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Face Recognition using Multiple Recognizers*

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Abstract *- In this paper we have presented a fusion of three face recognizers, LFA, LBA and KDDA, which combines the three Confidence Measure Factors (CMFs) using a RBF neural netwrok. This strategy is used to increase the accuracy of the face recognition system. The recognizer is tested on AT&T-ORL, AR and IITK Face database and the results are found to be more than 95%.*

Keywords: Face Recognition, Local Feature Analysis, Line Based Algorithm, Kernel Direct Discriminant Analysis, Radial Basis Function.

1 Introduction

Face recognition is defined as the identification of a person from an image of his face. It falls into a bracket of technology aptly named biometrics. Humans have an innate ability to recognize faces in cluttered scenes with relative ease, having the ability to identify distorted images, coarsely quantized images and faces with occluded details. Creating a computer system to try and compete with the human visual system is extremely complex and so far unsolved. In theory security systems involving face recognition would be impossible to hack, as the identification process involves unique identification methods and thus, only authorized users will be accepted. But in practical conditions the story is different. Till date not a single system is available which can satisfy the theoretical concepts of face recognition.

A formal method of classifying faces has been first proposed by Francis Galton in 1888 [1, 2]. But after that work on face recognition remained largely dormant till early 90's. Considerable research efforts have been devoted to the face recognition problem over the past decade only [3]. Although there are a number of face recognition algorithms [3] which work well in constrained environments, face recognition is still an open and very challenging problem in real world applications [3].

The main problem in video surveillance is to identify any individual in a complex scene, i.e. a system that automatically detects the faces present in a scene and normalizes them with respect to pose, lighting and scale and then tries to associate the face to one or more faces stored in its database and gives the set of faces that are considered as "nearest" to the detected face. Each of these three stages (Detection, Normalization and Recognition) of the system is so complex that it must be studied separately. Here, we are proposing an algorithm for the face recognition problem considering that we have the detected face as input. Our work is based on fusion of multiple recognizers so that we can overcome the limitation of single recognizer and improve the performance of the overall recognition system.

In our work we have taken three face recognition algorithms namely Local Feature Analysis (LFA) [4], Line based Algorithm (LBA) [5] and Kernal Direct Discriminant Analysis (KDDA) [6] and used it according to our fusion algorithm. The result found with the fusion algorithm is found to be more than 95%. In the following section, detailed description of the face recognition algorithm is given. In the third section experimental results are shown and the last section is the conclusion.

2 Face Recognition

Among the algorithms of face recognition, few of the algorithms show some promises for this biometrics trait. But not a single algorithm is claiming 100% accuracy on the test databases and/or real time system implementation. Now research in this field is gaining more attention on use of Multiple Classifier System (MCS) or sometimes called Multiple Recognizer System (MRS) which is the combination of two or more classifiers/recognizers to get more accuracy. Some examples of such type of work are given in [7, 8, 9, 10].

In our work we have chosen LFA, LBA and KDDA because these three are considering the problem of dimensionality and can handle variations (illumination, pose, etc.) up to a significant level. Also, these three individual recognizers have some drawbacks [5, 6, 7] but if we fuse these three by a fusion algorithm the combined recognizer can overcome those individual drawbacks. For example LFA and KDDA can not extract the exact features when someone puts a sunglass or if a big accidental or emotional change occurs but LBA can work in these cases. So a combined recognizer can handle most of the drawbacks.

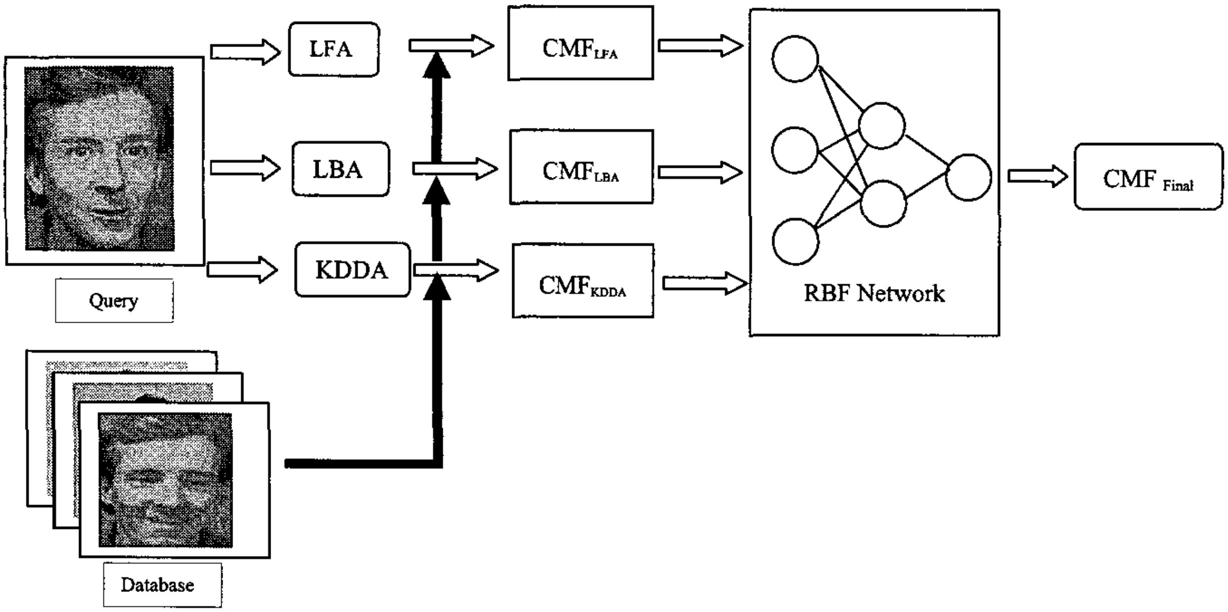

Figure 1: Illustration of the Combined Recognizer

The fusion algorithm is shown in Figure 1. Three recognizers (LFA, LBA & KDDA) are used to get the Confidence Measure Factor (CMF) and the strategy followed for fusion for these CMFs is the Radial Basis Network (RBF) based algorithm.

2.1 Three Recognizers – LFA, LBA, KDDA

Let there are n number of training images of N individuals. Now these training images are given as input to the three recognizers. These three recognizers now take the training set and extract the features. In case of LFA, prominent local features are extracted [4] and stored in the database. Similarly in case of KDDA the optimal discriminant features are calculated and stored in the database [6]. In LBA, we store the lines drawn on the face image in place of the facial features [5]. The three algorithms are explained as follows:

Algorithm LFA (*D*: Database)

begin

for each input/original image in database *D*

Step 1*:* Compute Eigenfaces and the mean face using Principal component analysis.

Step 2*:* Compute the prominent local features

- Compute the weight of the face by
  Value = face image – mean
  Face weight = Face weight + eigenface * value
- Compute the prominent local features by

Local output = Local output + Face weight *eigenface

Step 3: Apply prediction to sparsify the prominent local features and find the location of the maximum prediction error.

Step 4*:* Store the calculated prominent local features

End

The detailed algorithm for extracting the local features is given in [4]. Using this algorithm the local features of database images are extracted.

Algorithm LBA (*D*: Database)

begin

for each input/original image in database *D*

*Step*1*:* Get the facial boundary of the face image.

*Step*2*:* Draw the lattice line on face image using the boundary pixels.

*Step*3*:* Calculate the set of lattice lines for each face.

Step 4*:* Store these set of lattice lines.

End

Using LBA [5] the set of lattice lines are extracted and stored in the database for further matching process. Similarly, KDDA [6] gives the optimal discriminant features as the output which has been stored in the database.

Algorithm KDDA (*D*: Database)

begin

for each input/original image in database *D*

Step 1: Make a set of training face images where each face image is represented as n – dimensional vector.

Step 2: Calculate the Kernel matrix, eigenfaces, eigenvectors (whose corresponding eigenvalues are greater than 0) and matrix containing the numbers equal to square of the eigenvalues.

Step 3: Calculate the Kernel vector and a matrix Θ which cause the low dimensional representation. Apply the KDDA equation

$$y = \Theta * \gamma(\phi(z))$$

to get the feature representation of the image.

Step 4: Calculate and store the features extracted from the above algorithm

End

Thus for the database images (training set) all the features are calculated using the three algorithms. Now if any query comes to the algorithms, these algorithms first extract the features as stated above and then an individual comparison algorithm for each recognizer compares the set of features and calculates the CMFs. Algorithms for calculating the CMFs are as follows

Algorithm CMF_{LFA} (*D*: Database, *Q*: Query)

begin

for query image *Q*

Step 1: Reconstruct the query image from the prominent local features.

Step 2: Calculate the CMF_{LFA} as follows from the database as:

- Predict the prominent local output of the face at the location (m, n)
- Calculate the closest distance by Predicted value – face features
- If distance is less then threshold then D_i is set to 1 else 0.

Step 3: Now for all features

$$CMF_{LFA} = \sum_{i=1}^{x} D_i \text{, where } x = \text{no. of features.}$$

End

Algorithm CMF_{LBA} (*D*: Database, *Q*: Query)

begin

for query image *Q*

Step 1: Calculate the distance between two lattice lines (one from *Q* and other from *D*).

Step 2: Calculate the CMF_{LBA} as given in [5]

$$CMF_{LBA} = (TC_g - TC_j^{(2)}) / TC_j^{(2)},$$

where TC_g is Compounded Confidence Measure Factor,

$$TC_g = \max_{1 \le j \le n} \{TC_j\}$$

$TC_j^{(2)}$ is the second largest Compounded Confidence Measure.

End

Algorithm CMF_{KDDA} (D: Database, Q: Query)

begin

For each feature m in database and n in query image, reference feature is chosen depending on the distance and rotation between the position of the m and n belong to (the matching algorithm is taken from [10])

Step 1: If m and n can be chosen as reference features go to step 2 else continue.

Step 2: Translate the database and query feature set with respect to the reference feature chosen. Convert (x, θ, ϕ) into polar coordinates (r, θ, ϕ).

Step 3: Import the relevant bounding box and for each feature "*i*" in database find those which lie within the bounding box. Increment the matching score accordingly.

Step 4: Report the maximum score (among all the possibilities of reference features) divided by maximum number of features (among the query and database)

Step 5: Now CMF_{KDDA} is equal to the maximum score obtained.

CMF_{KDDA} = Maximum Score obtained by the above algorithm

End

2.2 Fusion Strategy

For the database images (training set) all the features are calculated using the three algorithms. Now for recognizing any query image, these algorithms first extract the features as stated above and then an individual comparison algorithm for each recognizer compares the set of features and calculates the Confidence Measure Factors (CMFs). These CMFs are then given as input to the Radial Basis Function (RBF) network [6] to determine the result for the combined algorithm. RBF networks are used for fusion because of the less training time required and the possibility of learning positive as well as negative samples. Also the experimental results of [11] show that RBF network gives the highest accuracy compared to any other fusion algorithms. RBF network is designed with three input nodes and the output obtained is the final verification result. For each test image, the m matching scores obtained from each classifier are used as a feature vector. Concatenating these feature vectors derived from three classifiers results in a feature vector of size $3m$. An RBF network is designed to use this new feature vector as the input to generate classification results. The input layer has $3m$ nodes and the output has c nodes, where c is the total number of classes (number of distinct faces). In the output layer, the class corresponding to the node with the maximum output is assigned to the input image. The number of nodes in the hidden layer is constructed empirically, depending on the sizes of the input and output layers.

3 Experimental Results

Algorithms are tested on AT&T-ORL [12], AR [14] and IITK [13] face databases. We have selected 50% of the images as database images and rest of the images for testing. The prototype system is implemented in MATLAB 6.5 using Pentium 4 (2.4 MHz and 256 MB RAM) Desktop PC.

We first tested the individual algorithms and calculate the accuracy of each algorithm. Table 1 shows the accuracy of the individual algorithms on AT&T-ORL face database.

Table 1: Accuracy of the Three Algorithms

Algorithm	LFA	LBA	KDDA
Accuracy (%)	92.0	93.0	90.1

In another experiment, we combined the two algorithms simultaneously and calculate the accuracy of LFA+LBA, LFA+KDDA, LBA+KDDA and after that fuse the three algorithms and calculate the accuracy of LFA+LBA+KDDA. Results of this experiment are shown in Table 2.

Table 2: Accuracy of the Combined Recognizers

Algorithm	LBA+LFA	LBA+ KDDA	LFA+ KDDA	LFA+LBA+ KDDA
Accuracy (%)	94.2	93.7	92.80	95.4

We have tested the combined recognizer on AR & IITK face database also and results are shown in Table 3.

Table 3: Accuracy of the Final Recognizer (LFA+LBA+KDDA) on the three databases

Database	IITK	AR	AT&T-ORL
Accuracy (%)	92.8	94.1	95.4

Accuracy vs. Rank graph shows the performance of each classifier which clearly indicates that the proposed combined recognizer can give accuracy up to 98 % for top five ranks. Table 3, Table 4 and Figure 2 show that the combined recognizer is useful as it shows a better accuracy than each of the individual recognizers or combination of any two.

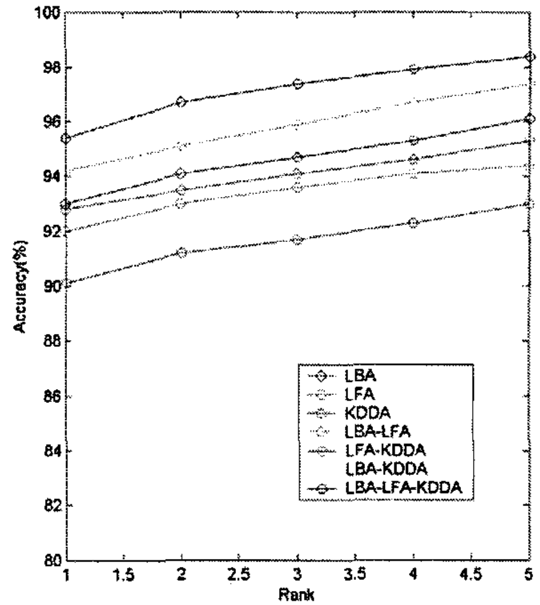

Figure 2: Graph showing accuracy

4 Conclusion

Here we have presented a fusion of three recognizers, LFA, LBA and KDDA, which combines the three Confidence Measure Factors (*CMFs*) using a RBF neural network. This strategy is used to increase the accuracy of the face recognition system. The recognizer is tested on AT&T-ORL, AR and IITK Face database and the results are found to be more than 95%. Results are also encouraging further research for use of classification based on expression analysis and illumination control algorithms to increase the level of accuracy.

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