Face Recognition System using Artificial Neural Networks Approach

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Face Recognition System using Artificial Neural Networks Approach

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Abstract: **Advances in face recognition have come from considering various aspects of this specialized perception problem. Earlier methods treated face recognition as a standard pattern recognition problem; later methods focused more on the representation aspect, after realizing its uniqueness using domain knowledge; more recent methods have been concerned with both representation and recognition, so a robust system with good generalization capability can be built by adopting state-of-the-art techniques from learning, computer vision, and pattern recognition. A face recognition system based on recent method which concerned with both representation and recognition using artificial neural networks is presented. This paper initially provides the overview of the proposed face recognition system, and explains the methodology used. It then evaluates the performance of the system by applying two (2) photometric normalization techniques: histogram equalization and homomorphic filtering, and comparing with Euclidean Distance, and Normalized Correlation classifiers. The system produces promising results for face verification and face recognition.**

I. Introduction

The demand for reliable personal identification in computerized access control has resulted in an increased interest in biometrics to replace password and identification (ID) card. The password and ID card can be easily breached since the password can be divulged to an unauthorized user, and the ID card can be stolen by an impostor. Thus, the emergence of biometrics has addressed the problems that plague the traditional verification methods. Biometric which make use of human features such as iris, retina, face, fingerprint, signature dynamics, and speech can be used to verify a person's identity. The biometrics data have an edge over traditional security methods since they cannot be easily stolen or shared. The face recognition system has the benefit of being a passive, non-intrusive system for verifying personal identity.

The proposed face recognition system consists of face verification, and face recognition tasks. In verification task, the system knows *a priori* the identity of the user, and has to *verify* this identity, that is, the system has to decide whether the a priori user is an impostor or not. In face recognition, the a priori identity is not known: the system has to decide which of the images stored in a database resembles the most to the image to recognize. The primary goal of this paper is to present the performance evaluation carried out using artificial neural network for face verification and recognition. The remainder of this paper is organized as follows. Section 2 describes the system process flow and the modules of the proposed face recognition system. Section 3 elaborates the methodology used for the preprocessing, feature extraction, and classification of the proposed system. Section 4 presents and discusses the experimental results and the conclusions are drawn in section 5.

II. System Overview

The proposed face recognition system consists of two (2) phases which are the enrollment and recognition/verification phases as depicted in Fig. 1. It consists of several modules which are Image Acquisition, Face Detection, Training, Recognition and Verification.

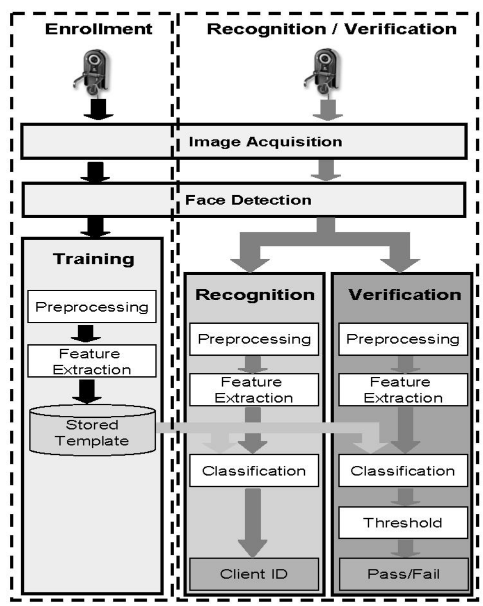

Fig. 1. Block Diagram for the Face Recognition System

A. Enrollment phase

The image is acquired using a web camera and stored in a database. Next, the face image is detected and trained. During

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training, the face image is preprocessed using geometric and photometric normalization. The features of the face image are extracted using several feature extraction techniques. The features data is then stored together with the user identity in a database.

B. Recognition/verification phase

A user's face biometric data is once again acquired and the system uses this to either identify who the user is, or verify the claimed identity of the user. While identification involves comparing the acquired biometric information against templates corresponding to all users in the database, verification involves comparison with only those templates corresponding to claimed identity. Thus, identification and verification are two distinct problems having their own inherent complexities. The recognition/verification phase comprises of several modules which are image acquisition, face detection, and face recognition /verification.

1) Image acquisition/face detection module

Face detection is used to detect face and to extract the pertinent information related to facial features. The image will then be resized and corrected geometrically so that it is suitable for recognition/verification. In this module, the background or the scenes unrelated to face will be eliminated. The system can detect a face in real-time. The face detection system is also robust against illumination variance and works well with different skin color and occlusions such as beards, moustache and with head cover.

The face detection consists of image acquisition module. Its purpose is to seek and then extracts a region which contains only the face. The system was based on the rectangle features using Adaboost algorithm. The outputs of the system are the rectangle which contains face features, and image which contains the extraction of the detection face features.

2) Face recognition/verification module

The face recognition module comprises of preprocessing, feature extraction, and classification sub-modules. The input to the face recognition/verification module is the face image, which is derived from two sources: from the camera and from the database. From these sources, each image is preprocessed to get the geometric and photometric normalized form of the face image. During feature extraction, the normalized image is represented as feature vectors. The result of the classification for the recognition purpose is determined by matching the client index with the client identity in the database.

III. METHODOLOGY

A. Preprocessing

The purpose of the pre-processing module is to reduce or eliminate some of the variations in face due to illumination [4, 9, 11]. It normalized and enhanced the face image to improve the recognition performance of the system. The preprocessing is crucial as the robustness of a face recognition system greatly depends on it. By performing explicit normalization processes, system robustness against scaling, posture, facial expression and illumination is increased. The photometric normalization consists of removing the mean of the geometrically normalized image and scaling the pixel values by their standard deviation, estimated over the whole cropped image. The photometric normalization techniques applied are Histogram Equalization, and Homomorphic Filtering.

1) Histogram equalization

Histogram equalization is the most common histogram normalization or gray level transform, which purpose is to produce an image with equally distributed brightness levels over the whole brightness scale. It is usually done on too dark or too bright images in order to enhance image quality and to improve face recognition performance. It modifies the dynamic range (contrast range) of the image and as a result, some important facial features become more apparent.

The steps to perform histogram equalization are as follow:

1. For an $N \times M$ image of G gray-levels, create two arrays H and T of length G initialized with 0 values.
2. Form the image histogram: scan every pixel and increment the relevant member of H-- if pixel X has intensity p, perform

$$H[p] = H[p] + 1 \tag{1}$$

3. Form the cumulative image histogram H_c, use the same array H to store the result.

$$H[0] = H[0]$$
$$H[p] = H[p-1] + H[p]$$

for $p = 1, \ldots, G-1$.

4. Set

$$T[p] = \frac{G-1}{MN} H[p] \tag{2}$$

Rescan the image and write an output image with gray-levels q, setting $q = T[p]$.

2) Homomorphic filtering

The homomorphic filtering algorithm is similar to that of Horn's algorithm except the low spatial frequency illumination is separated from the high frequency reflectance by Fourier high-pass filtering. In general a high-pass filter is used to separate and suppress low frequency components while still passing the high frequency components in the signal, if the two types of signals are additive, i.e., the actual signal is the sum of the two types of signals. However, in this illumination/reflection problem low-frequency illumination is *multiplied*, instead of added, to the high-frequency reflectance. To still be able to use the usual high-pass filter, the logarithm operation is needed to convert the multiplication to addition. After the homomorphic filtering process, $I(x,y)$, the processed illumination should be drastically reduced due to the high-pass filtering effect, while the reflectance $R(x,y)$ after this procedure should still be very close to the original reflectance. That is, color constancy results as the color of the surface is not affected much by the color illumination. The steps of this algorithm are as follow:

1. Take logarithm of the input light signal:

$$\begin{aligned} L'(x,y) &\underline{\underline{\Delta}} \log L(x,y) = \log[R(x,y)I\{x,y)] \\ &= \log R(x,y) + \log I(x,y) \underline{\underline{\Delta}} R'(x,y) + I'(x,y) \end{aligned} \tag{3}$$

2. Carry 2D Fourier transform of the signal :

$L'(x,y)=R'(x,y) + I'(x,y)$

$$L(u,v) \underline{\underline{\Delta}} FL'(x,y) = FR'(x,y) + FI'(x,y) \underline{\underline{\Delta}} R(u,v) + I(u,v) \tag{4}$$

where $R(u,v)$, $I(u,v)$ and $L(u,v)$ are the Fourier spectra of the corresponding spatial signals $R'(x,y)$, $I'(x,y)$ and $L'(x,y)$, respectively.

3. Suppress low frequency components in Fourier domain

$$H(u,v)L(u,v)=H(u,v)R(u,v)+H(u,v)I(u,v) \tag{5}$$

where $H(u,v)$ is a filter in the frequency domain whose entries corresponding to the low frequencies are smaller than 1 (suppression of low-frequency components, the illumination) while the rest entries are 1 to keep the high-frequency components in the signal (mostly the reflectance) unchanged.

4. Take inverse Fourier transform

$$\begin{aligned} L'(x,y) &\underline{\underline{\Delta}} F^{-1}[H(u,v)L(u,v)] \\ &= F^{-1}[H(u,v)R(u,v)] + F^{-1}[H(u,v)I(u,v)] \\ &\underline{\underline{\Delta}} R'(x,y) + I'(x,y) \end{aligned} \tag{6}$$

5. Take exponential operation

$$\begin{aligned} L(x,y) &\underline{\underline{\Delta}} \exp[L'(x,y)] = \exp[R'(x,y) + I'(x,y)] \\ &= \exp[R'(x,y)]\exp[I'(x,y)] \underline{\underline{\Delta}} R(x,y)I(x,y) \end{aligned} \tag{7}$$

B. Feature extraction

The purpose of the feature extraction is to extract the feature vectors or information which represents the face. The feature extraction algorithms used are Principal Component Analysis (PCA), and Linear Discriminant Analysis (LDA).

1) Principal component analysis (PCA)

PCA for face recognition is used in [1,2,3,5] is based on the information theory approach. It extracted the relevant information in a face image and encoded as efficiently as possible. It identifies the subspace of the image space spanned by the training face image data and decorrelates the pixel values. The classical representation of a face image is obtained by projecting it to the coordinate system defined by the principal components. The projection of face images into the principal component subspace achieves information compression, decorrelation and dimensionality reduction to facilitate decision making. In mathematical terms, the principal components of the distribution of faces or the eigenvectors of the covariance matrix of the set of face images, is sought by treating an image as a vector in a very high dimensional face space. The detailed explanation is provided in [6,12,16].

2) Linear discriminant analysis (LDA)

LDA is used in machine learning to find the linear combination of features which best separate two or more classes of object or event, where the resulting combinations are used as a linear classifier [7,10,13,14]. It is also considered as feature reduction, mapping a multidimensional space into a space of fewer dimensions, prior to later classification. LDA is used in a number of classification related applications. One of these is face recognition where each face, which consists of a large number of pixels, is reduced to a smaller set of linear combinations prior to classification. The linear combinations obtained using LDA are referred to as Fisherfaces. Linear Disriminant Analysis (LDA) is used for face recognition in [8], where face image retrieval is based on discriminant analysis of eigenfeatures. The LDA is the projection of a face image into the system of fisherfaces associated with nonzero eigenvalues, which will yield a representation which emphasize the discriminatory content of the image. LDA selects the linear subspace Φ which maximizes the ratio:

$$\frac{\left|\Phi^T S_b \Phi\right|}{\left|\Phi^T S_W \Phi\right|} \tag{8}$$

$$S_b = \frac{1}{c}\sum_{k=1}^{c}(\mu_k - \mu)(\mu_k - \mu)^T \tag{9}$$

is the between-class scatter matrix, and

$$S_w = \frac{1}{M}\sum_{k=1}^{c}\sum_{i|x_i \in C_k}(x_i - \mu_k)(x_i - \mu_k)^T \tag{10}$$

the within-class scatter matrix,

where c is the number of clients, M is number of training face images, x_i, μ is the grand mean, and μ_k is the mean of class C_k.

Intuitively, LDA finds the projection of the data in which the classes are most linearly separable.

C. Classification

The purpose of the classification sub-module is to map the feature space of a test data to a discrete set of label data that serves as template. The classification techniques used are, Artificial Neural Network, Euclidean Distance and Normalized Correlation.

Artificial neural networks (ANN)

ANN is a machine learning algorithm that has been used for various pattern classification problems such as gender classification, face recognition, and classification of facial expression. ANN classifier has advantages for classification such as incredible generalization and good learning ability. The ANN takes the features vector as input, and trains the network to learn a complex mapping for classification, which will avoid the need for simplifying the classifier. Being able to offer potentially greater generalization through learning, neural networks/learning methods have also been applied to face recognition in [8].

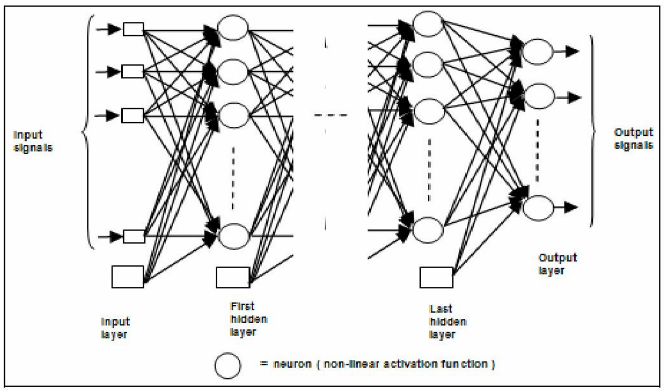

Fig. 2. Multilayer Feed Forward Neural Network (MFNN)

The ANN paradigm that is used in this application is Multi-layer Feed-forward Neural Networks (MFNNs). MFNNs are a form of non-linear network consisting of a set of inputs (forming the input layer), followed by one or more hidden layers of non-linear neurons and an output layer of non-linear neurons as shown in Fig. 2.

MFNN is an ideal means of tackling a whole range of difficult tasks in pattern recognition and regression because of its highly adaptable non-linear structure. In order to train the network to perform a given tasks the individual weights (w_{ij})for each neuron are set using a supervised learning algorithm known as the error-correction back-propagation algorithm as depicted in Fig. 3, which involves repeatedly presenting the network with samples from a training set and adjusting the neural weights in order to achieve the required output. It is essentially a gradient descent method, where when adjusting the weight matrices, the direction is move to the greatest descent.

The learning constant, η, must be chosen with care. If it is too large, the algorithm may repeatedly overshoot the solution, which will lead to slow convergence or even no convergence at all. However, if it is too small, the algorithm will only approach the solution at a very slow rate, again leading to a slow convergence and increasing the chances of the algorithm becoming stuck in local minima. Two main methods of overcoming these problems are momentum and adaptive learning.

For momentum method**,** if we are consistently moving in the same direction, then we want to build up some momentum in that direction. This will help us to go through any small local minima and hopefully speed up convergence.

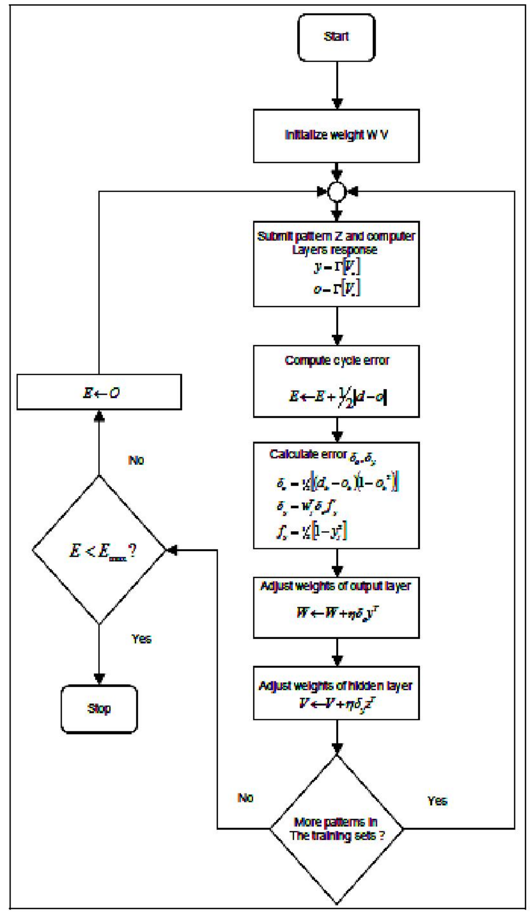

Fig. 3. Flowchart of Error-Correction Back-Propagation Algorithm

Standard: $\Delta w(t) = -\eta \nabla E(t)$ (11)

Momentum: $\Delta w(t) = -\eta \nabla E(t) + \alpha \Delta w(t-1)$ (12)

where α is the momentum term.

For adaptive learning rate**,** adjusting the learning rate dynamically, usually starting with a large value and then decreasing it as we approach the solution in order to prevent overshoot.. The input data for training comes from the output data of the feature extraction module.

Euclidean distance (E.D.)

The Euclidean distance is the nearest mean classifier which is commonly used for decision rule is denoted as [15]:

$$d_E(x, w_k) = \sqrt{(x - w_k)^T (x - w_k)} \quad (13)$$

where the claimed client is accepted if $d_E(x, w_k)$ is below the threshold τ_{Ek} and rejected otherwise.

Normalized correlation (N.C.)

The normalized correlation decision rule based on the correlation score denoted as:

$$d_C(x, w_k) = \frac{|x^T w_k|}{|x||w_k|} \tag{14}$$

where the claimed identity is accepted if $d_C(x, w_k)$ exceeds the threshold τ_{Ck}.

IV. Experimental Results

The purpose of the experiment is to evaluate the performance of the face recognition system by applying the photometric normalization techniques: homomorphic filtering and histogram equalization, to the face images. The face images are frontal face images, which are taken from our local face images database. The database consists of face images from twenty (20) individuals, each with ten (10) face images.

For verification, two measures are used, which are the false acceptance rate (FAR) and false rejection rate (FAR). FAR is the case when an impostor, claiming the identity of a client, is accepted, whilst FRR is the case when a client claiming his true identity is rejected. The FAR and FRR are given by:

$$FAR = IA/I, \quad FRR = CR/C \tag{15}$$

where *IA* is the number of impostor accepted, *I* is the number of impostor's trials, *CR* is the number of client rejected and *C* is the number of client's trials.

A. Face verification

The first experiment is to evaluate the verification performance of the face recognition system using the original face images. The result is tabulated in TABLE 1, which shows that even though E.D. classifier has the lowest HTER, N.N. classifier gives the best result in average for both PCA and LDA feature extractors.

In the second experiment, we initially apply the combination of histogram equalization and homomorphic filtering to the face images. The result for this experiment is tabulated in TABLE 2, which shows that N.C. classifier has the lowest HTER for both of the feature extractors.

Table 1: Verification Results using Original Image

Feature Extractor	Classifier	FAR = FRR (%)		HTER (%)
		FAR	FRR	
PCA	E.D.	7.250	7.410	7.330
	N.C.	14.440	15.560	15.000
	N.N	5.820	5.560	5.690
LDA	E.D.	3.700	3.330	3.515
	N.C.	10.920	10.370	10.645
	N.N	4.550	5.190	4.870

Table 2: Verification Results using Histogram Equalization and Homomorphic Filtering

Feature Extractor	Classifier	FAR = FRR (%)		HTER (%)
		FAR	FRR	
PCA	E.D.	9.320	11.850	10.585
	N.C.	5.750	6.300	6.025
	N.N	7.340	7.780	7.560
LDA	E.D.	6.580	6.670	6.625
	N.C.	5.250	6.300	5.775
	N.N	6.080	6.300	6.190

The third experiment is to apply the combination of homomorphic filtering, and histogram equalization to the face images. The result tabulated in TABLE 3 shows that N.N. classifier has the lowest HTER.

Table 3: Verification Results using Homomorphic Filtering and Histogram Equalization

Feature Extractor	Classifier	FAR = FRR (%)		HTER (%)
		FAR	FRR	
PCA	E.D.	6.540	12.590	9.565
	N.C.	5.690	5.560	5.625
	N.N	4.140	3.700	3.920
LDA	E.D.	6.030	6.300	6.165
	N.C.	3.660	4.810	4.235
	N.N	4.660	5.190	4.925

Thus, as a whole, for face verification N.N. classifier can be considered as the best classifier among the three classifiers since it performs consistently in all the experiments using both PCA and LDA feature extractors.

B. Face recognition

For recognition purpose, the performance is evaluated based on the recognition rate or accuracy. The result for experiment using the original image is tabulated in TABLE 4, which shows that E.D. classifier gives the highest recognition rate for both PCA and LDA feature extractors. When we apply the combination of histogram equalization and homomorphic filtering to the face images, still the E.D. classifier gives the highest accuracy as tabulated in Table 5.

Table 4: Recognition Results using Original Image

Feature Extractor	Classifier	Recognition (%)
PCA	E.D.	98.51
	N.C.	97.04
	N.N	87.03
LDA	E.D.	97.78
	N.C.	97.04
	N.N	84.44

However, in the last experiment, that is when we apply the combination of homomorphic filtering and histogram equalization, N.N classifier gives the highest accuracy using PCA feature extractor, while N.C. produces the highest accuracy using LDA feature extractor.

Table 5: Recognition Results using Histogram Equalization and Homomorphic Filtering

Feature Extractor	Classifier	Recognition (%)
PCA	E.D.	90.74
	N.C.	90.00
	N.N	87.78
LDA	E.D.	92.96
	N.C.	91.11
	N.N	88.89

Table 6: Recognition Results using Homomorphic Filtering and Histogram Equalization

Feature Extractor	Classifier	Recognition (%)
PCA	E.D.	91.85
	N.C.	91.85
	N.N	92.59
LDA	E.D.	90.00
	N.C.	92.22
	N.N	85.56

V. Conclusion

The paper has presented a face recognition system using artificial neural networks in the context of face verification and face recognition using photometric normalization for comparison. The experimental results show that N.N. is superior to the Euclidean distance and normalized correlation decision rules using both PCA and LDA for overall performance for verification. However, for recognition, E.D. classifier gives the highest accuracy using the original face image. Thus, applying histogram equalization and homomorphic filtering techniques on the face image do not give much impact to the performance of the system if conducted under controlled environment.

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