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Intelligent Local Face Recognition

Adnan Khashman
Near East University
Northern Cyprus

1. 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.

This chapter 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-based or feature-based methods that search for certain global or local representation of a face.

The chapter 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.

In previous work (Khashman, 2007) an intelligent global face recognition system which considers a person's face and its background was presented, and suggestions were made

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that a quick human "glance" can be simulated in machines using image pre-processing and global pattern averaging, whereas, the perception of a "familiar" face can also be achieved by exposing a neural network to the face via training. In this work, an intelligent local face recognition system which considers a person's essential face features (eyes, nose and mouth) will be presented, and suggestions are made that a person's face can be recognized regardless of his/her facial expression whether being smiley, sad, surprised…etc. Previous works successfully used local facial features for face recognition purposes (Campadelli et al., 2007), (Matsugu, 2007); and also for recognising the facial expression of a person (Matsugu, 2007), (Pantic & Bartlett, 2007).
The chapter is organized as follows: section 1 contains an introduction to the chapter. Section 2 presents a review on face recognition that includes: available face image databases, difficulties in face recognition, and brief description of available conventional and artificially intelligent face recognition methods. Section 3 presents in details our case study on intelligent local face recognition, including analysis and discussion of the results of implementing this method. The conclusion of this chapter is presented in section 4, which also provides a discussion on the efficiency of intelligent face recognition by machines. Finally, section 5 lists the references used in this chapter, and section 6 lists commonly used online resources for face recognition databases.

2. 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 Available face image databases

"Face Recognition" can be simply defined as the visual perception of familiar faces or the biometric identification by scanning a person's face and matching it against a library of known faces. In both definitions the faces to be identified are assumed to be familiar or known. Luckily, for researchers we have rich libraries of face images that are usually freely available for developers. Additionally, "own" face image databases can be built and used together with known databases. The commonly used known libraries include (online resources):

- The Color FERET Database, USA
- The Yale Face Database
- The Yale Face Database B
- PIE Database, CMU
- Project - Face In Action (FIA) Face Video Database, AMP, CMU
- AT&T "The Database of Faces" (formerly "The ORL Database of Faces")
- Cohn-Kanade AU Coded Facial Expression Database
- MIT-CBCL Face Recognition Database
- Image Database of Facial Actions and Expressions - Expression Image Database
- Face Recognition Data, University of Essex, UK
- NIST Mugshot Identification Database
- NLPR Face Database
- M2VTS Multimodal Face Database (Release 1.00)

- The Extended M2VTS Database, University of Surrey, UK
- The AR Face Database, Purdue University, USA
- The University of Oulu Physics-Based Face Database
- CAS-PEAL Face Database
- Japanese Female Facial Expression (JAFFE) Database
- BioID Face DB - HumanScan AG, Switzerland
- Psychological Image Collection at Stirling (PICS)
- The UMIST Face Database
- Caltech Faces
- EQUINOX HID Face Database
- VALID Database
- The UCD Colour Face Image Database for Face Detection
- Georgia Tech Face Database
- Indian Face Database

Web links to the above databases are included in section 6: Online Resources. The following section discusses some of the problems that should be accounted for when selecting a certain database or when making one's own database.

2.2 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):

- 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):

- 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.

2.3 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 appearancebased 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). Examples of these techniques are the Principal Component Analysis (PCA) (Turk & Pentland, 1991) and the Linear Discriminant Analysis (LDA) (Belhumeur et al., 1997).

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 pairwise decorrelated. 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 "eigenfaces".

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) 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 eigenfunctions of the Laplace Betrami 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).

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 eigenfunctions 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 authentification (Pang et al., 2005).
Approaches that use the Eigenfaces method (Turk & Pentland, 1991), the Fisherfaces method (Belhumeur et al., 1997) and the Laplacianfaces method (He et al., 2005) 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). On the other hand many face recognition methods, which use artificial intelligence within their intelligent systems, have been suggested; examples of these methods are reviewed in the following section.

2.4 Face recognition and artificial intelligence

Intelligent systems are being increasingly developed aiming to simulate our perception of various inputs (patterns) such as images, sounds…etc. Biometrics is an example of popular applications for artificial intelligent systems. Face recognition by machines can be invaluable and has various important applications in real life. The development of an intelligent face recognition system requires providing sufficient information and meaningful data during machine learning of a face.
The use of neural networks for face recognition has been addressed in (Pang et al., 2005), (Zhang et al., 2004), (Fan & Verma, 2005), (Lu et al., 2003). Recently, Li et al. (Li et al., 2006) suggested the use of a non-convergent chaotic neural network to recognize human faces. Lu et al. (Lu et al., 2006) suggested a semi-supervised learning method that uses support vector machines for face recognition. Zhou et al. (Zhou et al., 2006) suggested using a radial basis function neural network that is integrated with a non-negative matrix factorization to recognize faces. Huang and Shimizu (Huang & Shimizu, 2006) proposed using two neural networks whose outputs are combined to make a final decision on classifying a face. Park et al. (Park et al., 2006) used a momentum back propagation neural network for face and speech verification.
Many more face recognition methods that use artificial intelligence are emerging continually such as; (Abate et al., 2007), (Dominique et al., 2007), and (Hiremath et al., 2007), however, one intelligent face recognition method; namely intelligent local face recognition, will be studied in this chapter, and is described in the following section.

3. Intelligent local face recognition

This case study 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:

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



a- Faces of 15 persons (Own Database)



b- Faces of 15 persons (ORL Database (AT&T Laboratories Cambridge, online resources))

Fig. 1. Face Databases for Local Face Recognition

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.



a- Examples of Multi-expression faces from our database



b- Examples of Multi-expression faces from ORL database (AT&T Laboratories Cambridge, online resources)

Fig. 2. Examples of the different facial expressions

3.2 Image pre-processing and local averaging

The implementation of the recognition system comprises the image preprocessing 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.

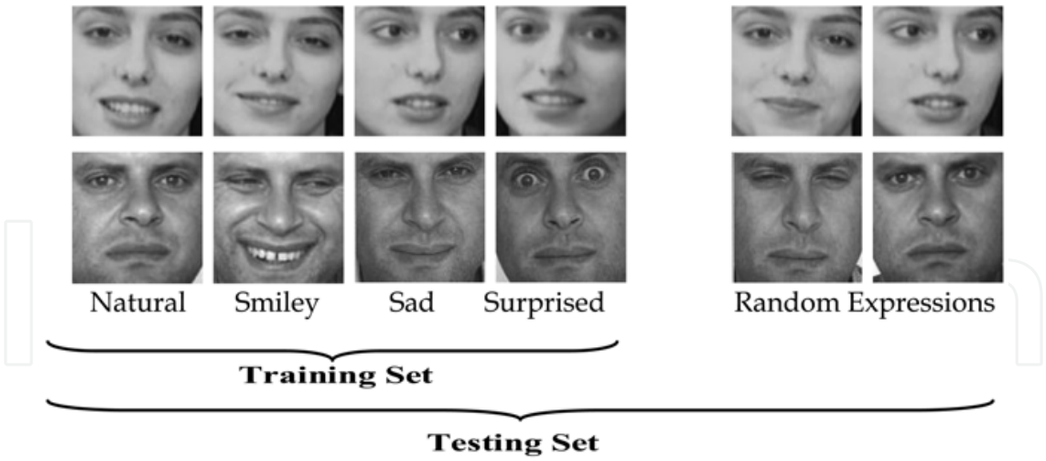


Fig. 3. Examples of training and testing face images

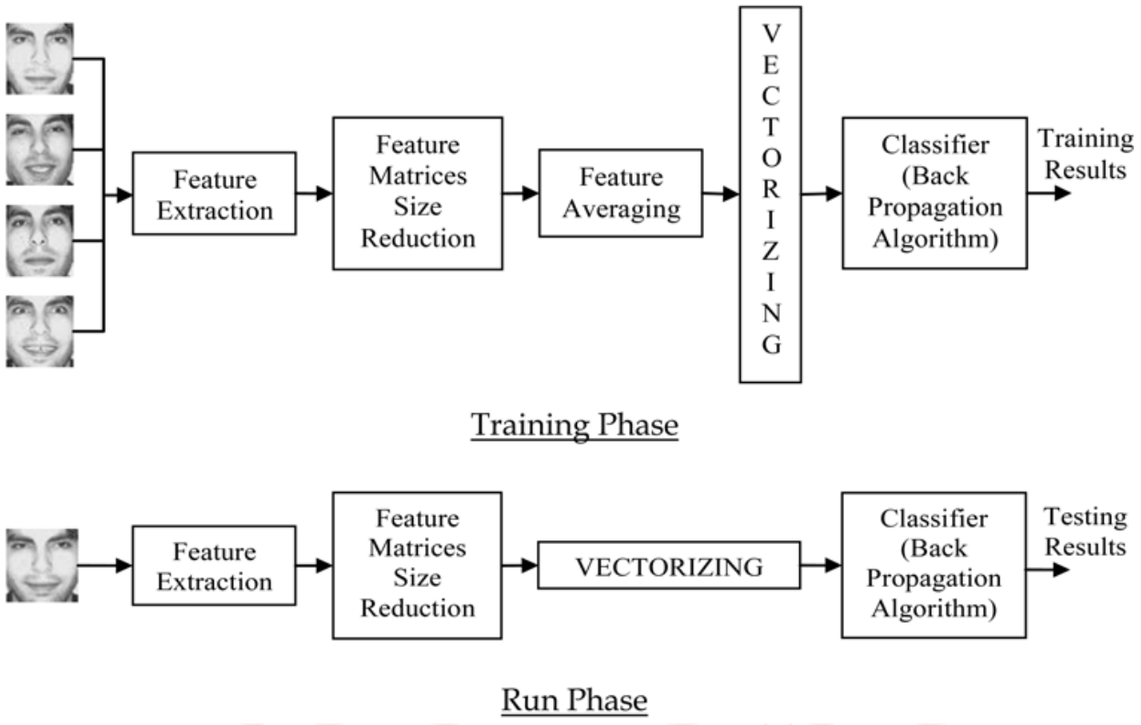


Fig. 4. General architecture of the intelligent local face recognition system

The features are, firstly extracted for each facial expression of each subject as shown in Fig. 5. Feature extraction is manually performed using Photoshop. Secondly, the dimensions of each feature are 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.



Fig. 5. Extracted local features from four different expressions

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.

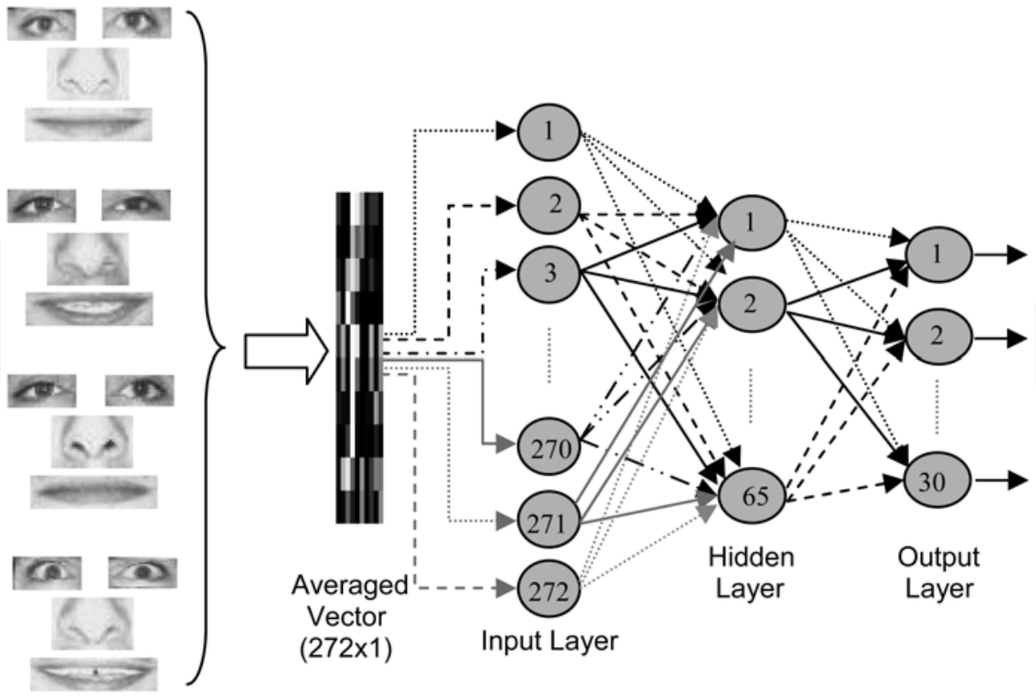


Fig. 6. Local pattern averaging and neural network design

3.4 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.

Input Layer Nodes	272
Hidden Layer Nodes	65
Output Layer Nodes	30
Bias Neurons Value	1
Learning Rate	0.0495
Momentum Rate	0.41
Minimum Error	0.001
Iterations	3188
Training Time (seconds)	265
Generalization/Run Time (seconds)	0.032

Table 1. Trained neural network final parameters using local face data

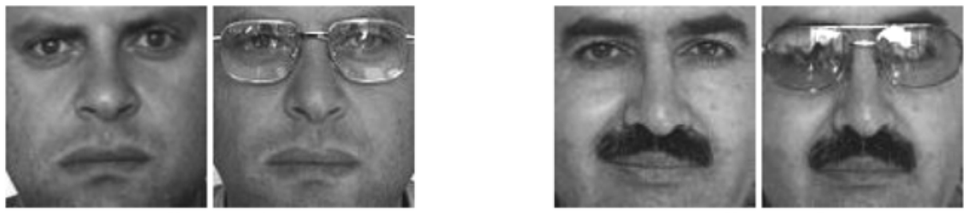
The overall recognition rate for the system was 96.7% where 174 out of the available 180 faces were correctly recognized with an accuracy rate of 89.3%. The recognition rate refers to the percent of correctly recognized faces, whereas the recognition accuracy refers to the classification real output value in comparison to the desired output value of “1”, using binary output coding.

The processing time for face image preprocessing and feature averaging was 7.5 seconds, whereas running the trained neural network took 0.032 seconds. The recognition rates and recognition accuracy the trained system are shown in Table 2.

Database	Own	ORL	Total
Recognition Rate	100 %	93.3 %	96.7 %
Recognition Accuracy	91.8 %	86.8 %	89.3 %

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.



(a) Person 1 (b) Person 2

Fig. 7. (a) Clear eyeglasses (b) 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.

Person 1		Person 2	
No Eyeglasses	Clear Eyeglasses	No Eyeglasses	Dark Eyeglasses
96 %	86%	90 %	73 %

Table 3. Recognition Accuracy With and Without Eyeglasses

3.5 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.

4. Discussions and conclusion

This chapter presented a review of related works on face recognition in general and on intelligent face recognition in particular. Research work on the later has been increasing

lately due to the advancement in Artificial Intelligence and the availability of fast computing power.

The recognition of a face that has been seen before is a natural and easy task that we humans perform everyday. What information we pick from a face during a glance may be mysterious but the result is usually correct recognition. Do we only look at features such as eyes or nose (local recognition) or do we ignore these features and look at a face as a whole (global recognition)? How about the other "input" information in addition to our visual information such as sounds or smell? The brain is an efficient parallel processor that receives enormous amount of data and processes it at incredibly high speeds. Therefore, in real life face recognition, the brain would be processing not only the image of a face, but also gestures, sounds, odor and any other information that might help achieving a quick recognition. Of course, to simulate such a parallel perceiving machine that would use multisenses is yet to be achieved. Meanwhile, we focus on the visual input that is represented as facial images.

Many research works on face recognition attempt to answer the above questions, while scientist differ in their approaches or methods to how face recognition can be simulated in machines. One common concept that is shared by most methods is that the detection of a face requires facial information, which can be obtained locally (using local facial features such as eyes) or globally (using a whole face).

The diversity of the different methods and approaches is more evident when investigating the development of artificial intelligent face recognition systems. These intelligent systems aim to simulate the way we humans recognize faces. Here one can pause for a while and think "What do I really look at when I look at a face?". The answer could be that we all have our own ways which might differ, thus the diversity in simulating intelligent face recognition in machines.

This chapter described one example of intelligent face recognition methods that has been previously suggested. The method uses essential local face features of a person with different facial expression, and is referred to as "Intelligent Local Face Recognition". The artificial intelligent system was implemented using supervised neural networks whose tasks were to simulate the function and structure of a brain that receives visual information.

The local averaging neural network learnt to classify the faces within 265 seconds, whereas the running time for the trained neural network was 0.032 seconds. These time costs can be further reduced by using faster machines, which will inevitably occur in the near future. The local average neural network implementation yielded 100% recognition rate when using the 30 locally averaged face images in the training set. Testing was carried out using 180 face images which contain different face expressions that were not exposed to the neural network before. Here, 174 out of the 180 test images were correctly identified yielding 96.7% recognition rate. Thus, the overall recognition rate was determined as 97.14%.

In conclusion, local averaging can be applied successfully to identify faces with different expressions. Here, the image databases contain only the faces as the method uses essential facial features such as eyes, nose and mouth; therefore the existence of background and occlusions is irrelevant. Although the local feature pattern values (pixel values) may change with the change of facial expression, the use of local averaging 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.

Despite successful implementations of artificial intelligent face recognition systems such as the one shown in the case study in this chapter, there are questions that are yet to be

answered before we can completely trust a machine whose intelligence "evolves" in minutes in comparison with our natural intelligence that took thousands of years to evolve. There is no doubt that the advancement in technology provides us with the means to develop artificially intelligent systems, but how intelligent are they really are?

Most of the currently developed intelligent recognition systems are aimed to be used as an aid to human operators. A completely, autonomous system would be our eventual target. The development of more powerful and faster computing systems is continuing, and with this increase in computational power we can design intelligent recognition systems that could perform many recognition tasks at once. So the simulation of our parallel information processing is getting closer albeit slowly and gradually.

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6. Online resources

6.1 Comprehensive face recognition resources

http://www.cbsr.ia.ac.cn/users/szli/FR-Handbook/
http://www.face-rec.org/general-info/
http://www.epic.org/privacy/facerecognition/
http://www.findbiometrics.com/Pages/face_articles/face_2.html

6.2 Fun with face recognition

http://www.myheritage.com/FP/Company/tryFaceRecognition.php
http://faculty.washington.edu/chudler/java/faces.html
http://faculty.washington.edu/chudler/java/facemem.html

6.3 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.ri.cmu.edu/projects/project_418.html

Project - Face In Action (FIA) Face Video Database, AMP, CMU
http://amp.ece.cmu.edu/projects/FIADataCollection/

AT&T "The Database of Faces" (formerly "The ORL Database of Faces")
http://www.cl.cam.ac.uk/Research/DTG/attarchive/facedatabase.html

Cohn-Kanade AU Coded Facial Expression Database
http://vasc.ri.cmu.edu/idb/html/face/facial_expression/index.html

MIT-CBCL Face Recognition Database
http://cbcl.mit.edu/software-datasets/heisele/facerecognition-database.html

Image Database of Facial Actions and Expressions - Expression Image Database
http://mambo.ucsc.edu/psl/joehager/images.html

Face Recognition Data, University of Essex, UK
http://cswww.essex.ac.uk/mv/allfaces/index.html

NIST Mugshot Identification Database
http://www.nist.gov/srd/nistsd18.htm

NLPR Face Database
http://nlpr-web.ia.ac.cn/english/irds/facedatabase.htm

M2VTS Multimodal Face Database (Release 1.00)
http://www.tele.ucl.ac.be/PROJECTS/M2VTS/m2fdb.html

The Extended M2VTS Database, University of Surrey, UK
http://www.ee.surrey.ac.uk/Research/VSSP/xm2vtsdb/

The AR Face Database, Purdue University, USA
http://rvl1.ecn.purdue.edu/~aleix/aleix_face_DB.html

The University of Oulu Physics-Based Face Database
http://www.ee.oulu.fi/research/imag/color/pbfd.html

CAS-PEAL Face Database
http://www.jdl.ac.cn/peal/index.html

Japanese Female Facial Expression (JAFFE) Database
http://www.irc.atr.jp/~mlyons/jaffe.html

BioID Face DB - HumanScan AG, Switzerland
http://www.humanscan.de/support/downloads/facedb.php

Psychological Image Collection at Stirling (PICS)
http://pics.psych.stir.ac.uk/

The UMIST Face Database
http://images.ee.umist.ac.uk/danny/database.html

Caltech Faces
http://www.vision.caltech.edu/html-files/archive.html

EQUINOX HID Face Database
http://www.equinoxsensors.com/products/HID.html

VALID Database
http://ee.ucd.ie/validdb/

The UCD Colour Face Image Database for Face Detection
http://ee.ucd.ie/~prag/

Georgia Tech Face Database
http://www.anefian.com/face_reco.htm

Indian Face Database
http://vis-www.cs.umass.edu/~vidit/IndianFaceDatabase/



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Edited by Kresimir Delac, Mislav Grgic and Marian Stewart Bartlett

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The main idea and the driver of further research in the area of face recognition are security applications and human-computer interaction. Face recognition represents an intuitive and non-intrusive method of recognizing people and this is why it became one of three identification methods used in e-passports and a biometric of choice for many other security applications. This goal of this book is to provide the reader with the most up to date research performed in automatic face recognition. The chapters presented use innovative approaches to deal with a wide variety of unsolved issues.

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INTECH
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InTech Europe
University Campus STeP Ri
Slavka Krautzeka 83/A
51000 Rijeka, Croatia
Phone: +385 (51) 770 447
Fax: +385 (51) 686 166
www.intechopen.com

InTech China
Unit 405, Office Block, Hotel Equatorial Shanghai
No.65, Yan An Road (West), Shanghai, 200040, China
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元
Phone: +86-21-62489820
Fax: +86-21-62489821

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