified using a set of weak classifiers.

Haar face detection involves two stages: training stage where the classifier is trained to detect faces and testing stage where the detection of face takes place in real-time. The Haar features computed are overcomplete [1]. Thus the computation of these features as such from the image is time consuming. A faster computation of Haar features is possible using an intermediate representation for the image which we call the integral image.

The integral image at location x, y contains the sum of the pixels above and to the left of x, y, inclusive:



(a) (b) (c)

Figure 2. (a) the input image (b) the computation of integral image for the given input image (c) the computation of rectangular block from the integral image.

$$Integral(x, y) = \sum_{x' \le x, y' \le y} image(x', y')$$

where *Integral(x,y)* is a pixel of the integral image at (x, y) and *image(x',y')* is a pixel of the image at (x', y'). Using the integral image any rectangular sum can be computed in four array references as shown in Figure2(b).

For computing the rectangular feature of block D, the value is given by

$$SumD = Integral_3(x,y) - Integral_4(x,y) - Integral_2(x,y) + Integral_1(x,y)$$

Haar features are the reminiscent of Haar basis functions, which are basically rectangular features. The different templates for extracting features are shown in Figure 3 and each feature is described by the template shape and size. Each feature consists of connected black and white rectangles. The Haar feature's value are calculated as the weighted sum of the two components, the pixel sum over the black rectangle and the sum over the whole area. The weights of the two components are of opposite sign and inversely proportional to the area of their respective rectangles [2]. Eg. for edge Features shown in Figure3(b) the rectangular feature is calculated as

$$Weight_{black} = -3 \text{ x } Weight_{whole}$$

(a) (b) (c) (d)

Figure 3. (a)Line features (b)Edge Features (c)Diagonal features (d)Centre-Surround features

The Haar features are extracted using detector windows of various size. A large set of features larger than the number of pixels is generated for an image and computing the complete set is prohibitively expensive. A very small number of these features can be combined to form an effective classifier. The main challenge is to find these features. This is achieved by a variant of the AdaBoost algorithm that is used to select the features and also to train the classifier. It is discussed in the following section.

B. *Adaboost classifier*

AdaBoost is a greedy feature selection process. The boosting is the combination of a large set of classification functions using a weighted majority vote. The challenge is to associate a large weight with each good classification function and a smaller weight with poor functions. AdaBoost is an aggressive mechanism for selecting a small set of good classification functions which have significant variety.

Boosting is a two-class (yes-or-no) classifier. AdaBoost is used to train T weak classifiers h_m, m={1 … M}. The decision stumps are generally used as simple weak classifiers. The Boosting algorithm is given below:

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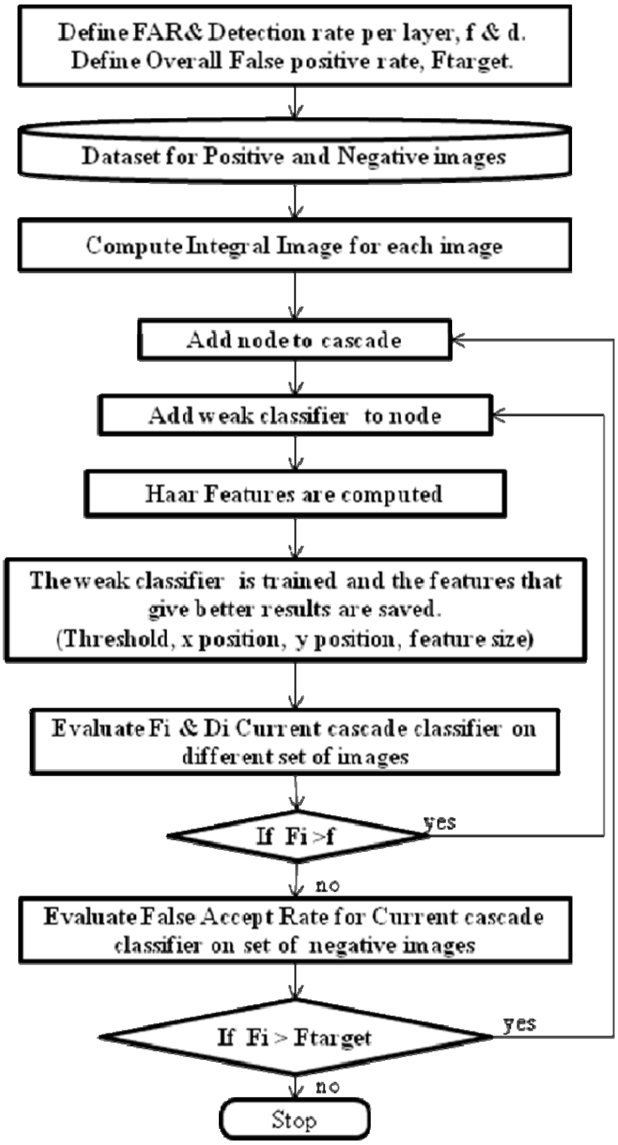

Figure 4.Flowchart for construction of cascaded AdaBoost Classifier

- Given example images $(a_1,b_1) \ldots (a_n,b_n)$ where $b_i = 0,1$ for negative and positive examples respectively.
- The weights are initialized as $w_{1,i} = 1/2r, 1/2s$ for $b_i = 0,1$, where r and s are the number of negative and positive examples.
- For m = 1, . . .,M:
  - Normalize the weights,

$$w_{m,i} \leftarrow \frac{w_{m,i}}{\sum_{j=1}^{n} w_{m,j}}$$

  - The best weak classifier is selected with respect to the weighted error $\varepsilon_m = \min(\sum_i w_i |h_m(a) - b_i|)$
  - Set Threshold function $h_m(a)$, dependent on feature size and position, feature value, such that it minimizes ε_t .
  - Update the weights: $w_{m+1,i} = w_{m,i}\lambda_m^{1-e_i}$ where $e_i = 0$ if given sample is classified correctly, e_i=1 otherwise, and $\lambda_m = \varepsilon_m / (1-\varepsilon_m)$.
  - The final strong classifier is:

$$R(a) = \begin{cases} 1, & \sum_{m=1}^{M} \delta_m h_m(a) \geq \sum_{m=1}^{M} \delta_m \\ 0, & Otherwise \end{cases}$$

where $\delta_m = \log 1/\lambda_m$.

The cascade of classifiers are constructed to increase detection performance and to reduce the detecting time. The training of the cascade detector described in the algorithm is given in the flow chart in Figure 4. A new weak classifier is added to the node till the false positive rate is satisfied for the node. And node gets added on to the cascade classifier till overall False positive and detection rate are achieved.

The main advantage of the Adaboost classifier is that the node of classifier rejects the sub-window that doesn't contain the object that's how reducing the no. of sub-windows to be processed by the subsequent nodes. And the classifier has the ability to scale the feature size according to the image size to detect the objects in the image.

C. BICA

The Independent component analysis [4] based face recognizer captures the higher order statistics of the image thus considering both the amplitude and phase spectrum of the image thus overcoming the drawback of PCA based system which considers only the second order statistics. Given training images as input, BICA extracts significant features and store it in the database. In BICA the optimal discriminant features are calculated. Face recognition using BICA is based on computation of feature space F (from training set). The whole image is partitioned into many sub-images, i.e. blocks of the same size and then a common demixing matrix for all the blocks are calculated [3]. Compared with ICA, whose training vector is stretched from the whole image, B-ICA stretches only part of the face image as the training vector. B-ICA greatly dilutes the dimensionality dilemma of ICA because the dimension of the training vector is much smaller. The algorithm for BICA is given below:

For each input image in database

- The training image is split the training face images into four blocks (a_1, a_2, a_3, a_4) where each block of face image is of same size.
- The whitening matrix of the block is acquired by calculating eigen value, ψ and eigenvectors, φ of covariance matrix for the block.

$$W_d = \left(\varphi\psi^{-1/2}\right)^T a_i = w_m{}^T a_i$$

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Where $w_m = \varphi \psi^{-1/2}$ is the whitened matrix.

- The Demixing matrix, d is attained using kurtosis method for each column vector of whitened block and extracts the ICA features from the blocks.

$$kurt(d^T w_d) = E\left[\left(d^T w_d\right)^4\right] - 3\left(E\left[\left(d^T w_d\right)^2\right]\right)^2$$

- The demixing vector for every column vector is put together to acquire demixing matrix. The demixing matrix is used to extract the ICA features of the entire facial image.

Similarly for each test image optimal discriminant features can be calculated by BICA. For recognition, the minimum distance is calculated using K-NN classifier.

D. *KNN Classifier*

The simplest classification scheme is a nearest neighbor classification in the image space .Under this scheme an image in the test set is recognized by assigning to it the label of the closest point in the learning set, where distance are measured in image space . The Euclidean distance metric [7] is often chosen to determine the closeness between the data points in KNN. A distance is assigned between all pixels in a dataset. Distance is defined as the Euclidean distance between two pixels. The Euclidean metric is the function $d : Rn \times Rn \rightarrow R$ that assigns to any two vectors in Euclidean n-space $X=(x_1,\ldots, x_n)$ and $Y=(y_1,\ldots, y_n)$ the number,

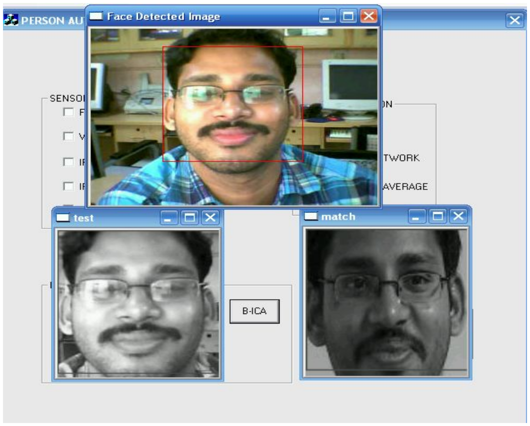
$$d(x,y) = \sqrt{((x_1 - y_1)^2 + \ldots + (x_n - y_n)^2)} \qquad (11)$$

This equation gives the "standard" distance between any two vectors in Rn. From these distances, a distance matrix is constructed between all possible pairings of points (x, y).

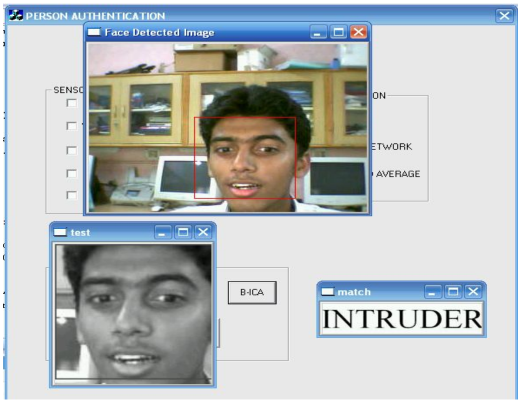
III. Result and Discussions

The Haar and BICA based face recognition system is tested on the real-time. The face detection system is trained on the 24x24 image size of 200 positive and 300 negative examples, and while testing the classifier runs the sub-window over the test image to detect various faces in the image. For face recognition system, image size of 32x32 is trained on MIT-India face database of 500 images with 10 images of each person.

Figure 5 shows the result for both face detection and recognition. The red square in top sub-window indicates the detected face in the captured image. The left-most bottom sub-window shows the test image, which is the input for BICA algorithm. The right-most bottom window indicates whether the tested face image has a match in Database or an intruder. Figure 5(a) shows the result for the image of person trained by the system. Figure 5(b) shows the result for the image of person not trained by the system. The face detection and recognition system performs well for the detected frontal face in the near vicinity of the camera. The system is not trained for the profile faces.



(a)



(b)

Figure5 Result of Face detection and Recognition system (a) Result for person trained by the system (b) Result for person not trained by the system

IV. Conclusion

In this paper, an approach for face detection and recognition system based on Haar wavelet and BICA is developed. For the face detection system, Haar based features capture the structural properties of the object and invariant to illumination, skin color and slight occlusions. The statistical approach of BICA partitions the image into sub-blocks and thus further reduces the dimensionality than the traditional ICA. The developed face detection and recognition system performs well and provide good recognition rate.

References

[1] C. Papageorgiou et T. Poggio, "A trainable system for object detection", International Journal of Computer Vision, 38(1):1533, 2000.

[2] Gary Bradski and Adrian Kaehler, "Learning OpenCV", Published by O'Reilly Media Inc., 1005 Gravenstein Highway North, Sebastopol, CA 95472.

[3] Lei Zhang, Quanxue Gao and David Zhang, "Block Independent Component Analysis for Face Recognition", 14th International Conference on Image Analysis and Processing (ICIAP), 0-7695-2877-5/07(2007)

[4] Marian Stewart Bartlett, Javier R. Movellan, and Terrence J. Sejnowski, "Face Recognition by Independent Component Analysis",

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IEEE Transactions on Neural Networks, VOL. 13, NO. 6, pp. 1450-1464, Nov. 2002.

[5] P. Viola and Michael J. Jones. "Robust real-time face detection", International Journal of Computer Vision, 57(2):137-154, 2004.

[6] R. Lienhart, J. Maydt, "An Extended Set of Haar-like Features for Rapid Object Detection", IEEE ICIP 2002, Vol. 1, pp. 900-903, Sep.2002.

[7] Rafael C.Gonzalez , Richard E.Woods, " Digital Image Processing," Prentice Hall Of India.(2005)

[8] N. Dalal, B. Triggs, "Histograms of oriented gradients for human detection", CVPR, pp. 886-893, Vol. 1, 2005.

[9] O. Tuzel, F. Porikli, P. Meer, "Human detection via classification on Riemannian manifolds", CVPR, 2007

[10] B. Wu, R. Nevatia, "Optimizing discrimination-efficiency tradeoff in integrating heterogeneous local features for object detection", CVPR, 2008.

[11] S. Maji, A. Berg, J. Malik, "Classification using intersection kernel support vector machines is efficient", CVPR, 2008.

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