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Face Recognition Enhancement for Security Purposes

A thesis
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Statement

This dissertation is submitted to Ain-Shams University in partial fulfillment for degree of Master of science in Electrical Engineering (Electronics and Communication Engineering).

The work included in this dissertation was carried out by the author at the Electronics and Communications Engineering Department, Ain Shams University.

No part of this dissertation has been submitted for a degree or a qualification at any other university or institute.

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Abstract

With the fast evolution in security fields in ministries and large firms, face recognition systems are needed to identify and recognize people. Given an input face image and a database of face images of known individuals, face recognition systems aims to verify or determine the identity of the person that in the input image.

Face Recognition is a task that human vision system seems to perform almost effortlessly. Yet the goal of building computer-based systems with comparable capabilities has proven to be difficult.

Many techniques for face recognition have been proposed over the last 30 years, and some were even proposed earlier. Some techniques extract local features from the face image (structural matching techniques), while others uses the face image as a whole (holistic matching techniques). Some techniques are a hybrid of both.

Subspace techniques which belong to the holistic category are the most successful techniques for face recognition. These techniques aim to reduce the dimensions of the face images by projecting the high-dimensional images to a lower-dimensional subspace, where each image is represented by a linear combination of vectors in the subspace.

In this work, a fully face recognition system to classify faces has been implemented. Principal Component Analysis (PCA) technique has been used as one of the holistic matching techniques for dimensionality reduction and feature extraction. Using PCA, features are extracted from the whole face, then an empirical method to choose the most principal "important" features from the face has been developed, this empirical method helps the classifier to recognize faces more easily and more efficiently. The mathematical model of PCA technique is proposed in this thesis, and its equations has been performed and implemented using Matlab Programming.

After the feature extraction phase, a Feed Forward Neural Network is used for classification, specifically, a Multi Linear Perceptron (MLP) networks is used, and a Back Propagation (BP) algorithm is used as a learning algorithm.

An empirical method has been developed to choose the number of hidden neurons of the hidden layer to avoid both underfitting and overfitting problems. The mathematical model of the back propagation algorithm is proposed in this thesis, and has been performed using the neural network tool box available in Matlab. The Olivetti Research Laboratory (ORL) database is used for performance evaluation.

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Abbreviations

ADALINE	Adaptive Linear Neuron
ANN	Artificial Neural Network
BP	Back Propagation
BPNN	Back Propagation Neural Network
CNN	Convolutional Neural Network
DCT	Discrete Cosine Transform
DLA	Dynamic Link Architecture
E	Eigen Space
EBGM	Elastic Bunch Graph Matching
FLD	Fisher Discriminant Analysis
HCI	Human-computer interaction
ICA	Independent Component Analysis
IR	Infra Red
KLT	Karhunen-Loeve Transform
Learngdm	Back propagation weight/bias learning function
LDA	Linear discriminant Analysis
LM	Levenberg Marquardt Algorithm
MLP	Multi Layer Perceptron
MSE	Mean Square Error
NN	Neural Network
Newff	Network design function
ORL	Olivetti Research Laboratory
PCA	Principal Component Analysis
R	A value to indicate the relationship between output and target
RBF	Radial Basis Function
RGB	Red-Green-Blue Model
RNG	Random Number Generator
RNN	Recurrent Neural Network
SLP	Single Layer Perceptron
SOM	Self Organizing Map
SVM	Support Vector Machine
Trainlm	Levenberg Marquardt Training Algorithm
TSP	Traveling Sales Man Problem

List of Symbols

I*(x,y)*	Image of two dimensional *m* by *n* array intensity values
m	Number of rows in I image
n	Number of columns in I image
R^N	The m*n dimensional space
M	Number of training images
N	Number of pixels contained in an image
Γ_M	M sample images contained in the database (the training set of images)
Ψ	Mean image
Φ_i	Mean centered face training image in the image space
A	Data Matrix.
C	Covariance matrix AA^T
L	Matrix $A^T A$
μ_i	Eigen values
v_i	Eigen vectors
U	Eigenvectors of the covariance matrix AA^T
e_k	The selected eigenfaces (the matrix of the first eigenfaces)

v_k	The largest selected eigenvectors
e_k	The selected eigenfaces (the matrix of the first eigenfaces)
y_i	The projection of the centered training image Φ_i to the PCA *eigenspace E* defined by the reduced matrix of eigenvectors of the covariance matrix C
T	New face image of an individual
t	The mean centered image of the new test image of an individual
F_k	The projection of the vector of the mean testing face image T into the eigenspace
Ω^T	Vector of the calculated values of F together which describes the contribution of each eigenface in representing the input face image, treating the eigenfaces as a basis set for face images
X_k	Vector of current weights and biases in the back propagation algorithm
g_k	Current gradient in the back propagation algorithm
α_k	Learning rate in the back propagation algorithm
J	Jacobian matrix for the system that contains first derivatives of the network errors with respect to weights and biases
λ	Levenberg's damping factor
δ	Weight update vector that we want to find
E	Error vector containing the output errors for each input vector used on training the network
H	Approximated Hessian matrix J^TJ
$F(x_i, w)$	Network function evaluated for the *i*-th input vector of the training set using the weight vector w in Jacobian matrix

w_j The j-th element of the weight vector w of the network in the Jacobian matrix.

g Error gradient in the back propagation algorithm

S_{nj} Target state of n patterns, and j images included in each n pattern