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PCA-ANN Face Recognition System based on Photometric Normalization Techniques

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1. Introduction

The human face is the main focus of attention in social interaction, and is also the major key in conveying identity and emotion of a person. It has the appealing characteristic of not being intrusive as compared with other biometric techniques. The research works on face recognition started in the 1960s with the pioneering work of Bledsoe and Kanade, who introduced the first automated face recognition system (Zhao *et al*, 2003). From that onwards, the research on face recognition has widespread and become one of the most interesting research area in vision system, image analysis, pattern recognition and biometric technology.

Recently, research on face recognition has received attention and interest from the scientific community as well as from the general public. Face recognition has become a major issue in many security, credit card verification, and criminal identification applications due to its applicability as a biometric system in commercial and security applications to prevent unauthorized access or fraudulent use of Automated Teller Machines (ATMs), cellular phones, smart cards, desktop personal computers, workstations and computer networks. Face recognition has been used by law enforcement agencies for finding criminals, by government agencies for fraud and homeland security, and by financial institutions for ATM and check-cashing security to protect customers against identity theft and fraudulent transactions. By using the face recognition, a picture identity, bankcard or Personal Identification Number (PIN) is no longer needed to verify a customer's identity. Face recognition is also applicable in areas other than security oriented applications such as computer entertainment and customized computer-human interaction applications that can be found in products such as cars, aids for disabled people, or buildings. The interest for face recognition will most likely increase even more in the future due to the increased penetration of technologies, such as digital cameras and the internet, and a larger demand for different security schemes.

Face recognition systems (FRS) are still in their infancy. The current FRS still experiencing low accuracy rates due to factors such as illumination, orientation and other disturbances. The quality of a face image has also a big impact on the performance of the FRS. If the illumination on the face image is too high, the face image will be too bright; however, if the illumination is too low, the face image will be too dark. The variation on the illumination will greatly affect the quality of the face image and reduce the performance of the FRS. Thus, it is crucial to improve the quality of the face image in order to have a better

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performance. In this work, we proposed to improve the face image quality by using photometric normalization techniques which will normalize the illumination variation of the face image. The techniques used are based on Histogram Equalization and Homomorphic Filtering. A face recognition system based on Principal Component Analysis (PCA) followed by Artificial Neural Networks (ANN) called PCA-ANN is proposed. PCA is used during the feature extraction phase since it is found to be the simple and popular technique used for feature extraction (Martinez et al, 2001; Li & Jain, 2005).

Sirovich and Kirby (1987) proposed the use of PCA to obtain a reduced representation of face images. Kirby and Sirovich (1991) then proposed the use of PCA for face analysis and representation. The work was followed by Turk and Pentland (1991) who first applied PCA for face recognition and named as "Eigenfaces" technique since the basis vectors constructed by PCA had the same dimension as the input face images. They used PCA as the projection scheme to obtain the feature vectors or Eigenfaces, and Euclidean distance as similarity function to solve face recognition problem. Lee and Lu (1998) proposed a method for generalizing the representational capacity of available face database. Lee *et al.* (1999) later proposed a method using PCA which detects the head of an individual in a complex background and then recognize the person by comparing the characteristics of the face to those of known individuals.

Meanwhile, the ANN based on feed-forward neural networks is used during classification phase because it is one of the machine learning algorithms which is widely used for classification. ANN have been commonly used as the classifier for FRS generally in a geometrical local feature based manner, but there are also some methods where ANN are applied holistically (Nazeer *et al.*, 2007a, 2007b). Lades *et al.* (1993) presented an object recognition system based on Dynamic Link Architectures (DLA) which is an extension of the ANN. The DLA uses correlations in the fine-scale cellular signals to group neurons dynamically into higher order entities. These entities can be used to code high-level objects, such as a 2-D face image. The face images are represented by sparse graphs, whose vertices are labeled by a multi-resolution description in terms of local power spectrum, and whose edges are labeled by geometrical distance vectors. Lawrence *et al.* (1997) presented a hybrid neural-network solution that combines local image sampling, a self-organizing map (SOM) neural network, and a convolutional neural network for face recognition. The SOM provides a quantization of the image samples into a topological space where inputs that are nearby in the original space are also nearby in the output space, thereby providing dimensionality reduction and invariance to minor changes in the image sample, and the convolutional neural network provides for partial invariance to translation, rotation, scale, and deformation. The convolutional network extracts successively larger features in a hierarchical set of layers. Thomaz *et al.* (1998) also studied on ANN by combining PCA and RBF neural network. Their system is a face recognition system consisting of a PCA stage which inputs the projections of a face image over the principal components into a RBF network acting as a classifier. Their main concern is to analyze how different network designs perform in a PCA+RBF face recognition system. They used a forward selection algorithm, and a Gaussian mixture model. According to the results of their experiments, the Gaussian mixture model optimization achieves the best performance even using less neuron than the forward selection algorithm. Their results also show that the Gaussian mixture model design is less sensitive to the choice of the training set.

Temdee *et al.* (1999) presented a frontal view face recognition method by using fractal codes which are determined by a fractal encoding method from the edge pattern of the face region

(covering eyebrows, eyes and nose). In their recognition system, the obtained fractal codes are fed as inputs to back-propagation neural networks for identifying an individual. They tested their system performance on the ORL face database, and reported a recognition rate of 85 %. Er *et al.* (2002) suggested the use of Radial Basis Function (RBF) neural networks on the data extracted by discriminant eigenfeatures. They used a hybrid learning algorithm to decrease the dimension of the search space in the gradient method, which is crucial on optimization of high dimension problem. First, they tried to extract the face features by both the PCA and Linear Discriminant Analysis methods. Next, they presented a hybrid learning algorithm to train the RBF neural networks, where the dimension of the search space is significantly decreased in the gradient method. Tolba and Abu-Rezq (2000) presented an invariant face recognition using the generalization capabilities of both Learning Vector Quantization (LVQ) and RBF neural networks to build a representative model of a face from a variety of training patterns with different poses, details and facial expressions. The combined generalization error of the classifier was found to be lower than that of each individual classifier. A new face synthesis method was implemented for reducing the false acceptance rate and enhancing the rejection capability of the classifier. The system was capable of recognizing a face in less than one second using ORL database for testing the combined classifier.

The chapter is organized as follows. The first part of the chapter provides the system overview of an automated face recognition system. The second part of the chapter elaborates on the methodology used for the proposed face recognition system which includes the photometric normalization techniques, Histogram Equalization and Homomorphic Filtering, the feature extraction technique using PCA and classification using ANN. The final part of the chapter explains the performances of the proposed face verification system using both original face image and the face image with photometric normalization.

2. System overview

An automated face recognition system consists of two main parts which are face detection and face recognition as depicted in Fig. 1. Each of these parts will be described in the following sections.

2.1 Face detection

Face detection is essentially the first fundamental step or front-end of any online face recognition system. It is used to determine whether there is human face in a scene either obtained from camera or still image. It then identifies where the human face is. If the human face is identified, it outputs a human face image consisting of the eyes, the nose and the mouth. The human face is identified using direct image processing techniques which determines the locations and sizes of the face in scene image, and separates them from other non-face objects and distracting background information. The face alignment which involves translation, rotation, and scaling is carried out using the center or edges of the eyes as a reference point since the eyes are an important feature that can be consistently identified.

In Fig. 1, the scene image is captured using a web camera. The captured color image is transformed into a grayscale image. Face localization is applied to determine the image position of a face in the scene image. When the face image is detected, eyes detection is applied to detect the presence and location of the eyes in an image. The eyes location is used

for face alignment to correct the orientation of the face image into an upright frontal face image using affine transformation. The geometrical normalization is used to crop the upright frontal face image and scale it to a desired resolution. The cropped face image is used as the input image for face recognition.

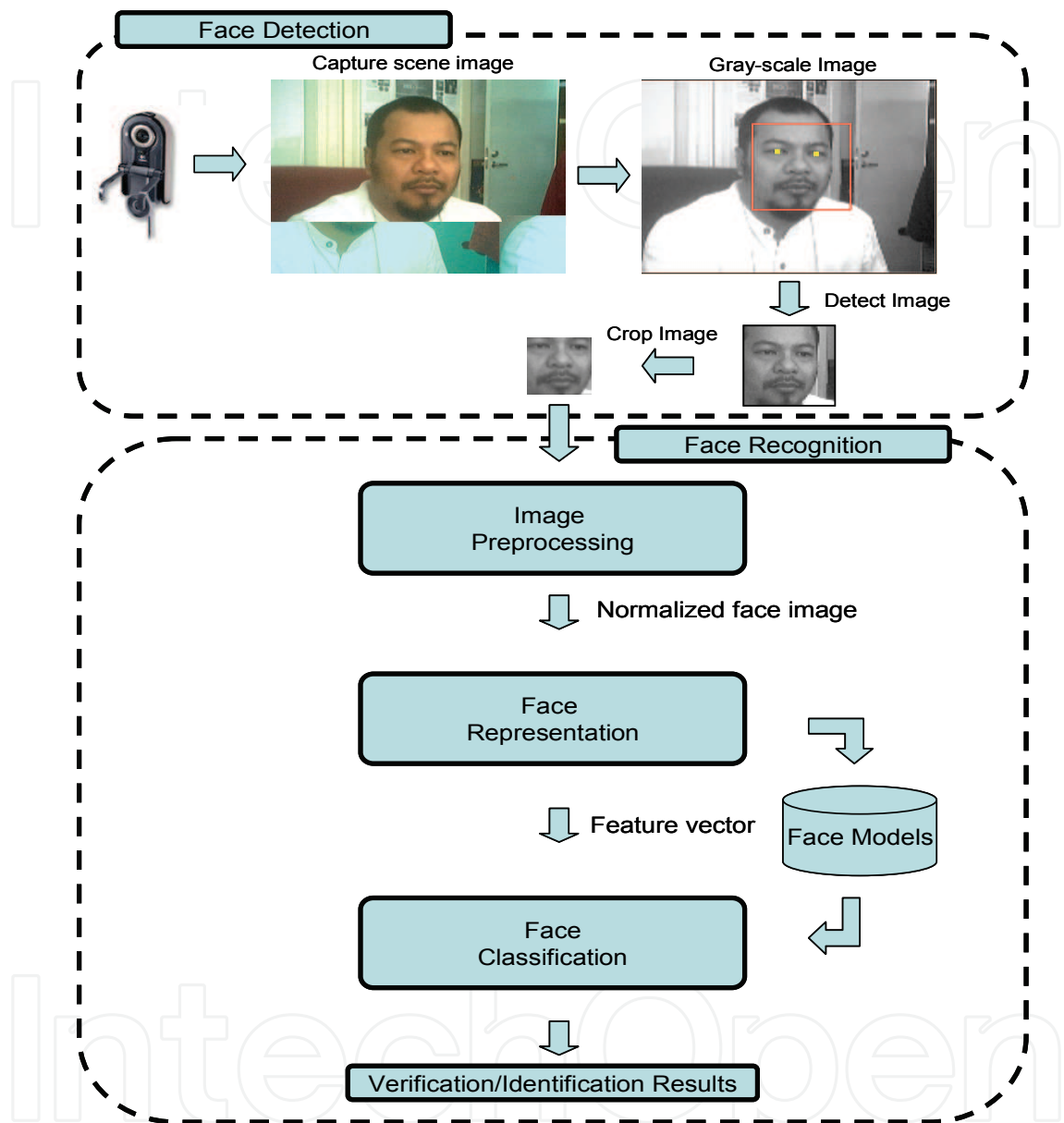


Fig. 1. The main parts of an automated face recognition system

2.2 Face recognition

Face recognition establishes the identity of a person based on the person’s face with reference to a database of known faces. In Fig. 1, face recognition comprises of three main stages which are the image preprocessing, face representation, and face classification. Each of these stages is explained in the following subsections.

(a) Image Preprocessing

The aim of the image preprocessing is to preprocess a face image to enhance the data, remove noise and segment out the crucial data. The image preprocessing involves face

normalization which is used to compensate or normalize a face for position and illumination so that the variance due to these is minimized. A histogram of the face alone is computed to compensate for lighting changes in the image. Consequently, the small variation in the image due to identity, or muscle actuation will become the dominant source of intensity variance in the image and can thus be analyzed for recognition purposes.

(b) Face Representation

Face representation is used to generate a low-dimensional feature representation intrinsic to face objects with good discriminatory power for pattern classification using feature extraction. Feature extraction refers to applying a mapping or transformation of the multidimensional space into a space of fewer dimensions. The aim of feature extraction is to extract a compact set of interpersonal discriminating geometrical or photometrical features of the face. Feature extraction analyzes the variances left in the image using linear statistical techniques to generate a low-dimensional feature representation intrinsic to face objects with good discriminatory power for pattern classification. These techniques are used to classify and characterize the variances that remain in the image since they are now constrained and limited. After been preprocessed to such conditioned data, the unique features are then extracted and a template is then generated to represent the face image. The template will be the basis form to associate the uniqueness of the data with the identity of the user.

(c) Face Classification

Face classification or feature matching is the actual recognition process. Given the feature representation of face objects, a classifier is required to learn a complex decision function to implement the final classification. The feature representation is optimized for the best discrimination which would help reduce the complexity of the decision function, and ease the classifier design. Thus, a good classifier would be able to further learn the different between the subjects. The feature vector obtained from the feature extraction is classified or matched to classes (persons) of facial images already enrolled in a database. The classification or feature matching algorithms used vary from the nearest neighbor classifier such as the Euclidean distance to advanced schemes like Artificial Neural Network (ANN). If the user is using the face recognition system for the first time, the user will be registered and the user template will be stored for future references. Face recognition involves comparing the generated template against the stored reference template. For verification, the matching is made against a claimed identity, where the matching process will be a one to one comparison between the generated template and the stored reference template. For identification, the matching is made by comparing the generated template against a list of reference templates of legitimate users which will be a one to many comparisons.

3. Methodology

3.1 Photometric normalization

The purpose of the image preprocessing module is to reduce or eliminate some of the variations in face due to illumination. The image 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 image preprocessing includes photometric normalization which removes the mean of the geometrically normalized image and scales the pixel values by their standard deviation, estimated over the whole cropped image. The photometric normalization techniques applied are based on Histogram Equalization and Homomorphic Filtering.

a) Histogram Equalization

Gray level transformation is an image processing system that looks at every input pixel gray level and generates a corresponding output gray level according to a fixed gray level map. Histogram Equalization is the most common histogram normalization or image-specific gray level transformation used for contrast enhancement with the objective to obtain a new enhanced image with a uniform histogram or to produce an image with equally distributed brightness levels over the whole brightness scale. Histogram equalization is usually achieved by equalizing the histogram of the image pixel gray-levels in the spatial domain so as to redistribute them uniformly. 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.

Histogram Equalization arranges the gray-levels of the image by using the histogram form information. Histogram, an array of 256 elements containing the counts or number of pixels of all gray levels, is applied by Histogram Equalization to generate a special gray level mapping suited for a particular image. The accumulated density function of the histogram for the processed image histogram would approximate a straight line. The redistribution of pixel brightness to approximate the uniform distribution improves the contrast of the image. The result of this process is that the histogram becomes approximately constant for all gray values. The steps for Histogram Equalization algorithm are depicted in Fig. 2.

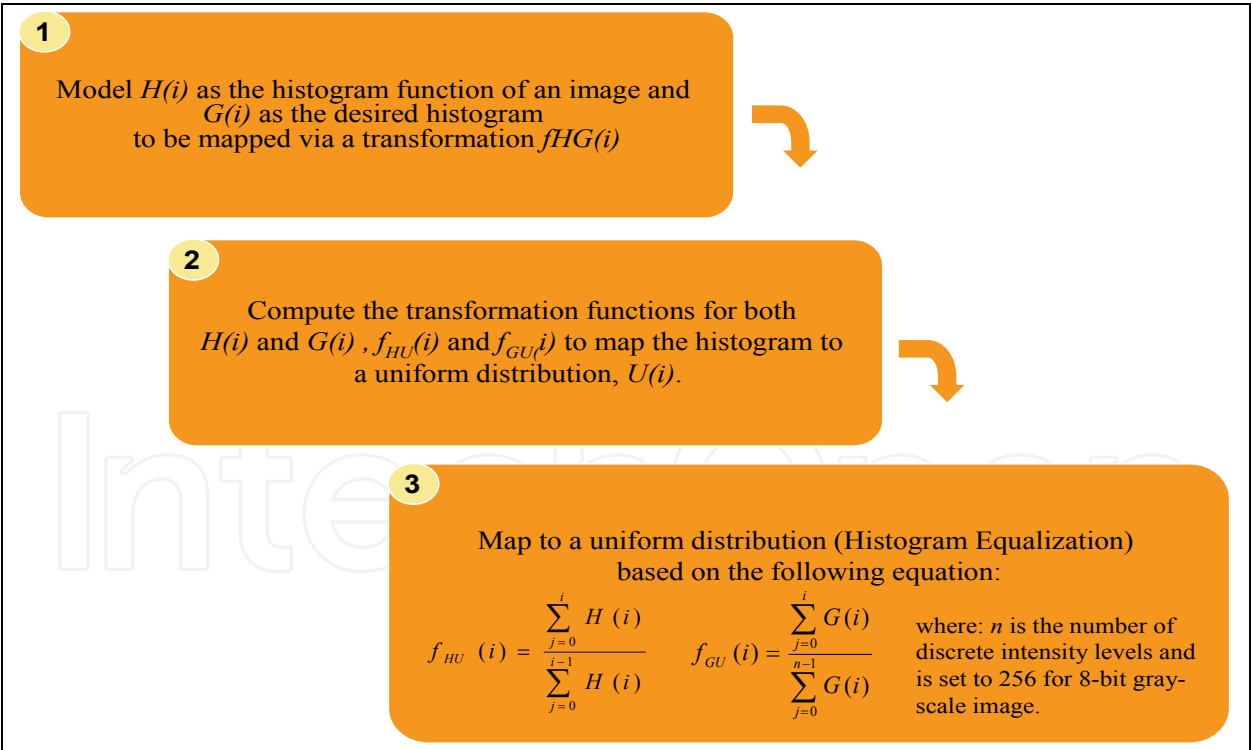


Fig. 2. Histogram Equalization algorithm

b) Homomorphic Filtering

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 signal are additive then the actual signal is the sum of the two types of signals. However, in this illumination or 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, the processed illumination should be drastically reduced due to the high-pass filtering effect, while the reflectance, after this procedure should still be very close to the original reflectance. The steps for Homomorphic Filtering algorithm are depicted in Fig. 3.

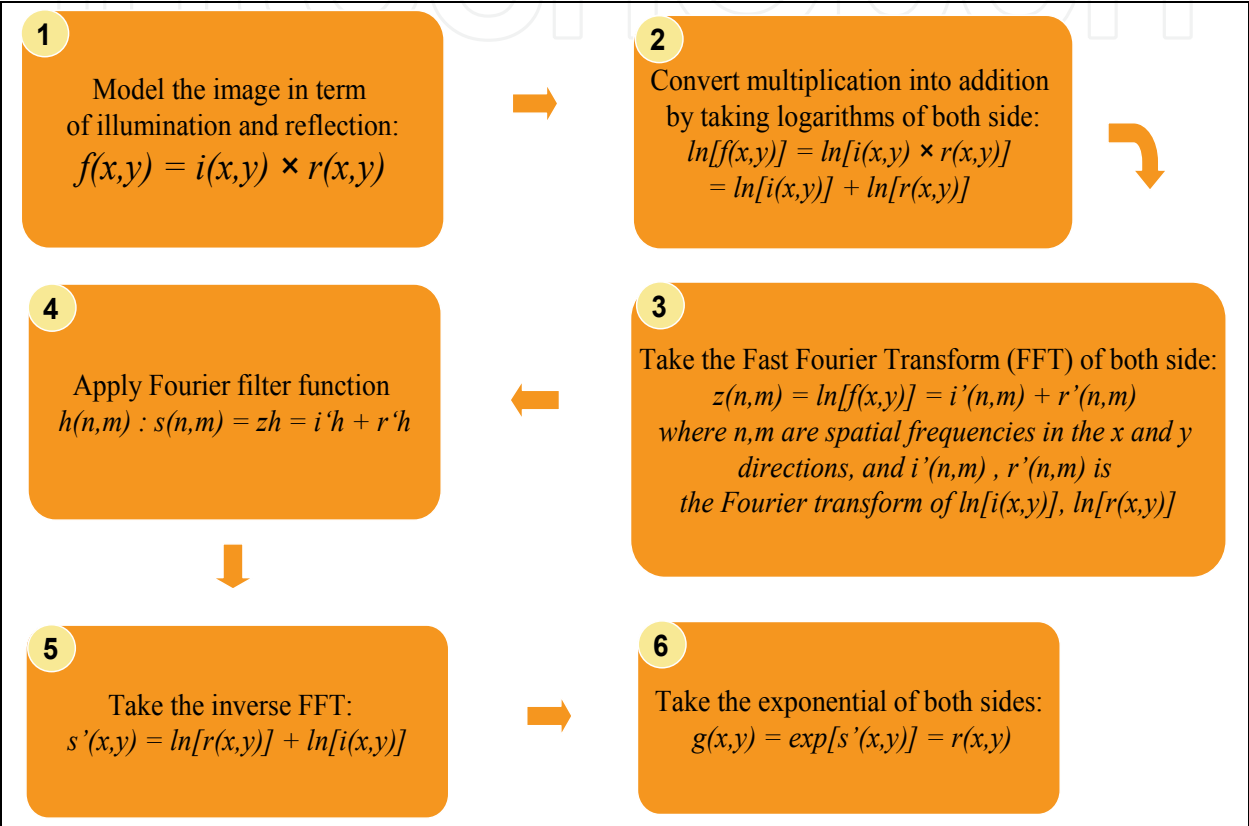


Fig. 3. Homomorphic Filtering algorithm

3.2 Feature extraction

Face recognition is a high dimensional pattern recognition problem which requires large computation time and memory storage. The purpose of feature extraction is to extract the feature vectors or information which represents the face to reduce computation time and memory storage. Nowadays, face recognition research has witnessed a growing interest based on techniques that capitalized, and apply algebraic and statistical tools for extraction and analysis of the underlying manifold. Face images are represented as a high dimensional pixel arrays that belongs to a manifold of intrinsically low dimension. Computer analysis of gray-scale face images deals with visual signal or light reflected off the surface of a face that is registered by a digital sensor as an array of pixel values. The pixel array is represented as a point or vector in an m -by- n dimensional image space after image preprocessing which involved normalization and rescaling to a fixed m -by- n size. Since faces are similar in

appearance and contain significant statistical regularities, the intrinsic dimensionality of the face space is much lower than the dimensionality of the input face image. For that reason, dimensionality reduction techniques based on linear subspace feature extraction, PCA is used to reduce the dimensionality of the input face space.

PCA is based on the information theory approach which is a dimensionality reduction technique based on extraction of the desired number of principal components of the multi-dimensional data. It is related to the Karhunen-Loeve Transform, which is derived in the signal processing context as the orthogonal transform. It is a statistical and computational method used to identify the linear directions in which a set of vectors are best represented in a least-square sense, to reduce multi-dimensional dataset into two dimensions for analysis by performing a covariance analysis between factors, and to identify new meaningful underlying variables or principal component.

PCA extracts the relevant information in a face image and encodes it as efficient as possible. It identifies the subspace of the image space spanned by the training face image data and de-correlates the pixel values. This involves the computation of the eigenvalue decomposition of a dataset, after mean centering the data for each attribute that transforms a number of correlated variables into a (smaller) number of uncorrelated variables called principal components. The principal components are obtained by projecting the multivariate data vectors on the space spanned by the eigenvectors. The first principal component is the linear combination of the original dimensions that has the maximum variance; the n -th principal component is the linear combination with the highest variance, subject to being orthogonal to the $n-1$ of the first principal component (Shakhnarovich and Moghaddam, 2004). The sum of the eigenvalues equals the trace of the square matrix and the maximum number of eigenvectors equals the number of rows (or columns) of the matrix.

The basis vectors constructed by PCA have the same dimension as the input face images. The results of a PCA method are discussed in terms of scores and loadings. 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, de-correlation 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 steps for the PCA algorithm are as follow:

Step 1: The normalized training image in the N -dimensional space is stored in a vector of size N . Let the normalized training face image set,

$$T = \{X_1, X_2, \dots, X_N\} \text{ where } X = \{x_1, x_2, x_3, \dots, x_n\}^T \quad (1)$$

Step 2: Create Eigenspace

- a. Center data: Each of the normalized training face images is mean centered. This is done by subtracting the mean face image from each of the normalized training images. The mean image is represented as a column vector where each scalar is the mean of all corresponding pixels of the training images,

$$\overline{X}_i = X_i - \overline{X} \quad (2)$$

where the average of the training face image set is defined as:

$$\bar{X} = \frac{1}{N} \sum_{i=1}^N X_i \quad (3)$$

- b. Create data matrix: Once the training face images are centered, the next process is to create the eigenspace which is the reduced vectors of the mean normalized training face images. The training images are combined into a data matrix of size N by P , where P is the number of training images and each column is a single image.

$$\bar{X} = \{\bar{X}_1, \bar{X}_2, \dots, \bar{X}_p\} \quad (4)$$

- c. Create covariant matrix: The column vectors are combined into a data matrix which is multiplied by its transpose to create a covariance matrix. The covariance is defined as:

$$\Omega = \bar{X} \cdot \bar{X}^T \quad (5)$$

- d. Compute the eigenvalues and eigenvectors: The eigenvalues and corresponding eigenvectors are computed for the covariance matrix using Jacobian transformation,

$$\Omega V = \Lambda V \quad (6)$$

where V is the set of eigenvectors associated with the eigenvalues Λ .

- e. Order eigenvectors: Order the eigenvectors $V_i \in V$ according to their corresponding eigenvalues $\lambda_i \in \Lambda$ from high to low with non-zero eigenvalues. This matrix of eigenvectors is the eigenspace V , where each column of V is an eigenvector. The principal components are the eigenspace V .

$$V = \{V_1, V_2, \dots, V_p\} \quad (7)$$

Step 3: Project training images

Each of the centered training images (\bar{X}_i) is projected into the eigenspace. The projected training images (T_p) are computed based on the dot product of the centered training images with each of the ordered eigenvectors denoted as,

$$T_p = V^T \bar{X}_i \quad (8)$$

The new vectors of the projected images are the feature vectors of the training face images. Let $T_p = \{X_{p1}, X_{p2}, \dots, X_{pn}\}$ as feature vectors from the projection of the training set onto the principal components. The feature vector is defined as $X_p = \{p_1, p_2, p_3, \dots, p_m\}^T$.

Step 4: Project testing image

The vector of the testing face image (Y) is initially mean centered by subtracting the mean image.

$$\bar{Y} = Y - \bar{X} \quad (9)$$

The feature vector of the testing image (Y_p) is obtained by projecting the vector of the mean testing face image (\bar{Y}) into the eigenspace or the principal components,

$$Y_p = V^T \bar{Y} \quad (10)$$

3.3 Face classification

The purpose of the classification stage is to map the feature space of a test data to a discrete set of label data that serves as template. For the proposed face recognition systems, the method used for classification is based on ANN. The ANN paradigm used is based on the Multi-layer Perceptrons (MLP) neural network. MLP is the most widely used ANN model today, which has also been extensively analyzed and for which many learning algorithms have been developed. MLP applies the back-propagation learning algorithm. The back-propagation learning algorithm consists of forward pass and backward pass. The parameters for the back-propagation learning algorithm include the number of hidden nodes, learning rate, momentum coefficient, number of training cycles, size of training subset, and size of test subsets. The back-propagation training algorithm requires a good selection of values for these parameters where they should not be set too high (large) or too low (small), and thus should be optimized or carefully selected commonly through trial and error. Training a network by back-propagation involves three stages: the feed-forward of the input training pattern, the back-propagation of the associated error, and adjustment of the weights. Back-propagation is a training process where the input data is repeatedly presented to the neural network. With each presentation the output of the network is compared to the desired output and an error is computed. The error is then fed back to the network and is used to adjust the weights such that the error decreases with each of the iteration and the neural model gets closer and closer to producing the desired output. The whole process of the back-propagation algorithm is depicted in Fig. 4.

4. Experimental results

The performance of the proposed face recognition systems using photometric normalization, linear subspace feature extraction, and Artificial Neural Network (ANN) classification are evaluated using two (2) face datasets, which are AT&T face dataset, and local face dataset. In addition to the proposed face recognition system, we also implement the conventional face recognition systems using classifiers such as similarity distance techniques based on Euclidean Distance (ED), Normalized Correlation (NC), and Bayesian classifier as baselines for experimental comparison.

In these experiments, a comparison of face verification performance, namely FRR and FAR using different set of frontal face images, namely the original cropped face images, and face images which have undergone the photometric normalization techniques, Histogram Equalization, Homomorphic Filtering, combination of Histogram Equalization and Homomorphic Filtering, and combination of Homomorphic Filtering and Histogram Equalization. These sets of face images are evaluated using the proposed face recognition systems based on hybrid of PCA feature extraction and ANN classification (PCA+ANN). The experiments are conducted based on five (5) types of photometric normalization techniques which are:

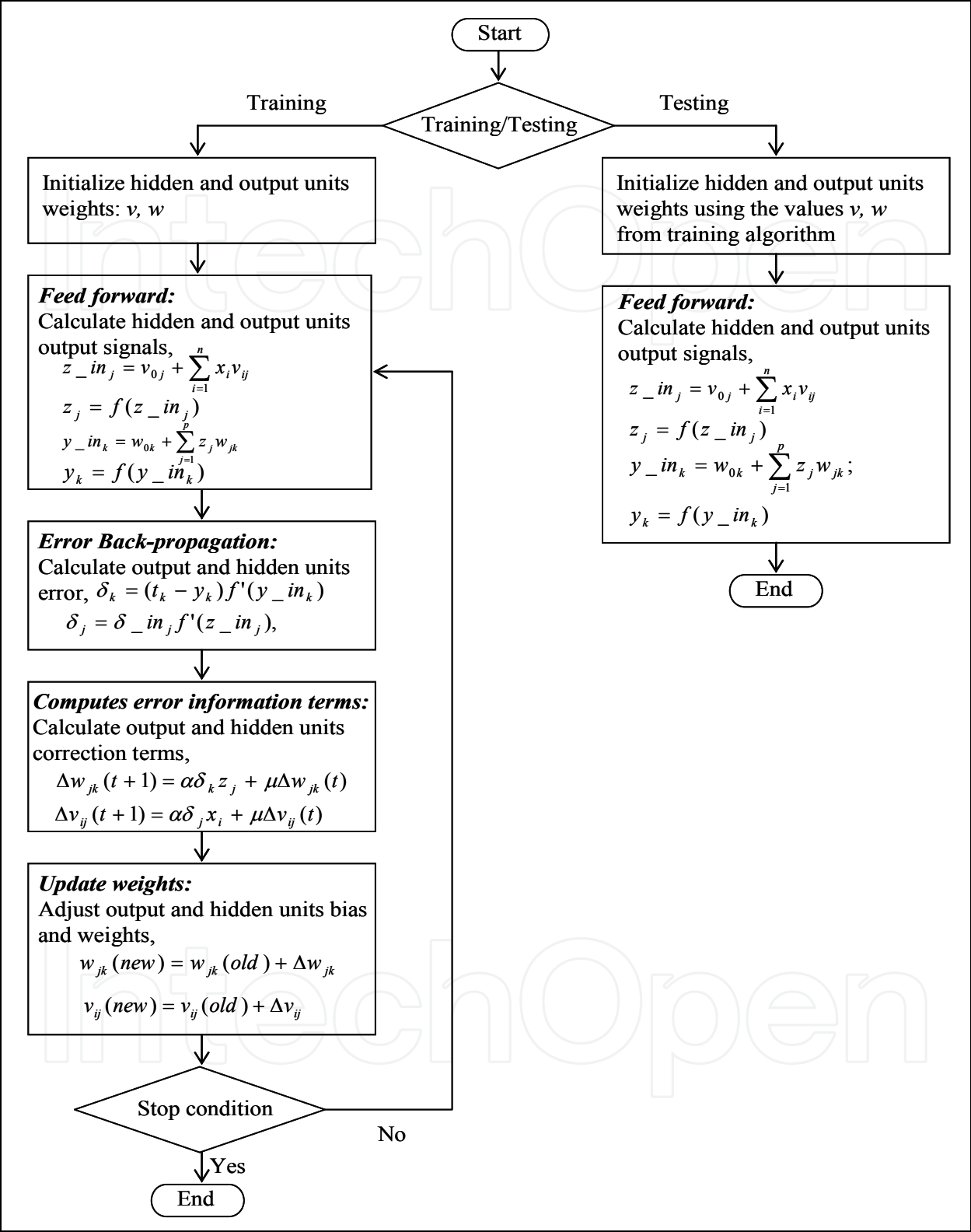


Fig. 4. The process flow of the back propagation algorithm

a) Type 1: without photometric normalization preprocessing

b) Type 2: photometric normalization preprocessing using Histogram Equalization

c) Type 3: photometric normalization preprocessing using Homomorphic Filtering

d) Type 4: photometric normalization preprocessing using combination of Histogram Equalization and Homomorphic Filtering

e) Type 5: photometric normalization preprocessing using combination of Homomorphic Filtering and Histogram Equalization.

Sample of the face images which have been preprocessed using Type 1, Type 2, Type 3, Type 4, and Type 5 photometric normalization preprocessing techniques are shown in Fig. 5, Fig. 6, Fig. 7, Fig. 8, and Fig. 9, respectively.

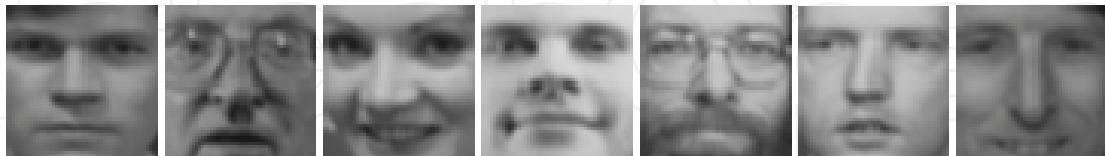


Fig. 5. Sample of images based on Type 1 photometric normalization



Fig. 6. Sample of images based on Type 2 photometric normalization

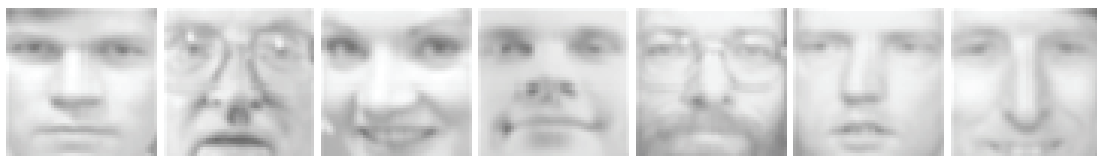


Fig. 7. Sample of images based on Type 3 photometric normalization

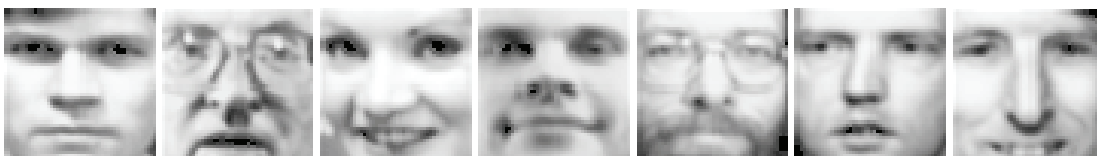


Fig. 8. Sample of images based on Type 4 photometric normalization



Fig. 9. Sample of images based on Type 5 photometric normalization

The proposed face recognition system main decision making tool investigated is based on ANN classification. The parameters used for ANN classification are number of hidden neurons, learning rate, and momentum constant. For the experiments, the configuration of the optimal value for the number of hidden neurons is 100, for learning rate is 0.2, and for momentum constant is 0.7.

The experiments were conducted using the prescribed types of photometric normalization face image sets based on AT&T and local face datasets. For both of these datasets, five (5) images per subject were chosen as training images and the remaining images of each subject are used as the testing images. There were two hundreds (200) training images from AT&T and one hundred (100) training images from the local face datasets, respectively. Meanwhile, there were two hundreds (200) testing images from AT&T, and three hundreds

(300) test images from the local face dataset, respectively. The experiments were conducted based on the proposed face recognition system, PCA+ANN, and compared with the conventional face recognition systems, PCA+ED, PCA+NC and Bayesian PCA.

The face verification experiments were performed with different photometric normalization techniques (without normalization, Histogram Equalization, Homomorphic Filtering, combination of Histogram Equalization and Homomorphic Filtering, combination of Homomorphic Filtering and Histogram Equalization), linear subspaces feature extraction based on PCA, and decision rule or classification based on ANN classifier which was compared with Euclidean Distance, Normalized Correlation, and Bayesian classifiers. The results using local and AT&T face datasets are summarized in Table 5.1 and Table 5.2, respectively. For local face dataset, the best verification performance was achieved using ANN classifier and Homomorphic Filtering with Half Total Error Rate (HTER) of 2.58%, and the worst performance of 21.15% was resulted using Bayesian classifier and Histogram Equalization. Meanwhile, the best verification performance for AT&T face dataset was achieved using ANN classifier, and combination of Histogram Equalization and Homomorphic Filtering with HTER of 5.02%, and the worst performance of 20.78% was resulted using ED classifier and Homomorphic Filtering.

The results presented in Table 5.1 and Table 5.2, show the system performance evaluation based on the proposed and conventional face recognition systems, namely PCA+ANN, PCA+ED, PCA+NC, and Bayesian PCA. In both AT&T face dataset and local face dataset experiments, it is interesting to note that the best HTER was achieved using PCA feature extraction and ANN classification, but using different photometric normalization technique. The differences in the test set performance are indicative of the different generalization capabilities of the respective methods. When the representation space already captured and emphasized, the discriminatory information content as in the case of PCA bases, ANN was superior to the simple Euclidean distance or correlation decision rules. ANN also shows a superior capability to cope with illumination changes, provided these were adequately represented in the training data. This was the main reason for the large difference between the observed performance of the Euclidean Distance, Normalized Correlation and Bayesian classification methods used as a benchmark and ANN.

The performance of the face recognition systems that use two-dimensional (2D) images is dependent on the consistent conditions such as illumination, pose and facial expression. The experimental results demonstrate that the proposed face recognition system improves the verification performance in the presence of illumination variations along with pose changes. One of the reasons for low verification performance is that the current optimization process is still subject to local minimum. Furthermore, the decision theoretic problems are best handled by classification methods based on an ANN classifier that yield the required decision functions directly via training rather than by methods based on distance metrics such as Euclidean distance, Normalized Correlation and Bayesian classifiers which make assumptions regarding the underlying probability density functions or other probabilistic information about pattern classes under consideration. The study proved that the enhancement of face recognition systems based on photometric normalization, linear subspace feature extraction, and ANN classification is able to improve the verification performance, and can be recommended for identity verification system.

Photometric Normalization	Feature Extractor	Classifier	Threshold	FAR	FRR	HTER
Without normalization	PCA	ED	6.10	7.32	7.41	7.37
		NC	0.54	14.44	16.56	16.00
		Bayesian	1.22	14.88	16.19	16.04
		ANN	0.37	6.62	6.56	6.59
Histogram Equalization		ED	9.63	12.96	12.96	12.96
		NC	0.23	6.21	6.93	6.07
		Bayesian	1.15	21.19	21.11	21.15
		ANN	0.20	4.42	4.44	4.43
Homomorphic Filtering		ED	4.91	6.58	6.30	6.44
		NC	0.42	7.80	7.41	7.61
		Bayesian	1.22	16.51	16.93	16.72
		ANN	0.43	2.57	2.59	2.58
Histogram Equalization + Homomorphic Filtering		ED	6.85	11.87	11.85	11.86
		NC	0.23	6.75	6.30	6.03
		Bayesian	0.92	20.70	20.74	20.72
		ANN	0.17	6.99	7.41	7.20
Homomorphic Filtering + Histogram Equalization		ED	9.67	12.57	12.59	12.58
		NC	0.24	6.69	6.56	6.63
		Bayesian	1.18	19.98	20.37	20.18
		ANN	0.17	3.79	3.70	3.75

Table 5.1. Verification performance as function of photometric normalization, PCA feature extractor, and classifiers based on local face dataset

5. Conclusions

The chapter has presented an enhancement of face recognition using photometric normalization, linear subspace feature extraction, and Artificial Neural Network (ANN) classification to improve the verification performance. The proposed face recognition systems based on the enhancement of FRS using photometric normalization, linear subspace feature extraction, and ANN classification has improved the performance of the proposed FRS. The proposed FRS using the combination of photometric normalization based on Homomorphic Filtering, feature extraction based on PCA, and ANN classification clearly outperform comparable conventional face recognition systems. Based on the experimental results, the proposed face recognition using photometric normalization based on Homomorphic Filtering, feature extraction based on PCA, and ANN classification produces the best verification performance rate for local face dataset by yielding the lowest verification performance rate, HTER of 2.58%. On the other hand, the proposed face recognition using photometric normalization based on the combination of Histogram Equalization and Homomorphic Filtering, feature extraction based on PCA, and ANN classification produces the best verification performance rate for AT&T face dataset by yielding the lowest verification performance rate, HTER of 5.02%. Furthermore, the ANN classification based on Multilayer Perceptrons proved to be superior compared to that of distance metric techniques such as Euclidean distance, Normalized Correlation and Bayesian classifier. The reason for better verification performance using ANN classification

is because the classifier is trained through supervised learning known as error back-propagation algorithm. In supervised learning, a machine chooses the best function that relates between the inputs and outputs. This function is judged by its ability to generalize on new inputs which were not given in the training data. Therefore, the experimental results point out the overall robustness of the proposed face recognition system in comparison with the conventional face recognition systems. Thus, it proves the feasibility of using photometric normalization in the early stage of a face recognition system, which gave much impact to the verification performance.

Photometric Normalization	Feature Extractor	Classifier	Threshold	FAR	FRR	HTER
Without normalization	PCA	ED	6.30	13.56	13.50	13.53
		NC	0.30	11.42	12.50	11.96
		Bayesian	1.05	16.65	16.00	16.83
		ANN	0.11	6.67	6.50	6.59
Histogram Equalization		ED	12.28	16.29	16.50	16.40
		NC	0.24	7.53	7.50	7.52
		Bayesian	1.10	17.25	17.00	17.13
		ANN	0.12	6.47	6.50	6.49
Homomorphic Filtering		ED	4.19	20.56	21.00	20.78
		NC	0.25	12.50	11.50	12.00
		Bayesian	0.89	17.96	19.00	18.48
		ANN	0.07	9.23	9.50	9.37
Histogram Equalization + Homomorphic Filtering		ED	16.71	9.96	10.00	9.98
		NC	0.32	8.32	7.50	7.91
		Bayesian	1.12	18.02	18.00	18.01
		ANN	0.17	5.04	5.00	5.02
Homomorphic Filtering + Histogram Equalization		ED	11.89	14.99	16.00	16.00
		NC	0.25	6.94	7.50	7.22
		Bayesian	1.11	17.46	17.50	17.48
		ANN	0.11	6.41	6.50	6.46

Table 5.2. Verification performance as function of photometric normalization, PCA feature extractor, and classifiers based on AT&T face dataset

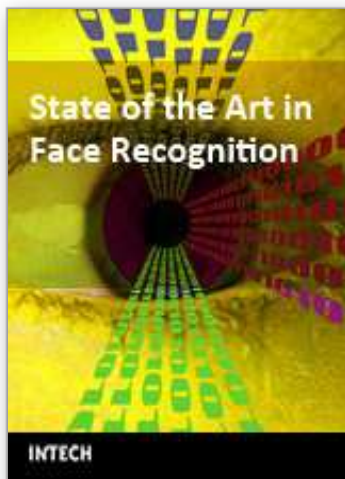
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Notwithstanding the tremendous effort to solve the face recognition problem, it is not possible yet to design a face recognition system with a potential close to human performance. New computer vision and pattern recognition approaches need to be investigated. Even new knowledge and perspectives from different fields like, psychology and neuroscience must be incorporated into the current field of face recognition to design a robust face recognition system. Indeed, many more efforts are required to end up with a human like face recognition system. This book tries to make an effort to reduce the gap between the previous face recognition research state and the future state.

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