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A ROBUST FACE RECOGNITION ALGORITHM USING A TEMPLATE APPROACH

Yusuff A. A., Okelola M. O, Adeyemo I.A.

Electronic and Electrical Engineering Department, Faculty of Engineering and Technology
Ladoke Akintola University of Technology, P.M.B. 4000, Ogbomoso Oyo-state Nigeria

ABSTRACT

In this paper a system that uses a template matching approach along with a training algorithm for tuning performance was described. The system solves two types of problems at the same time: 1. Correct identification of individuals in the Image database. 2. Rejection of individuals who are not in the database. Results show that this training method is capable of a consistent correct classification rates and a low false positive rates.

INTRODUCTION

Many face recognition algorithms are tuned to perform o one of these face recognition problems. 1 Correct classification experiments. 2. False positive experiments. The task here is to design a system that gives a good classification results.

The proposed algorithm is used with a simple nearest neighbor template matching classifier. The experimental results obtained are better than results gotten using a variety of different classifiers, such as Fisherfaces, wavelet, eigenfaces, e.t.c.

This paper is organized as follows: Section 2 describes how the template matching classifier works and how the output of the classifier is computed. Next we describe a training method whereby the parameters of the classifier system can be determined from the available training set. In section 4 we describe the database of face images that was used in these experiments. Finally, we present and analyze the experimental results.

Classification and Decision Algorithm

The face recognition algorithm is stated as follows: Given a database of human face images and an input image, the system must decide on one of the following: 1. Identify the best matching individual in the database.

2.Reject the input image if no match is found for it.

Suppose the database of face images of N known individuals is denoted D. And suppose that D contains K different samples of each individual with different facial expressions.

$$D = \{I_{nk} : n = 1,2,\cdots,N, k = 1,2,\cdots,K\}$$

Each image in the database is mapped as follow:

$$X = \{x_{nk} = \rho(I_{nk}) : n = 1,2,\cdots,N, k = 1,2,\cdots,K\}$$

For a nearest neighbor classifier ρ is simply an identity map. For eigenfaces method, ρ maps each image in database D onto the corresponding coordinates.

In order to compute the output of the nearest neighbor classifier, we first need a way of measuring the distance between two images representation. Let the distance between images x and y be $d(x, y)$.

The design of the nearest neighbor classifier is as follow: Store all of the images representation in X into memory. Then, given an input image I, first apply ρ to compute its coordinates in the chosen representation: $x = \rho(I)$. Then compute the distance between x and each of the samples in the database samples and determine the closest sample $x_{n_{\min},k_{\min}}$:

$$d(x_{n_{\min},k_{\min}}, x) \le d(x_{n,k}, x)$$

for all n = 1,2,…,N and k = 1,2,…,K.

The output is taken as $n_{\min}$, the individual whose image has minimum $d(x_{n,k}, x)$. In order to address the issue of rejecting individuals whose images are not in the database, a more useful decision rule might use a threshold to decide whether or not to identify the image or reject it:

$$output = \begin{cases} n_{\min} & if \quad d(x_{n_{\min},k_{\min}}, x) \le T \\ otherwise, reject \end{cases}$$

A more sophisticated decision algorithm would involve determining and storing a different threshold for each individual in the database. In this case, the only modification needed in the decision rule above would be to replace T by $T_{n_{\min}}$, where $T_{n_{\min}}$ is the threshold for the matching image

The decision rule we propose involves computing and storing two different thresholds for each individual in the database: a lower threshold L_n and an upper threshold U_n , n = 1,2,...,N

$$\text{output} = \begin{cases} n_{min} & \text{if } d(x_{n_{min},k_{min}}, x) \le L_{n_{min}} \\ \text{reject} & \text{if } d(x_{n_{min},k_{min}}, x) > U_{n_{min}} \\ \text{apply heuristic} & \text{if } L_{n_{min}} \le d(x_{n_{min},k_{min}}, x) \le U_{n_{min}} \end{cases}$$

The lower threshold is used to determine when there is a sufficiently close match between the input x and the closest sample image $x_{n_{min},k_{min}}$, such that the input image can be reliably identified as individual n_{min}. The upper threshold is used to determine when there is a sufficient mismatch between x and all of the sample images, even the closest one $x_{n_{min},k_{min}}$, such that the input should be rejected as not known to the system. The only other possibility is when the minimum distance falls between the two thresholds: $L_{n_{min}} \le d(x_{n_{min},k_{min}}, x) \le U_{n_{min}}$. In this case, we propose the following heuristic:

Identify the input as person n_{min} if the second best matching is also a sample of individual n_{min} ;

Otherwise, reject the input as not known to the system.

The proposed decision rule is shown in Fig.1

Fig.1. The threshold used for the decision stage

Training Phase for Threshold Computation

We require two set of data sets: a classification training set X and a false positive training set Y. The classification training set consists of samples of the people in the database, and is used to tune the identification and classification capability of the system. The false positive training set consist of samples of individuals who are not in the database, and is used to tune the rejection capability of the system.

We first partition the classification database into two disjoint sets: X_1 and X_2 . Both X_1 and X_2 contain all samples of all the individuals in the database.

$$X_1 = \{x_{nk} \in X : n = 1,2,\cdots,N, k = 1,2,\cdots,K/2\}$$

$$X_2 = \{x_{nk} \in X : n = 1,2,\cdots,N, k = K/2+1,\cdots,K\}$$

is a valid partition

Next, intraclass distances are computed for each individual in the database. For a fixed individual n, we select an image x_{nk} from X_1 and then compute the distance between x_{nk} and each image of person n in X_2 . This process is repeated for all such images of person n in X_1 . The average of all these distances is computed and this value is set as an approximate lower threshold L_n for individual n.

To compute the upper threshold, interclass distances are computed. For each image x_{nk} in X, we compute the distance between x_{nk} and each of the images I the false positive training set Y. The minimum such distance is recorded as upper threshold U_n for n

It is possible to avoid creating a separate false positive training set Y. Here, for an individual n and image x_{nk} , to compute the interclass distance, we simply compute he distance x_{nk} and each other image in the classification data set, excluding all those images of individual n. In this case, the false positive set consist of a sequence of 1- deleted training sets; that is, training set with one individual removed.

The Database of Faces Images

The database consists of 260 different men and women of various background and ages between 22 and 28 years old that graduated in Electronic and Electrical Engineering Department, LAUECH, Ogbomoso. For each person, two sets of 5 images were snapped, giving a total of 10 training images per person. The first group of 5 images all shows a blank facial expression. The second group of 5 images shows different facial expressions: angry, smile, surprised, wink and blank.

Two test images were also collected for each person: a blank image and an arbitrary image, where the subject gives an unusual expression, which might fool the recognition system.

All images were snapped at a dimension of 82 X 115 and stored as 8-bit gray scale. The images were later cropped to a size of 72 X 72 in other to eliminate the hair, neck and shoulder of the person from image. Intensity normalization was then carried out on the images.

Fig2 shows a set of 72 X 72 sample images for one of the subject in the database. In (a), the 45 blank images are shown; in (b), the 5 facial expression images are shown. And in (c), the two test images are shown: blank and arbitrary.

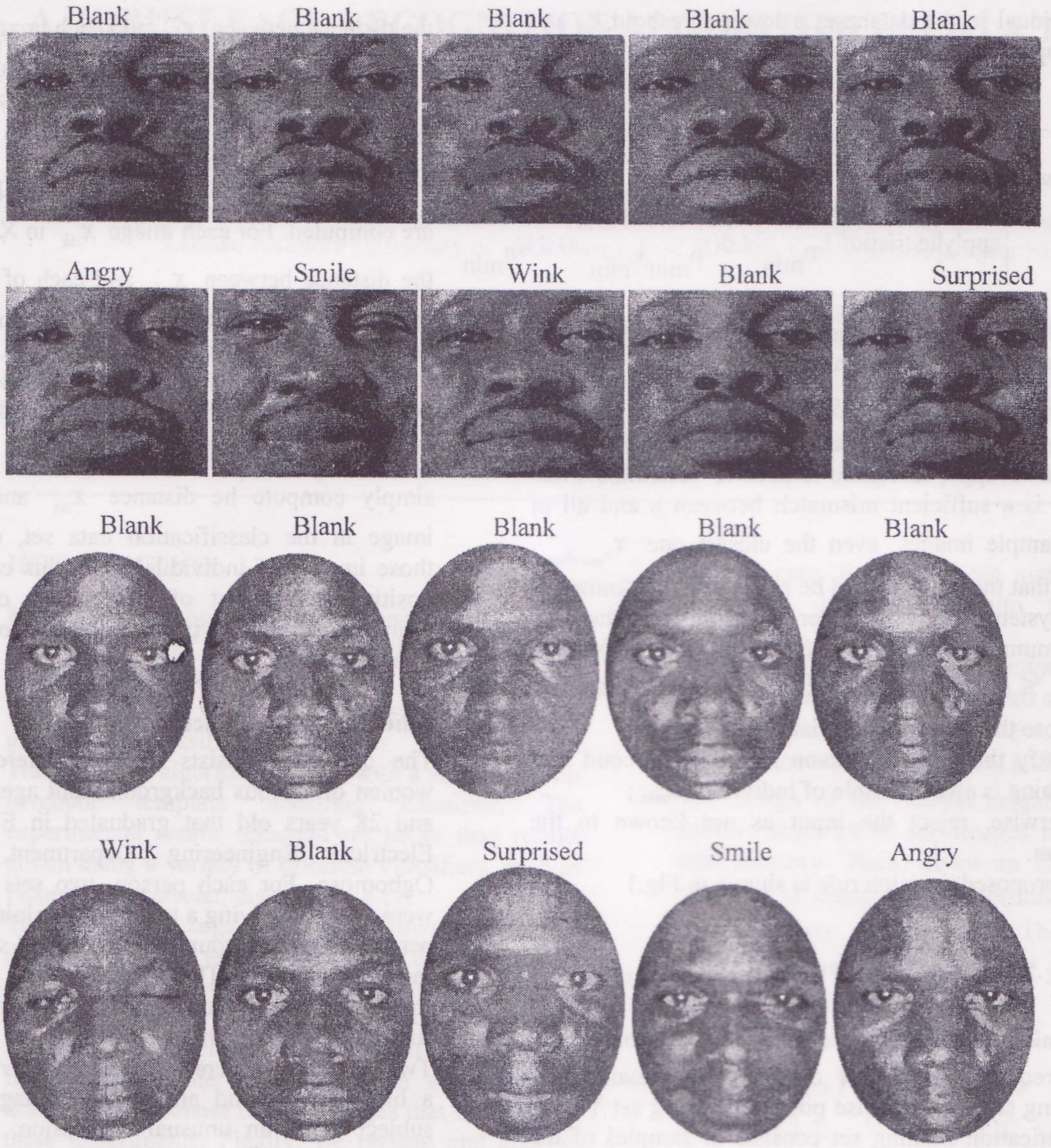

Fig.2 Sample images from the database showing (a) the 5 blank expression images (b) the five different expressions: angry, smile, surprised, wink and blank.

Experimental Results

The training set X consists of all 10 training images for each person in the database. X_1 consists of the 5 blank expressions for each person and X_2 consists of the 5 facial expression images. After training, the system was tested for both correct classification performance and false positive performance. We also looked at the performance as the number of people in the database varied from 20 to 260 individuals; this helped in checking how the performance scales with increasing number of subjects in the database.

Table1 shows the results of the correct classification experiments for both the blank and arbitrary test images. Each number in Table 1 is an average over 3 different trials of the experiment. In each trial, a different database was randomly chosen.

Table 1: Classification results for the blank expression test set and the arbitrary expression test set

Number of people	Blank		Arbitrary		Training Time (min)
	Reject	Error	Reject	Error	
20	4.1	0	37.0	0	1
80	4.0	0	37.0	0	9
100	4.3	0	37.1	0	14
160	3.0	0.1	37.3	0	22
200	3.0	0	39.5	0	30
260	4.0	0.3	37.2	0	39

The results show that the algorithm scales well and for the test images gives an error rate of less than 1% with a reject rate of about 4.5. As expected, for the arbitrary test images, the system rejects a much larger number 37%. However, on this test set, there are no classification errors.

Table 2 shows the results of the false positive experiments. Here, the error rate is slightly higher than 1%, and all other images are properly rejected by the system.

Table 2: False positive results

Number of People	False Positive %
20	1.8
80	1.6
100	1.5
160	1.5
200	1.2
260	1.1

Fig.3 shows how the training time scales as a function of the number of people in the database. The training scales linearly with the number of people in the database.

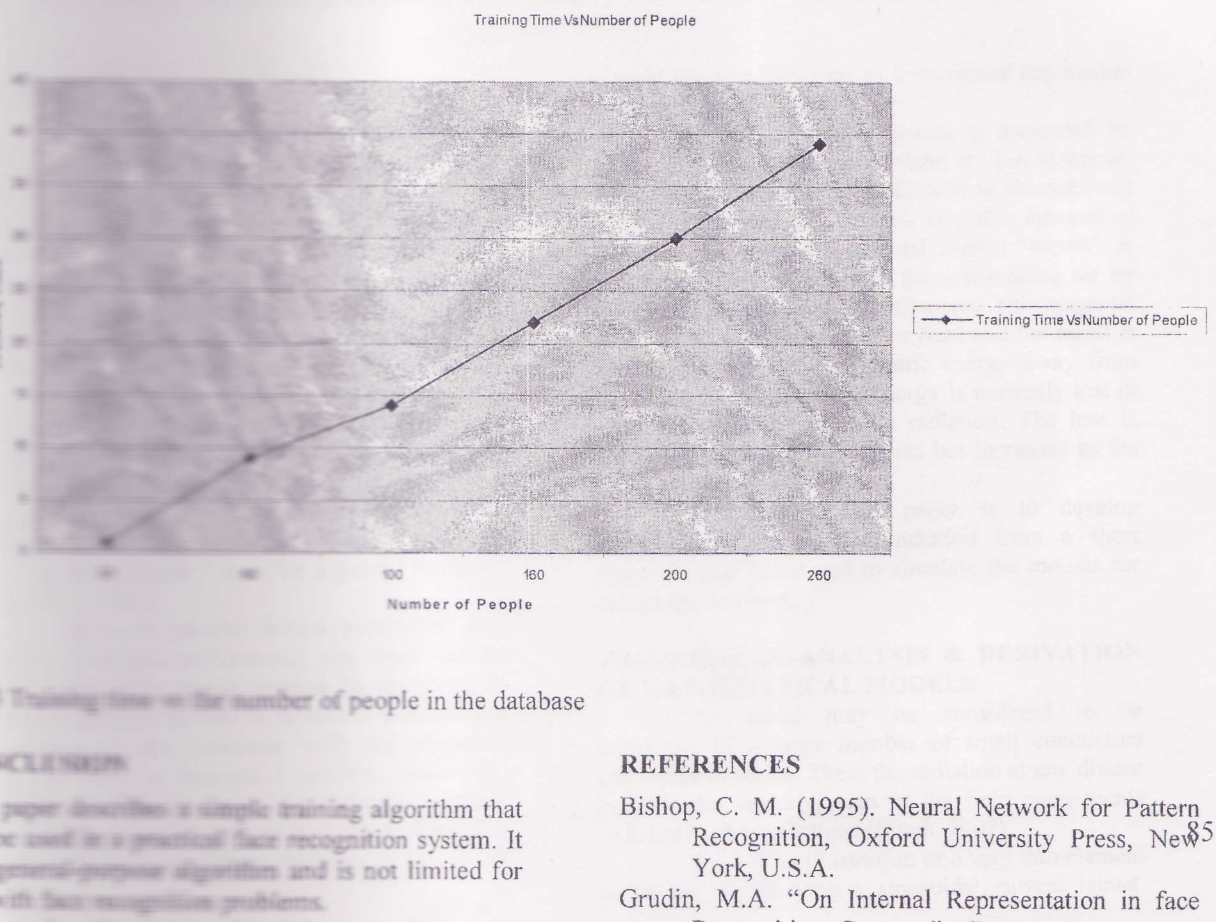

Fig.3 Training time vs the number of people in the database

CONCLUSIONS

This paper describes a simple training algorithm that can be used in a practical face recognition system. It is a general-purpose algorithm and is not limited for use with face recognition problems.

When using the proposed training algorithm on a 260-person face recognition problem, the result indicate that the system can achieve a correct classification rate of over 99%, with a rejection rate of about 4.5% and a false positive rate of less than 1.8%.

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