Neural Network Based Intelligent Local Face Recognition Using Local Pattern Averaging
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Abstract— This paper presents a brief review of known face recognition methods such as Principal Component Analysis (PCA) (Turk & Pentland, 1991), Linear Discriminant Analysis (LDA) (Belhumeur et al., 1997) and Locality Preserving Projections (LPP) (He et al., 2005), in addition to intelligent face recognition systems that use neural networks such as (Khashman, 2006) and (Khashman, 2007). There are many works emerging every year suggesting different methods for face recognition (Delac & Grgic, 2007); these methods are mostly appearance. This paper will also provide a detailed case study on intelligent local face recognition, where a neural network is used to identify a person upon presenting his/her face image. Local pattern averaging is used for face image preprocessing prior to training or testing the neural network. Averaging is a simple but efficient method that creates "fuzzy" patterns as compared to multiple "crisp" patterns, which provides the neural network with meaningful learning while reducing computational expense.

Keywords— Principal Component Analysis, Linear Discriminant Analysis, Locality Preserving Projections, neural networks, fuzzy, crisp

I. INTRODUCTION
Our faces are complex objects with features that can vary over time. However, we humans have a natural ability to recognize faces and identify persons in a glance. Of course, our natural recognition ability extends beyond face recognition, where we are equally able to quickly recognize patterns, sounds or smells. Unfortunately, this natural ability does not exist in machines, thus the need to simulate recognition artificially in our attempts to create intelligent autonomous machines. Intelligent systems are being increasingly developed aiming to simulate our perception of various inputs (patterns) such as images, sounds...etc. Biometrics, in general, and facial recognition in particular are examples of popular applications for artificial intelligent systems. Face recognition by machines can be invaluable and has various important applications in real life, such as, electronic and physical access control, national defence and international security. Simulating our face recognition natural ability in machines is a difficult task, but not impossible. Throughout our life time, many faces are seen and stored naturally in our memories forming a kind of database. Machine recognition of faces requires also a database which is usually built using facial images, where sometimes different face images of a one person are included to account for variations in facial features. The development of an intelligent face recognition system requires providing sufficient information and meaningful data during machine learning of a face.

II. REVIEWING FACE RECOGNITION
This section provides a brief review of face recognition in general. Commonly used face databases will be listed, difficulties with face detection will be discussed and examples of successful face recognition methods will be briefly described.

2.1 Problems in face detection
Most commonly used databases for developing face recognition systems rely on images of human faces captured and processed in preparation for implementing the recognition system. The variety of information in these face images makes face detection difficult. For example, some of the conditions that should be accounted for, when detecting faces are (Yang et al., 2002):[17]

- Pose (Out-of Plane Rotation): frontal, 45 degree, profile, upside down
- Presence or absence of structural components: beards, mustaches and glasses
- Facial expression: face appearance is directly affected by a person's facial expression
- Occlusion: faces may be partially occluded by other objects
Orientation (In Plane Rotation): face appearance directly varies for different rotations
- about the camera's optical axis
- Imaging conditions: lighting (spectra, source distribution and intensity) and camera characteristics (sensor response, gain control, lenses), resolution
- Face Recognition follows detecting a face. Face recognition related problems include (Li & Jain, 2005)[8]
  - Face localization
  - Aim to determine the image position of a single face
  - A simplified detection problem with the assumption that an input image contains only one face
  - Facial feature extraction
  - To detect the presence and location of features such as eyes, nose, nostrils, eyebrow, mouth, lips, ears, etc
  - Usually assume that there is only one face in an image
  - Face recognition (identification)
  - Facial expression recognition
  - Human pose estimation and tracking

The above obstacles to face recognition have to be considered when developing face recognition systems. The following section reviews briefly some known face recognition methods.

2.2 Recognition methods

Much research work has been done over the past few decades into developing reliable face recognition techniques. These techniques use different methods such as the appearance-based method (Murase & Nayar, 1995); where an image of a certain size is represented by a vector in a dimensional space of size similar to the image. However, these dimensional spaces are too large to allow fast and robust face recognition. To encounter this problem other methods were developed that use dimensionality reduction techniques (Belhumeur et al., 1997), (Levin & Shashua, 2002), (Li et al., 2001), (Martinez & Kak, 2001)[3]. Examples of these techniques are the Principal Component Analysis (PCA) (Turk & Pentland, 1991) and the Linear Discriminant Analysis (LDA) (Belhumeur et al., 1997)[3]. PCA is an eigenvector method designed to model linear variation in high-dimensional data. PCA performs dimensionality reduction by projecting an original n-dimensional data onto a k (<< n)-dimensional linear subspace spanned by the leading eigenvectors of the data's covariance matrix. Its aim is to find a set of mutually orthogonal basis functions that capture the directions of maximum variance in the data and for which the coefficients are pair wise decor related. For linearly embedded manifolds, PCA is guaranteed to discover the dimensionality of the manifold and produces a compact representation. PCA was used to describe face images in terms of a set of basis functions, or “Eigen faces”. LDA is a supervised learning algorithm. LDA searches for the projection axes on which the data points of different classes are far from each other while requiring data points of the same class to be close to each other. Unlike PCA which encodes information in an orthogonal linear space, LDA encodes discriminating information in a linearly separable space using bases that are not necessarily orthogonal. It is generally believed that algorithms based on LDA are superior to those based on PCA. However, some recent work (Martinez & Kak, 2001) shows that, when the training data set is small, PCA can outperform LDA, and also that PCA is less sensitive to different training data sets.

Another linear method for face analysis is Locality Preserving Projections (LPP) (He & Niyogi, 2003)[17] where a face subspace is obtained and the local structure of the manifold is found. LPP is a general method for manifold learning. It is obtained by finding the optimal linear approximations to the Eigen functions of the Laplace Beltrami operator on the manifold. Therefore, though it is still a linear technique, it seems to recover important aspects of the intrinsic nonlinear manifold structure by preserving local structure. This led to a recently developed method for face recognition; namely the Laplacianface approach, which is an appearance-based face recognition method (He et al., 2005)[8]. The main difference between PCA, LDA, and LPP is that PCA and LDA focus on the global structure of the Euclidean space, while LPP focuses on local structure of the manifold, but they are all considered as linear subspace learning algorithms. Some nonlinear techniques have also been suggested to find the nonlinear structure of the manifold, such as Locally Linear Embedding (LLE) (Roweis & Saul, 2000). LLE is a method of nonlinear dimensionality reduction that recovers global nonlinear structure from locally linear fits. LLE shares some similar properties to LPP, such as a locality preserving character. However, their objective functions are totally different. LPP is obtained by finding the optimal linear approximations to the Eigen functions of the Laplace Beltrami operator on the manifold. LPP is linear, while LLE is nonlinear. LLE has also been implemented with a Support Vector Machine (SVM) classifier for face authentication (Pang et al., 2005)[8]. Approaches that use the Eigen faces method (Turk & Pentland, 1991), the Fisher faces method (Belhumeur et al., 1997) and the Laplacianfaces method (He et al., 2005)[8] have shown successful results in face recognition. However, these methods are appearance-based or feature-based methods that search for certain global or local representation of a face. More recently, other face recognition methods which do not use artificial intelligence within its implementation have also emerged; these include (Dai & Yan, 2007), (Kodate & Watanabe, 2007), (Padilha et al., 2007), and (Park & Paik 2007) [1][2][4][7][9]. On the other hand many face recognition methods, which use artificial intelligence within their intelligent systems, have been suggested.

III. INTELLIGENT LOCAL FACE RECOGNITION

This paper presents an intelligent face recognition system that uses local pattern averaging of essential facial features (eyes, nose and mouth). Here, multiple face images of a person with different facial expressions are used, where only
eyes, nose and mouth patterns are considered. These essential features from different facial expressions are averaged and then used to train a supervised neural network (Khashman, 2006). A real-life application will be presented using local averaging and a trained neural network to recognize the faces of 30 persons.

3.1 Image database

The face images, which are used for training and testing the neural network within the intelligent local face recognition system, represent persons of various ethnicities, age and gender. A total of 180 face images of 30 persons with different facial expressions are used, where 90 images are from the ORL face database (AT&T Laboratories Cambridge, online resources), and 90 images are from our own face database. Our face database was built using face images captured under the following conditions:

- a- Similar lighting condition
- b- No physical obstruction
- c- Head pose is straight without rotation or tilting
- d- Camera at the same distance from the face

Each person has six different face expressions captured and the image is resized to (100x100) pixels, thus resulting in 90 face images from each face database. Fig. 1 shows the faces of the 30 persons from our face database and the ORL face database, whereas Fig. 2 shows examples of the six facial expressions. The 180 face images of the 30 persons with different expressions were used for the development and implementation of the intelligent local face recognition system. Approximation or local averaging of four multi-expression faces is applied only during the neural network training phase where the four facial expressions (natural, smiley, sad and surprised) images are reduced to one face image per person by separately averaging the essential features (eyes, nose, and mouth), thus providing 30 averaged face images for training the neural network. Testing the neural network is implemented using the six facial expressions without the averaging process, thus providing 180 face images for testing the trained neural network.

3.2 Image pre-processing and local averaging

The implementation of the recognition system comprises the image pre-processing phase and the neural network arbitration phase. Image pre-processing is required prior to presenting the training or testing images to the neural network. This aims at reducing the computational cost and providing a faster recognition system while presenting the neural network with sufficient data representation of each face to achieve meaningful learning. The back propagation neural network is trained using approximations of four specific facial
expressions for each person, which is achieved by averaging the essential features, and once trained; the neural network is tested using the six different expressions without approximation. There are 180 face images of 30 persons with six expressions for each. Training the neural network uses 120 images (which will be averaged to 30 images) representing the 30 persons with four specific expressions. The remaining 60 images of the 30 persons with random different expressions are used together with the 120 training images (prior to averaging) for testing the trained neural network, as can be seen in Fig. 3, thus resulting in 180 face images for testing. The four essential features (eyes, nose and mouth) from four expressions (natural, smiley, sad and surprised) are approximated via local averaging into one single vector that represents the person. Fig. 4 shows the scheme for the intelligent local face recognition system.

The features are, firstly extracted for each facial expression as shown in Fig. 5. Feature extraction is manually performed using Photoshop. Secondly, the dimensions of each feature is reduced by interpolation. The right eye, left eye, nose and mouth Dimensions are reduced to (5 x 10) pixels, (5 x 10) pixels, (7 x 10) pixels and (6 x 17) pixels respectively. Thus, the output matrices dimension after interpolation process will be 1/3 of the input matrices; for example, the 15x30 pixels input matrix will be after interpolation 5x10 pixels. Local averaging is then applied where the 120 training images are reduced to 30 averaged images by taking the average for each feature in the four specific expressions for each subject.

The local feature averaging process for each feature can be implemented using the following Equation:

$$f_{avg} = \frac{1}{4} \sum_{i=1}^{4} f_i$$

where $f_{avg}$ is the feature average vector and $f_i$ is feature in expression $i$ of one person. Finally, The averaged features are represented as (272x1) pixel vectors, which will be presented to The input layer of the back propagation neural network.

3.3 Neural network training

The back propagation algorithm is used for the implementation of the proposed intelligent Face recognition system, due to its simplicity and efficiency in solving pattern recognition Problems. The neural network comprises an input layer with 272 neurons that carry the Values of the averaged features, a hidden layer with 65 neurons and an output layer with 30 Neurons which is the number of persons. Fig. 6 shows the topology of this neural network and data presentation to the input layer. Fig. 6. Local pattern averaging and neural network design.
IV. RESULTS AND DISCUSSION

The neural network learnt the approximated faces after 3188 iterations and within 265 seconds, whereas the running time for the trained neural network using one forward pass was 0.032 seconds. These results were obtained using a 1.6 GHz PC with 256 MB of RAM, Windows XP OS and Matlab 6.5 software. Table 1 shows the final parameters of the Successfully trained neural network. The reduction in training and testing time was achieved by the novel method of reducing the face data via averaging selected essential face features for training, while maintaining meaningful learning of the neural network. The face recognition system correctly recognized all averaged face images in the training set as would be expected. The intelligent system was tested using 180 face images which contain different face expressions that were not exposed to the neural network before; these comprised 90 images from our face database and 90 images from the ORL database. All 90 face images in our database were correctly identified yielding 100% recognition rate with 91.8% recognition accuracy, whereas 84 out of the 90 images from the ORL database were correctly identified yielding 93.3% recognition rate with 86.8% recognition accuracy.

<table>
<thead>
<tr>
<th>Database</th>
<th>Own</th>
<th>ORL</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recognition Rate</td>
<td>100%</td>
<td>93.3%</td>
<td>96.7%</td>
</tr>
<tr>
<td>Recognition Accuracy</td>
<td>91.8%</td>
<td>86.8%</td>
<td>89.3%</td>
</tr>
</tbody>
</table>

Table 2. Recognition Rates, Accuracy and Run Time

Further investigations of the capability of the developed face recognition system were also carried out by testing the trained neural network ability to recognize two subjects with eyeglasses. Fig. 7 shows the two persons with and without glasses; person 1 wears clear eyeglasses whereas, person 2 wears darker eyeglasses.

The effect of the presence of facial detail such as glasses on recognition performance was investigated. The neural network had not been exposed to the face images with glasses prior to testing. Correct recognition of both persons, with and without their glasses on, was achieved. However, the recognition accuracy was reduced due to the presence of the glasses. The ability of the trained neural network to recognize these faces despite the presence of eyeglasses is due to training the network using feature approximations or “fuzzy” feature vectors rather than using “crisp” feature vectors. Table 3 shows the accuracy rates for both persons with and without glasses.
Table 3. Recognition Accuracy With and Without Eyeglasses

<table>
<thead>
<tr>
<th></th>
<th>Person 1</th>
<th>Person 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Eyeglasses</td>
<td>96%</td>
<td>80%</td>
</tr>
<tr>
<td>Clear Eyeglasses</td>
<td>80%</td>
<td>33%</td>
</tr>
<tr>
<td>No Eyeglasses</td>
<td>80%</td>
<td>33%</td>
</tr>
<tr>
<td>Dark Eyeglasses</td>
<td>73%</td>
<td>13%</td>
</tr>
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</table>

V. CONCLUSIONS

This case study, which is based on using local (facial features) data averaging, described another method to intelligent face recognition. The method approximates four essential face features (eyes, nose and mouth) from four different facial expressions (natural, smiley, sad and surprised), and trains a neural network using the approximated features to learn the face. Once trained, the neural network could recognize the faces with different facial expressions. Although the feature pattern values (pixel values) may change with the variations in facial expression, the use of averaged-features of a face provides the neural network with an approximated understanding of the identity and is found to be sufficient for training a neural network to recognize that face with any expression, and with the presence of minor obstructions such as eyeglasses. The successful implementation of this method was shown throughout a real-life implementation using 30 face images showing six different expressions for each. An overall recognition rate of 96.7% with recognition accuracy of 89.3% was achieved. The use of feature approximation helped reducing the amount of training image data prior to neural network implementation, and provided reduction in computational cost while maintaining sufficient data for meaningful neural network learning. The overall processing times that include image preprocessing and neural network implementation were 272.5 seconds for training and 0.032 seconds for face recognition.

REFERENCES

[2] Intelligence Environment Scenario, In K. Delac and M. Grjic (Eds.), Face Recognition, (1-14), Ch. 1, I-Tech Education and Publishing, Vienna, Austria

ONLINE RESOURCES

A. Comprehensive face recognition resources
http://www.cbsr.ia.ac.cn/users/szli/FR-Handbook/
http://www.face-rec.org/general-info/

B. Face databases
The Color FERET Database, USA
http://www.itl.nist.gov/iad/humanid/colorferet/home.html
The Yale Face Database
http://cvc.yale.edu/projects/yalefaces/yalefaces.html
The Yale Face Database B
http://cvc.yale.edu/projects/yalefacesB/yalefacesB.html
PIE Database, CMU
http://www.rni.cmu.edu/projects/project_418.html
Project - Face In Action (FIA) Face Video Database, AMP, CMU
http://amp.ece.cmu.edu/projects/FIADataCollection/