FACE IDENTIFICATION AND LOCALIZATION USING BACKPROPAGATION ALGORITHM

[1]Mohd Salman Khan, [2]Bhavya Mittal, [3]Anusuya

[1]Assistant Professor,[2,3] B.Tech. Scholar

ABESIT Ghaziabad Uttar Pradesh (India)

ABSTRACT

The entire process of face detection, identification and localization of faces should preferably be almost orientation or rotation invariant. The present paper aims to design one optimal Back Propagation (BP) Network model to perform these face identification tasks. The task is partially independent of orientation or rotation of the faces in the image. Also the identification rate of the faces is quiet moderate.

Keywords: Face Detection, Face Identification, ANN, BP Network, Machine Learning, Detection Rate, Identification Rate, False Positive and False Negative.

I INTRODUCTION

Pattern recognition is the most classical and vital part of all computer vision activities. In the present paper, we have developed an image based pattern recognition technique for recognizing and localizing human faces. The recognition of faces is orientation or rotation invariant, and is associated with localization of faces in the image also.

1.1 The Problem of Face Detection

The purpose of face detection [1,2] is to determine the presence or absence of faces in a given image and perform further processing associated with it. These are face localization, authentication or recognition or identification. Face localization determines the position(s) of faces in a given image [1,4,5,8,17]. Face identification or recognition or authentication compares an input facial image against a set of known model faces stored in a database and report for a match. The problem of face detection and identification is a very hard problem, because the faces are highly variable in size, shape, orientation or rotation etc.

Detection Rate: Face detection rate is the ratio of the number of faces correctly detected by the system and the number of faces detected by humans.

\Face Detection Rate = No. of faces correctly detected by the system / No. of faces determined by humans.

Identification Rate: Face Identification rate is the ratio of the number of faces correctly identified by the system and the number of faces identified by humans.

Face Identification Rate = No. of faces correctly identified by the system

/ No. of faces identified by humans.

1.2 Appearance Based Face Identification Methods

If we make the system learn the different types of faces with a set of facial examples, then this technique is called "appearance base method". One method to implement this type of machine learning is the use of multilayer neural networks [12].

1.3 Neural Networks

Neural Networks have been applied successfully in many pattern recognition problems, like Optical Character Recognition (OCR), object recognition and face detection / recognition etc.

Face detection can be treated as two class pattern recognition problem, while face identification as multiclass pattern recognition problem. The advantage of neural networks for face detection or identification is that it can be conveniently trained to learn the complex feature conditional density of face patterns. But the major drawback is that the number of hidden layers, number of neurons in each layer has to be perfectly selected to achieve optimal performance. There are several approaches of faced detection and identification with Neural Networks[7,8,9,10,12].

In the present paper we treat face identification as a pattern recognition problem where the patterns are made to learn by Machine Learning through ANN. The ANN model which is adopted is the conventional Back Propagation (BP) Network with an optimal number of hidden layers and hidden units in each layer.

II OVERVIEW AND ALGORITHMS

2.1 Preprocessing

The image has to be preprocessed before learning or recognition. There are several steps in preprocessing.

(i) Background Elimination: The first step of preprocessing is to eliminate the background of sample patterns in the "faces" training database.

(ii) Image Normalization: This process normalizes all image patterns into 18*27 pixels and stores in training or test database.

(iii) Histogram Equalization and Image Binarization: The third step is to convert training database or test database of 18*27 pixels into grey image. Thereafter histogram equalization for training or test images are performed to compensate for imaging effects due to illumination, brightness etc. Lastly the image is converted into binary image.

(iv) Conversion of 2D matrix image files into 1D matrix: The last step is to convert training database or test database of 2D matrix pixels (18*27) into 1D matrix pixel (18*27). This set is the input to the different training and testing systems.

2.2 Theory of Operation

The BP Network classifier is used for identification.

2.2.1 Identification Learning: The preprocessed training database containing 5 different model poses of each of the 5 persons as well as the set of 5 different unidentifiable model persons together is fed as input to the BP Network containing 18*27 input units, one hidden layer with adjustable hidden units (adjustable from 10 through 40) and 6 output units. When the network has learned all the 5 different poses of all the 5 different persons as well as the unidentifiable person set of 5 persons, the network is ready for identification and localization of test images.

2.2.2 Identification and Localization with test image: First we discuss how to identify one unknown test image and then how to localize the unknown test images in an image frame.

2.2.2.1 Identification: The test image from the test image set is rotated by an angle of 0, 90, 180 and 270 degrees and all the versions are fed as input to the preprocessor. The preprocessor produces 4 outputs (each of which is 1D matrix of 18*27 pixels) for all the angles of 0 through 270 degrees. Now all the 4 rotated preprocessed outputs are fed as input to the previously trained BP Network. If for any rotated version, any of the first five outputs of the BP Network is active high, then the corresponding person is identified or recognized. Otherwise if the 6th output of the network is high, then the system cannot recognize the person.

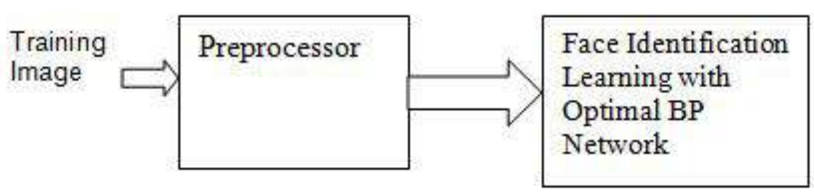

Fig. 1 Block Diagram for Learning Identification

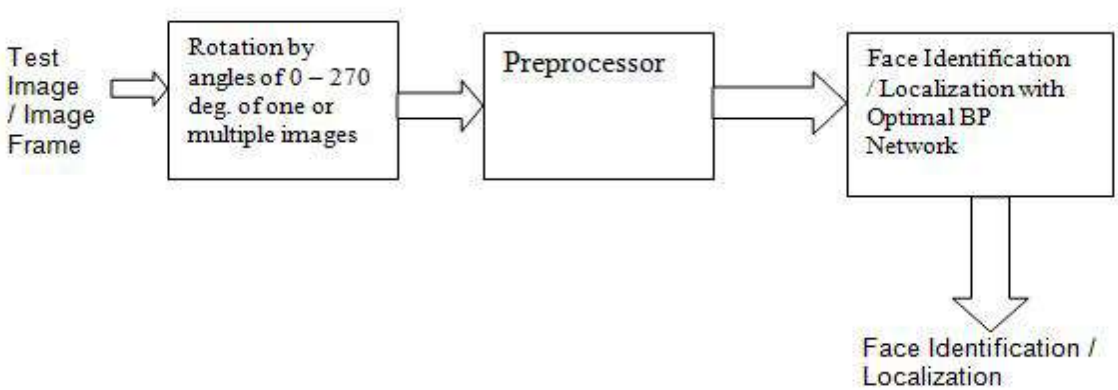

Fig. 2 Block Diagram for testing Identification and Localization

2.3 Algorithms

2.3.1 Learning Face Identification

Input: Folder for different poses of five persons and one set of unidentifiable person.

Output: Trained BP Network for face identification.

Steps:

1. Get the different set of persons with different poses and the set of unidentifiable person. Input the preprocessed images to the BP Network to make the network learn face identification.
2. Stop.

2.3.2 Algorithm for Face Identification

Input: Test folder containing identifiable and unidentifiable persons.

Output: Given a test face, identification of the face.

Steps:

1. Get the face to test.
2. Rotate the face from 0 to 270 degrees by steps of 90 degrees. For each rotated version, preprocess the image and input it to the trained BP Network for Face Identification.
3. If the nth output (1<=n<=5) of the BP Network is " 1" then conclude " person n" . Otherwise, in the case the 6th output of the Network is " 1" then 26 conclude " unidentifiable person" . Get the feedback from " humans" and display the " current " face identification rate" .
4. If any more testing is required, go to step 1.
5. Stop.

2.3.3 Algorithm for Face Identification with Localization

Input: A set of image frames containing multiple images.

Output: Localization of identified faces at different positions of the image frame.

Steps:

1. Get an image frame containing multiple images for identification and localization.
2. Identify and localize the positions of faces in the image frame. Also display the image frame containing faces identified.
3. If any more image frame has to be tested, go to step 1
4. Stop.

2.4 Wavelet Gabor Filter

Gabor filters are believed to function similarly to the visual neurons of the human visual system. From an information theoretic viewpoint, Okajima [17][18] derived Gabor functions as solutions for a certain mutual-information maximization problem.

Among various wavelet bases, Gabor functions provide the optimal resolution in both the time (spatial) and frequency domains, and the Gabor wavelet transform seems to be the optimal basis to extract local features for several reasons :

Biological motivation: The simple cells of the visual cortex of mammalian brains are best modeled as a family of self-similar 2D Gabor wavelets[19].

Mathematical and empirical motivation: Gabor wavelet transform has both the multi-resolution and multi-orientation properties and are optimal for measuring local spatial frequencies. Besides, it has been found to yield distortion tolerance space for pattern recognition tasks[19].

The Gabor receptive field can extract the maximum information from local image regions. For face recognition applications, by experiment we found that the number of Gabor filters 40 filters (5 scales and 8 orientations) is the best because it is get us best results in our, in the following the function Gabor wavelets to generate one filter (these steps are part of our programs):

```
function GW= GaborWavelet (R, C, Kmax,
f, u, v, Delt2);
k = ( Kmax / ( f ^ v ) ) * exp( i * u * pi/8 );
kn2 = ( abs( k ) ) ^ 2;
GW = zeros ( R , C );
for m = -R/2 + 1 : R/2
for n = -C/2 + 1 : C/2
GW(m+R/2,n+C/2) = ( kn2 / Delt2 ) *
exp( -0.5 * kn2 * ( m ^ 2 + n ^ 2 ) /
Delt2) * ( exp( i * ( real( k ) * m +
imag (k) * n ) ) - exp ( -0.5 * Delt2 ) );
end
end
```

III RESULTS AND PERFORMANCE ANALYSIS

3.1 Face Identification

The training example set is comprised of five different faces each of which is having five different poses. Two sample faces is shown in Fig. 3. and 4. Fig. 5 shows a set of five unidentifiable faces.

Fig. 3 First training example set for face identification

Fig. 4 Second training example set for face identification

Fig. 5 First test example set for face identification

Some user system interaction for face identification is shown below:

< NUMBER OF UNITS IN HIDDEN LAYER IS SET = 20>

Name the Image to test : C:\Face

Identification \Test 1.jpg

This is person 1

Is it correct? (y/n): y

Identification rate = 100%

Any more identification? (y/n): y

Name the Image to test : C:\Face

Identification \Test 3R.jpg

This is person 3

Is it correct? (y/n): y

Identification rate = 100%

Any more identification? (y/n): n

3.2 Face Identification with Localization

The system is able to identify as well as localize faces. The test example set for face identification with localization is shown in Fig. 6.

Some user system interaction for face / non face localization is shown below:

< NUMBER OF UNITS IN HIDDEN LAYER IS SET = 20>

Name the image frame to test:

C:\Frame Identification\Multiple1.jpg

Face of person3 at row, column =14.0, 9.5

Face of person6 at row, column =14.0, 27.5

Face of person4 at row, column =14.0, 45.5

Face of person1 at row, column = 14.0, 63.5

Face of person6 at row, column = 41.0, 9.5

Face of person5 at row, column = 41.0, 27.5

Face of person2 at row, column = 41.0, 45.5

Face of person6 at row, column = 41.0, 63.5

Any more localization? (y/n): y

Name the image frame to test:

C:\Frame Identification\Multiple2.jpg

Face of person6 at row, column = 14.0, 9.5

Face of person2 at row, column =14.0, 27.5

Face of person3 at row, column =14.0, 45.5

Face of person2 at row, column = 14.0, 63.5

Face of person4 at row, column = 41.0, 9.5

Face of person1 at row, column = 41.0, 27.5

Face of person4 at row, column = 41.0, 45.5

Face of person5 at row, column = 41.0, 63.5

Any more localization? (y/n): n

Successful face identification & Localization

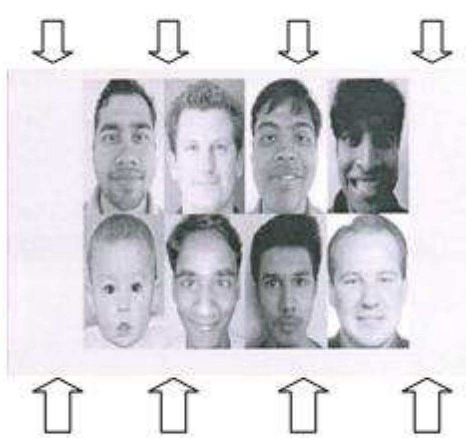

Fig. 6 First text example for face identification and localization (Multiple1.jpg)

IV CONCLUSION

An optimal multilayer neural network using BP Learning has been designed and developed for face identification and localization. These are partially independent of orientation and rotation of the identifiable faces. The identification rate for the optimal network (with optimal number of hidden layers and units) is moderately high, although the network size is small. And the localization with the limitation is perfect. Some limitations of the present system is that the number of identifiable persons is finite and the face identification is possible, if the test images are only rotated through a limited number of angles with respect to the model training images. Also during identification with localization, the maximum number of test faces is limited to eight. Over and above if the image is not almost lying in any one of the 8 slots of image frame, it may not be localized. We can extend the work by increasing the number of identifiable persons, angles of rotation for the test image with respect to the model training image. Also for localization during identification, the image frame size can be increased to accommodate images beyond eight.

REFERENCES

[1] G. Bruel and D. Carel, “Detection and Localization of Faces on Digital Images,” Pattern Recognition Letters, vol. 15, no. 10, pp. 963-967, 1994

[2] I. Craw, H. Ellis, and J. Lishman, “Automated Extraction of Face Features,” Pattern Recognition Letters, vol. 5, pp 183-187, 1987.

[3] A Dempster, “A Generalization of Bayesian Theory,” J. Royal Statistical Soc., vol. 30, pp. 205-247, 1978.

[4] H. P. Graf, T. Chen, E. Petajan, and E. Cosatto, “Locating Faces and Facial Parts,” Proc. First Int’l Workshop Automatic Face and Gesture Recognition, pp. 41-46, 1995

[5] A. C. Loui, C. N. Judice, and S. Liu, “An Image Database for Benchmarking of Automatic Face Detection and Recognition Algorithms,” Proc. IEEE Int’l Conf. Image Processing, pp. 146-150, 1998

[6] A. Martinez and A. Kak, “PCA versus LDA,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 23, no. 2, pp. 228-233, Feb. 2001.

[7] H. Rowley, S. Baluja, and T. Kanade, “Neural Network Based Face Detection,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 20, no. 1, pp. 23-38, Jan. 1998.

[8] H. Rowley, S. Baluja, and T. Kanade, “Rotation Invariant Neural Network Based Face Detection,”

[9]. Avinash Kaushal, J P S Raina, “*Face detection using neural network & Gabor wavelet transform*”, IJCST vol. 1, issue 1, sep. 2010.

[10] L. Shen and L. Bai, *“A review of Gabor wavelets for face recognition”*, Patt. Anal. Appl. 9: 273-292, 2006.

[11] Ming-Husan Yang, David J.Kriegman, and Narendra Ahuja, “*Detecting Faces in Images: A Survey “*, IEEE transaction on pattern analysis and machine intelligence, vol.24 no.1, January 2002.