Changeable Face Biometrics by Combining Appearance-Based Methods

MinYi Jeong

The Graduate School

Yonsei University

Graduate Program in Biometrics

Changeable Face Biometrics by Combining Appearance-Based Methods

A Master's Thesis

Submitted to the Graduate Program in Biometrics

and the Graduate School of Yonsei University

in partial fulfillment of the

requirements for the degree of

Master of Science

MinYi Jeong

December 2006

This certifies that the master's thesis of
MinYi Jeong is approved.

Thesis Supervisor: Jaihie Kim

Kar-Ann Toh

Jeung-Yoon Choi

The Graduate School

Yonsei University

December 2006

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Abstract

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MinYi Jeong
Graduate Program in Biometrics
The Graduate School
Yonsei University

In this thesis, a changeable biometric system for appearance-based face recognition is proposed. In terms of user authentication, biometric systems offer many advantages in that information cannot be lost, forgotten or shared. However, they also suffer from disadvantages in some applications, for example, in the area of privacy protection. Changeable (cancelable) biometrics has been suggested as a solution to this problem of enhancing security and privacy. The idea is to transform a biometric signal or feature into a new one for the purposes of enrollment and matching. In this paper, we propose a changeable biometric system that can be applied to appearance based face recognition system. In the first technique, when using feature extraction, PCA, ICA and NMF coefficient vectors extracted from an input face image are normalized using their norm. The two normalized vectors are scrambled randomly and a new transformed face coefficient

vector (transformed template) is generated by addition of the two normalized vectors. When this transformed template is compromised, it is replaced with a new scrambling rule. Because the transformed template is generated by the addition of two vectors, the original PCA, ICA and NMF coefficients could not be recovered from the transformed coefficients. In our experiments, we compared performance when the PCA, ICA and NMF coefficient vectors is used and when the transformed coefficient vectors are used for verification.

Key Words : biometrics, changeable biometrics, face recognition, principal component analysis, independent component analysis, non-negative matrix factorization

Chapter 1

Introduction

1.1 Biometrics

Biometric systems [1-3] refer to personal authentication methods that use individual information from a given person such as fingerprints [4], face [5], iris [6], palmprints [7], voice [8] or signature [9]. In the past years, the idea of maintaining security by the use of passwords (knowledge-based security) and ID cards (token-based security) has been used to restrict access to many applications. However, security can easily come under attack if a password is divulged to an unauthorized user or an impostor. To prevent this, biometric systems have emerged. These systems are believed to provide a greater degree of security than traditional authentication methods. Among the many advantages of biometric systems is the fact that most biometric information cannot be stolen, forgotten, or shared. Biometric systems show many distinguished characteristics with respect to the following points:

1. Universality, which means that each person must have the identified char-

acteristic.

2. Distinctiveness, which means that it must be easy to distinguish between any two persons sufficiently in terms of the identified characteristic.

3. Permanence, which means that the identified characteristic must be fully invariant over a given period of time.

4. Collectibility, which means that the identified characteristic can be measured quantitatively.

In a practical system which makes use of biometrics for personal identity recognition, there are a number of other important requirements, as follows.

1. Performance, which refers to achievable identification accuracy, the resource requirements necessary to achieve acceptable identification accuracy, and the working or environmental factors that affect identification accuracy.

2. Acceptability, which indicates to what extent people are willing to accept a given biometric system.

3. Circumvention, which refers to how easy it is to fool the system by fraudulent techniques.

A practical biometric system should meet the specified recognition accuracy, speed, and resource requirements, be harmless to users, be accepted by the intended population, and be sufficiently robust to various fraudulent attacks.

1.2 Changeable Biometrics

Although biometric systems offer many advantages for user authentication, there are also some disadvantages. One of these is that there are privacy issues concerning non-revocable biometric information, especially in cases of identity theft. When a biometric template becomes compromised, it is rendered unusable. The only remedy is to replace this template with another biometric feature. However, a person has a limited number of biometric features, for example, the face, iris, voice and hand. Changeable biometrics offers an alternative to these problems [3]. Changeable biometrics refers to biometrics that can be changed canceled, or replaced. These systems consist of an intentional, repeatable distortion of a biometric signal based on a chosen transform. This transform can be applied in either the signal domain or the feature domain. The biometric signal is then changed in the same way at each presentation, for enrollment and for authentication. With this approach, every instance of enrollment can use a different transform, thus rendering cross-matching impossible. Furthermore, if one variant of the transformed biometric data is compromised, then the transform function can simply be changed to create a new variant for re-enrollment. For changeable biometric systems, there are five points to be considered.

The first point is that even if the biometric features are known, the original biometrics cannot be recovered. This is called non-invertibility. Functions that change the template have to be non-invertible transformations. An example of this is changeable biometrics of the face and fingerprints [3]. The second point is that after transformation, the recognition rate must not be much lower than the original recognition rate. Ideally, the methods should provide better recognition rates. The third point is that transform functions can be created indefinitely. Changeable biometric systems change because the number of biometrics is insufficient. Therefore, the number of possible changed templates must be either unlimited or numerous. This process is called reproducibility, and is calculated through a measure of entropy. The fourth point is that the level of complexity should be simple. It is not as necessary to satisfy this characteristic, but it is needed as a changeable biometric performance measure. The fifth point is that the changeable biometrics template has to look like a conventional biometric system. Recently, research has been done on changeable biometric systems using fingerprints [10], palmprints [11, 12], and faces [13-19].

1.3 Related Research

Several changeable biometrics methods have already been developed in the field of face recognition. Ratha et al. [3, 13] proposed a morphing method to transform face images. When the transformed biometric information was compromised, a new biometric template was generated by introducing a new morphing function. However, when using this method, it was still possible for the original face image to be reconstructed if the attacker were to discover the morphing function.

Savvides et al. [14] used random kernels and MACE (Minimum Average

Correlation Energy) filters. A transformed training image was created by convolving the given face image with a random kernel. The transformed image was then used to generate the MACE filter. For authentication, a test image was convolved with the same random kernel and this convolved test image was then cross-correlated with the MACE filter.

Teoh et al. [15-18] proposed a method called BioHashing in which a feature vector was projected onto a random vector basis and then scaled in a binary way. The Fourier-Mellin transform and Fisher Discrimination Analysis (FDA) were used for feature extraction. The feature vector was then calculated using the extracted face feature, and the feature vector was projected onto a random basis. Next, a random basis was found using the Gram-Schmidt procedure, with a randomly generated vector set. Finally, a value of 0 or 1 was determined using an arbitrary threshold. From the experimental results, this method was shown to yield a zero EER.

However, contrary evidence was presented by Kong et al. [18], who showed that the zero EER of the BioHashing method was produced under the impractical assumption that the random basis can never be lost, stolen, shared or duplicated. This assumption does not hold generally. Kong et al. also pointed out that if this assumption held, there would be no need to use the random basis since it could serve as a perfect password. Adopting an assumption generally used within the biometric community, experimental results have since showed that the true performance of BioHashing is far from perfect.

Kang et al. [19] proposed a changeable face biometric system which combines the PCA template and a Password-Based Key Derivation Function (PBKDF). In their method, authentication was performed in the permuted domain using a permutation function which was created from a user's password with the PBKDF. If the transformed face template was compromised, a new face template was generated by alternating the password.

Chapter 2

Background

In this section, we give a brief related research about face recognition and changeable biometrics for face recognition.

2.1 Face Recognition

Face-based systems [20] are very useful in many applications, since they are easy to use, natural, and non-intrusive. A face recognition system generally consists of four modules: detection, alignment, feature extraction, and matching.

Detection and alignment are processing steps that occur before feature extraction and matching. The detection process separates the face areas from the background, and alignment achieves accurate localization and normalization of faces. Feature extraction is performed to provide information that is effective and useful for distinguishing between the faces of different persons. Matching refers to comparing the input face with faces in the database and deciding whether a match is true or false. In a general sense, true means that the input face is equal to a face in the database. For matching, the extracted feature vector of the input face is matched against those of the enrolled faces in the database.

Face recognition can be further classified into two types: verification and identification. Verification refers to a one-to-one match that compares a query face image with a template face image. To evaluate performance, the verification rate versus the false acceptance rate is calculated. This is called a Receiver Operation Curve (ROC). A good verification system must try to balance these two rates based on operational needs. Identification refers to a one-to-many matching process that compares a query face image with all the template images in a face database in order to determine the identity of the query face. Identification of the test image is done by locating an image in the database which is most similar to the test image. The test subject's features are compared to the other features in the system's database and a similarity score is found for each comparison. These similarity scores are then numerically ranked in descending order. The percentage of times that the highest similarity score is the correct match for all individuals is referred to as the top match score.

2.2 Appearance Based Method

Some typical algorithms for face recognition are presented below; namely, appearance based and model-based approaches. Appearance-based techniques have been widely used in face recognition research [21-23]. These techniques represent a face as a linear combination of low-ranking basis images. They employ

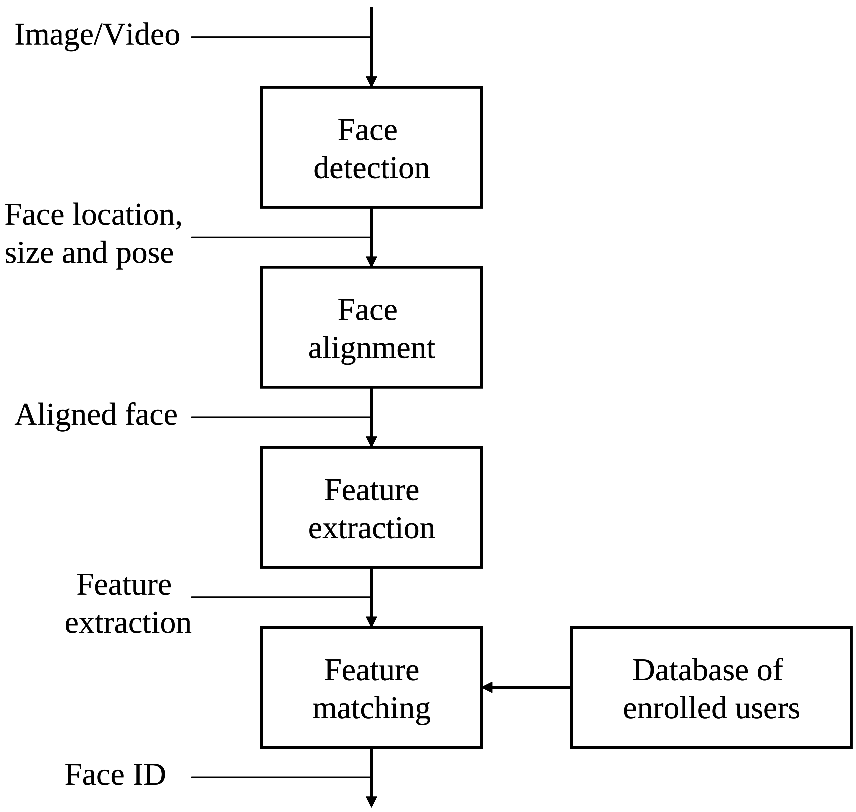


Figure 2.1: Face recognition processing. A face recognition system generally consists of four modules as depicted in Figure 2.1 : detection, alignment, feature extraction, and matching.

feature vectors consisting of coefficients that are obtained by simply projecting facial images onto their basis images. Appearance-based approaches represent an object in terms of several object views. An image is considered to be a high-dimension vector (a point in a high-dimensional vector space). Many appearance-based approaches use statistical techniques to analyze the distribution of the object image vectors in the vector space, and derive an efficient and effective representation according to different applications. Principal Component Analysis (PCA), Independent Component Analysis (ICA) and Nonnegative Matrix Factorization (NMF) are representative techniques for appearance-based face recognition.

2.2.1 Principal Component Analysis

PCA [21-23] is a method which efficiently represents a collection of sample data. Matthew A. Turk [21, 22] published a face recognition scheme that used eigenfaces and was based on PCA. PCA is a way of identifying patterns, and expressing the identified information to highlight similarities and differences. PCA is a method which efficiently represents a collection of sample information. The eigenface algorithm uses PCA for dimensionality reduction in order to identify the vectors which best account for the distribution of face images within the entire image space. These vectors define the subspace of the face images. This subspace is also called the face space. An eigenface is a face space that can be obtained by analyzing sample face images with the PCA method, and it contains features for identifying whether an acquired image is actually a face. In the PCA method, the following equations are commonly used.

The training set of face images can be represented by $\Gamma_1, \Gamma_2, ..., \Gamma_M$. The average face of the training set is defined as $\Psi = \frac{1}{M}\sum\limits_{n=1}^{M}\Gamma_n$ and different faces are defined as $\Phi_i = \Gamma_i - \Psi$. A covariance matrix can then be obtained in the following way:

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n\Phi_n^T. \tag{2.1}$$

Each different face image Φ_i is represented as a linear combination of the eigenvectors. And each normalized training face Φ_k is represented by a vector $\Omega_k = \left[w_1^k, w_2^k, \cdots, w_{M'}^k\right]^T$.

$$\Omega_k = U^T\Phi_k. \tag{2.2}$$

where, $U = [u_1 u_2 \cdots u'_M]$ denotes the eigenvector for $i = 1, ..., M'$, and where M' is the value that is found for face detection ($M' \leq M$).

Given an unknown face image Γ, it can be normalized and projected onto the eigenspace.

$$\Omega = U^T\left(\Gamma - \Psi\right). \tag{2.3}$$

Similarly, all new face images can then be projected onto the face space to find a set of weights that describe the contribution of each vector in the face space. Fig. 2.2 shows facial image representations using PCA.

2.2.2 Independent Component Analysis

ICA [23-29] is an unsupervised learning rule that was derived from the principle of optimal information transfer through sigmoidal neurons [30, 31]. ICA min-

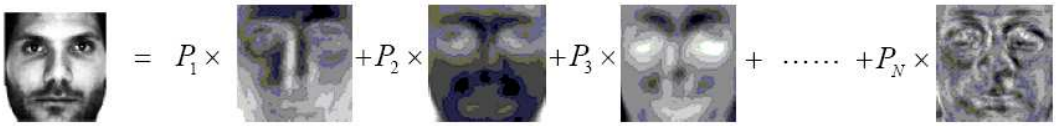


Figure 2.2: Facial image representations using PCA.

imizes both second-order and higher-order dependencies in the input. It keeps the assumption of linearity but abandons all the other aspects that PCA uses. Although the amplitude spectrum is captured by second-order statistics in PCA, there remains the phase spectrum that lies in higher-order statistics. ICA attempts to find the basis along which the data (when projected onto them) are statistically independent. ICA is a way of finding a linear non-orthogonal coordinate system in any multivariate data. The directions of the axes of this coordinate system are determined by both the second and higher order statistics of the original data. The goal is to perform a linear transform, which makes the resulting variables as statistically independent from each other as possible. This refers to a generalization of PCA (therefore, PCA can be derived as a special case of ICA). The main principle is to iteratively optimize a smoothing function whose global optima occurs when the output vectors U are independent.

To define ICA, we considered a statistical model. We observed n random variables $x_1, x_2, \cdots, x_n$, which were assumed to be linear combinations of n unknown random variables $s_1, s_2, \cdots, s_n$. The independent components s_i were latent variables, meaning that they could not be directly observed. We denoted the observed variables x_i as an observed vector $\mathbf{x} = [x_1, x_2, \cdots, x_n]^T$ and the

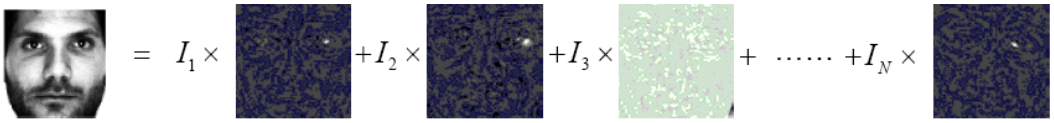


Figure 2.3: Facial image representations using ICA.

component variables s_i as a vector $\mathbf{s} = [s_1, s_2, \cdots, s_n]^T$. The relation between $\mathbf{s}$ and $\mathbf{x}$ was modeled as

$$\mathbf{x} = \mathbf{A}\mathbf{s} = \sum_{i=1}^{n} \mathbf{a}_i s_i, \tag{2.4}$$

where A is an unknown fixed $n \times n$ matrix of full rank, called the mixing matrix, whose columns are denoted by $\mathbf{a}_i, i = 1, \cdots, n$. Its columns were called the ICA basis vectors or the ICA basis functions. Implementation of ICA was performed to estimate the de-mixing matrix $\mathbf{B}$, such that the vector $\mathbf{x}$ was transformed into

$$\mathbf{y} = \mathbf{B}\mathbf{x} \tag{2.5}$$

yielding as mutually statistically independent components of $\mathbf{y}$ as possible. The estimation of $\mathbf{B}$ is done by optimizing independence of the components in $\mathbf{y}$ using training data. Thus, it is understood that the vector $\mathbf{y}$ is an estimate of the true source $\mathbf{s}$. There are two kinds of architectures based on ICA, statistically independent basis images (architecture I) and a factorial code representation (architecture II). In this paper, we used ICA architecture I. Fig. 2.3 shows facial image representations using ICA.

2.2.3 Nonnegative Matrix Factorization

NMF is suggestive of some aspects of activation patterns in response to images. In NMF, as the name implies, the amount of non-negativity adds constraints to the matrix factorization, allowing only additions in the synthesis. There are no cancellations or interference of patterns via subtraction or negative feature vector values. This leads more naturally to the notion of parts-based representation of images [32-34]. With the underlying non-negative constraints, NMF is able to identify localized parts-based representations. Sparse coding with NMF seems befitting especially for face recognition applications as the features of face images are naturally represented as a small collection of features, namely eyes, nose and mouth, which are distributed all over the face. Because the outputs of NMF are localized features, these parts-based features can be used collectively to represent a face.

Given a data matrix F, non-negative matrix factorization refers to the decomposition of the matrix F into two matrices W and H of size $n \times r$ and $r \times m$, such that

$$F = WH \tag{2.6}$$

where the elements in W and H are all positive values.

In NMF, no negative entries are allowed in matrix factors W and H whereby non-negativity constraint is imposed in factorizing the data matrix F limiting data manipulation only to additions (no subtractions are allowed). This leads to the idea of reconstructing an object by adding its representative parts collectively. Each column in the matrix W is called a basis image, and a column in the matrix H is called an encoding. An image in F can be reconstructed by linearly combining basis images with the coefficients in an encoding. The encodings influence the activation of pixels in the original matrix via basis images.

Given a data matrix F, Lee and Seung [33] developed a technique for factorizing the F to yield matrices W and H as given in Eq. (2.6). Each element in the matrix F can be written as $F_{ij} = \sum_{p=1}^{r} W_{ip} H_{pj}$ where T represents the number of basis images and the number of coefficients in an encoding. The following iterative learning rules are used to find the linear decomposition:

$$H_{pj} \leftarrow H_{pj} \sum_{i=1}^{n} \left(\frac{W_{ip} F_{ij}}{\sum_{k=1}^{r} W_{ik} H_{kj}} \right) \tag{2.7}$$

$$W_{ip} \leftarrow W_{ip} \sum_{j=1}^{m} \left(\frac{F_{ij} H_{pj}}{\sum_{k=1}^{r} W_{ik} H_{kj}} \right) \tag{2.8}$$

$$W_{ip} \leftarrow \frac{W_{ip}}{\sum_{k=1}^{n} W_{kp}} \tag{2.9}$$

The above unsupervised multiplicative learning rules are used iteratively to update W and H. The initial values of W and H are fixed randomly. At each iteration, a new value for W or H is evaluated. Each update consists of a multiplication and sums of positive factors.

The data matrix F, is constructed such that the training face images occupy the columns of the F matrix. Let the training face set be $\Gamma^{train} = \{f_1^{train}, f_2^{train}, \cdots, f_m^{train}\}$, $F = [f_1 f_2 \cdots f_m]$ and μ represents the mean of all training images. Learning is

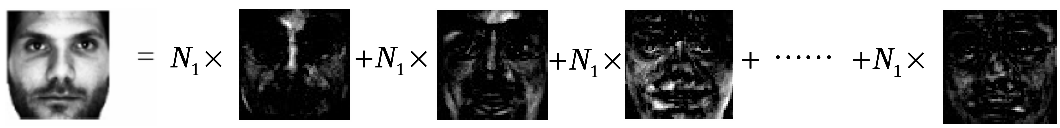


Figure 2.4: Facial image representations using NMF.

done using Eq.s (2.7)-(2.9) to decompose the matrix F into 2 matrices, H and W. Let the basis images be represented as $W = [w_1 w_2 \cdots w_r]$ and encodings as $H = [h_1 h_2 \cdots h_m]$: where each face f_i in F can be approximately reconstructed by linearly combining the basis images, and the corresponding encoding coefficients $h_i^T = [h_{1i} h_{2i} \cdots h_{ri}]$ as shown in Figure 1. Hence: a face can be modeled in terms of a linear superposition of basis functions together with encodings as follows:

$$f_i = \sum_{j=1}^{r} w_j h_i \tag{2.10}$$

For each face f_i in the training set and test set, we calculate the corresponding encoding coefficients. The basis images in W are generated from the set of training faces;Γ^{train}. The encodings, h_i of each training face f_i is given by

$$h_i = W^{\dagger} f_i \tag{2.11}$$

where $W^{\dagger}$ is the pseudo-inverse of the matrix W. Once trained, the face image set, $\{f_1, f_2, \cdots, f_m\}$ is represented by a set of encodings $\{h_1, h_2, \cdots, h_m\}$ with reduced dimension, r. A distance metric is used to calculate the similarity between h_i^{train} and h_j^{test}; encodings of a training image and a test image. Fig. 2.4 shows facial image representations using NMF.

Chapter 3

Changeable Biometrics for Appearance-Based Methods

In this section, we describe the proposed method using appearance based method for changeable face biometrics. The main idea of the proposed method is to generate transformed coefficients by addition of the coefficients of the scrambled PCA and ICA coefficients (or the PCA and NMF) coefficients. In this section

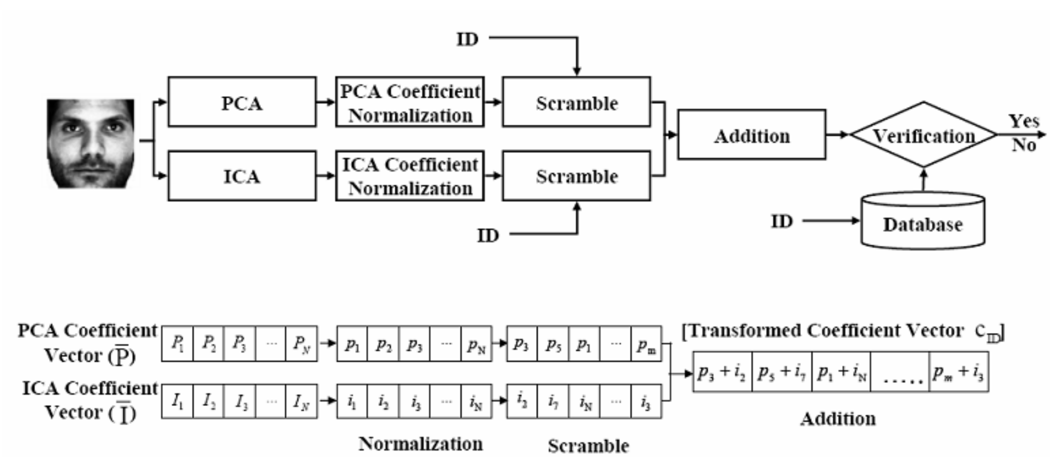


Figure 3.1: Overall Procedure of Proposed Method.

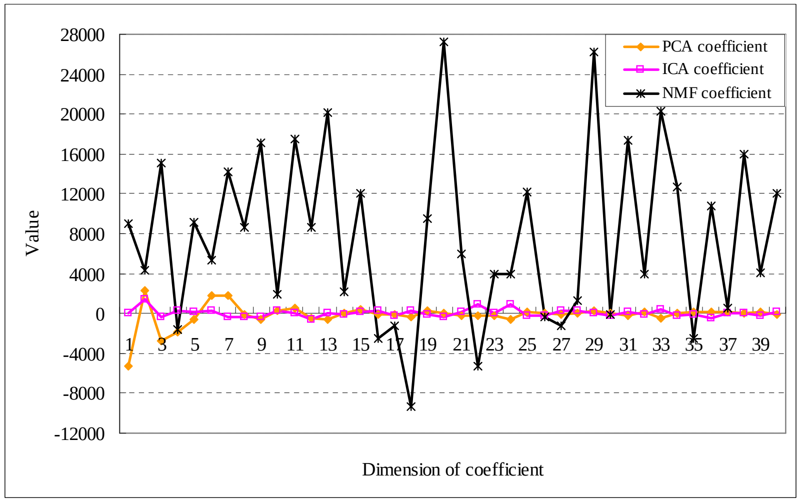
the method using PCA and ICA is explained for the sake of convenience, but other appearance method can be applied by same way. In the first technique, the PCA and ICA coefficient vectors are extracted from an input face image and normalized. The two normalized vectors are scrambled randomly and a new transformed face coefficient vector is generated by addition of the two normalized vectors. Fig. 3.1 shows the overall procedure of the proposed method.

3.1 Normalization

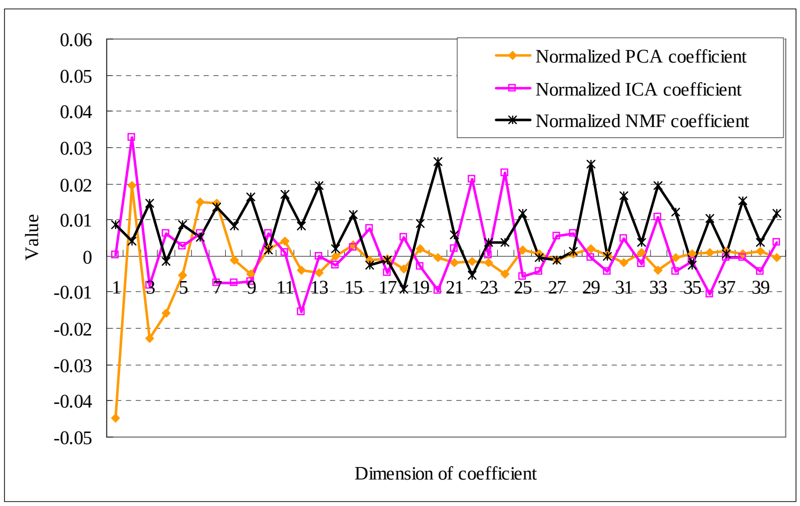
Using PCA and ICA algorithm, an n-dimensional PCA coefficient vector $\bar{\mathrm{P}} = [P_1, P_2, P_3, ..., P_N]$ and ICA coefficient vector $\bar{\mathrm{I}} = [I_1, I_2, I_3, ..., I_N]$ are extracted from an input face image, when the range of PCA and ICA coefficient vectors is very different. Even though both coefficient vectors are added, the influencing power of PCA is very large because the PCA coefficient vector is larger than the ICA. When adding two vectors which are different from the influencing power, the original face information can be disclosed if an attacker tries to use the coefficient vector of the large influencing power. Therefore, we have to consider the influencing power of the PCA and ICA coefficient vectors. Therefore, the two coefficient vectors are normalized using their norm as follows:

$$\begin{array}{l} \mathrm{p} = \bar{\mathrm{P}} / \left|\bar{\mathrm{P}}\right| = [p_1, p_2, p_3, \ldots, p_{\mathrm{N}}] \\ \mathrm{i} = \bar{\mathrm{I}} / \left|\bar{\mathrm{I}}\right| = [i_1, i_2, i_3, \ldots, i_{\mathrm{N}}] \end{array}, \tag{3.1}$$

where $\left|\bar{\mathrm{P}}\right|$ and $\left|\bar{\mathrm{I}}\right|$ denotes the L_2 norm of vector $\bar{\mathrm{P}}$ and $\bar{\mathrm{I}}$. Fig. 3.2 show the distribution of the eigencoefficients before and after the proposed method.



(a)



(b)

Figure 3.2: Example of appearance based method eigencoefficients. (a) Example of PCA, ICA and NMF eigencoefficients. (b) Example of PCA, ICA and NMF normalized eigencoefficients.

3.2 Scramble the normalized coefficient vector

To increase the reproducibility and complexity of non-invertiblity, we use a scrambling method. The principal axes of the PCA and ICA vectors show a large amount of information. By adding the arranged two vectors, the summation value is even larger. Therefore the principal axis is revealed easily. Attackers would be able to obtain similar information as existed in the original one. The principal axis of PCA and ICA is difficult to disclose using randomly scrambled coefficient vectors.

This scrambling method is useful for the reproducibility of changeable biometrics, since the number of possible changed templates must be unlimited or numerous. The scrambling method exists in a large number of cases and contributes to reproducibility. In this case, the number of cases is numerous because each of the PCA and ICA vectors orders are differently scrambled and added.

Each coefficient vector is randomly scrambled and the scrambling rule is determined by a user ID. It is possible to define the two scrambling functions $\mathrm{S}_{ID}^{PCA}(\bullet)$ and $\mathrm{Z}_{ID}^{\mathrm{ICA}}(\bullet)$. $\mathrm{S}_{ID}^{PCA}(\bullet)$ is a function for scrambling the normalized PCA coefficient vector p, and $\mathrm{Z}_{ID}^{\mathrm{ICA}}(\bullet)$ is a function for scrambling the normalized ICA coefficient vector i. The scrambled PCA and ICA coefficient vectors are given by;

$$\begin{aligned} \mathrm{p}^{\mathrm{s}} &= \mathrm{S}_{ID}^{PCA}(\mathrm{p}) \\ \mathrm{i}^{\mathrm{s}} &= \mathrm{Z}_{\mathrm{ID}}^{\mathrm{ICA}}(\mathrm{i}) \end{aligned} \tag{3.2}$$

When the transformed coefficient vector is found to be compromised, new transformed coefficient vectors can be generated by replacing the user ID or the scrambling rule associated with the user ID. In this way, many transformed face coefficient vectors can be easily generated.

3.3 Addition between normalized coefficient vectors

Finally, the transformed face coefficient vector is generated by adding the scrambled PCA and ICA coefficient vectors as follows:

$$\mathrm{c_{ID}}=\partial \mathrm{p^s}+\beta \mathrm{i^s} \tag{3.3}$$

where $\partial = \beta = 1$ in this paper.

One of the conditions for changeable biometrics is that transformed biometric data should not be easily converted back to the original biometric data even if an attacker knows both the transformed biometric data and the transforming method. In the proposed method, the information that an attacker can find is the transformed face coefficient vector ($\mathrm{c_{ID}}=\mathrm{S}_{ID}^{PCA}(\mathrm{p})+\mathrm{Z_{ID}^{ICA}}(\mathrm{i})$) and the two scrambling functions ($\mathrm{S}_{ID}^{PCA}(\bullet)$,$\mathrm{Z}_{ID}^{\mathrm{ICA}}(\bullet)$). However, because the PCA coefficient vector p and the ICA coefficient vector i are not stored, an attacker cannot discover the PCA coefficients nor the ICA coefficients (extra degree of freedom). Therefore, it is impossible to recover the PCA and ICA coefficients from the transformed coefficients $\mathrm{c_{ID}}$. Therefore, this method satisfies the condition of non-invertibility.

Chapter 4

Experiments

In this section, the experimental results are presented in three parts. In the first part, we show how the performance rate varies when the number of dimensions is changed from 10 to 300. Also, we compare performance when using PCA, ICA (or PCA, NMF) and the proposed method. In the second part, we present two experiments that address the changeability of changeable biometrics. The first of these represents the changeability of the distribution of the eigencoefficients when using the proposed method, and the second represents changeability through an system threshold and distribution of pseudo genuine elements. In the last part, we calculate the amount of reproducibility.

4.1 Database

We used the AR Face database [35] to evaluate recognition performance. This database consists of over 3,200 frontal view images of 126 subjects. There were 26 different images per subject, recorded in two different sessions separated by

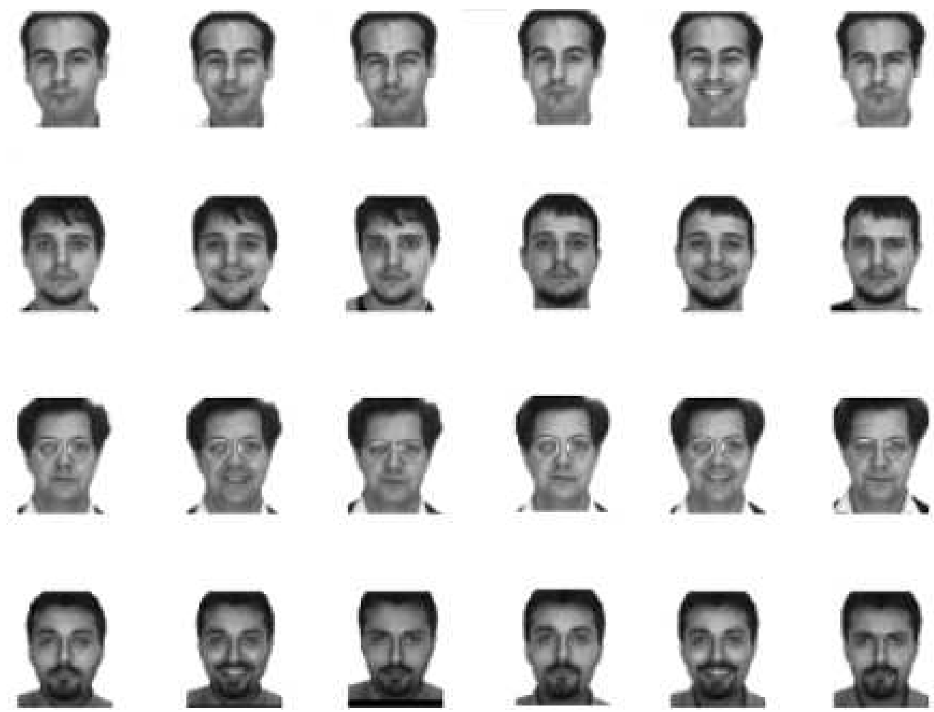


Figure 4.1: Sample images from the AR Face database.

two weeks, each weekly session comprising 13 images. Each subject was captured under a large variety of conditions, including occlusion and changing facial expressions. All images were obtained under controlled illumination and viewpoint conditions. Each image consisted of a 46 by 56 array of pixels. We used only 672 frontal facial images without occlusion and illumination changes, for a total of 6 different images per subject. Fig. 4.1 shows some sample images taken from the database. The number of images used for training and testing was both 336, respectively. The training set contained images for each of the 56 subjects. The images of the remaining 56 subjects were used as the test set.

4.2 Experimental Design

4.2.1 Matching performance

Two samples of the same biometric feature from the same person can never be exactly the same due to imperfect imaging conditions, ambient conditions, and the user's current state. A meaningful performance method is to use distance distributions which show the distinctiveness and repeatability (consistency) of the feature vectors transformed from the biometric signals. Genuine distribution is created from the distance measures resulting from comparisons of a number of face image pairs from the same face. Imposter distribution is created from the distance measures generated by comparisons of a number of face images pairs from different faces. The system decision is regulated by a threshold t. The higher the score, the more certain it is that the two measurements come from the same person.

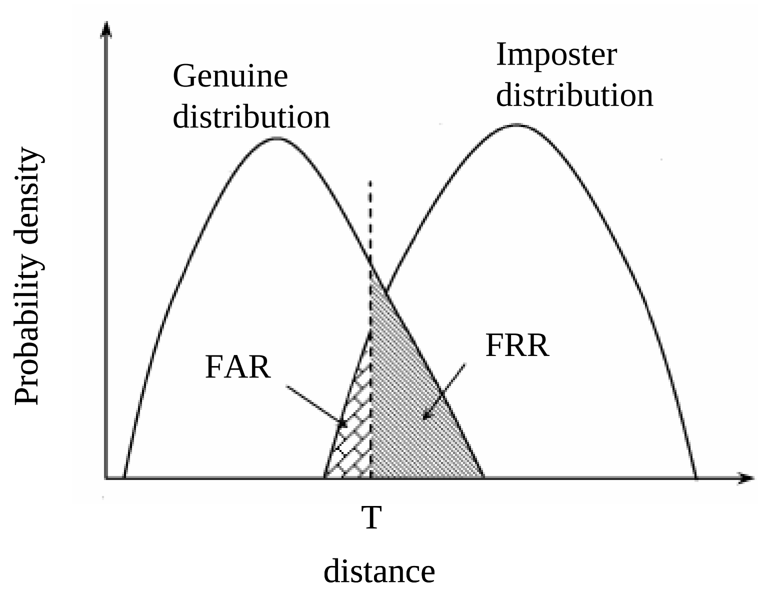
A biometric verification system makes two types of errors: false rejections and false acceptances[36]. These two types of errors are often termed as false matches and false non-matches. False rejections refer to the likelihood (in transaction percentage terms) of an authorized user being wrongly rejected by the system. False acceptances refer to the likelihood of an imposter being wrongly rejected by the system. These two types of error usually have different costs associated with them, depending on the security requirements of the application. If high security is the main goal, then the false acceptance rate (FAR) must be very low. This can lead to a large false rejection rate (FRR) and potential user annoyance. If user comfort with only mild security is the main goal, then a higher false acceptance rate must be tolerated. Performance is often measured in terms of the Equal Error Rate (EER), which is the point where the false acceptance rate and the false rejection rate are approximately the same.

Fig. 4.2(a) graphically illustrates the computation of the FAR and the FRR over genuine and imposter distributions. There is a strict tradeoff between FAR and FRR in every biometric system. In fact, both the FAR and the FRR are functions of the system threshold t. A ROC curve is used to report system performance at all operating points (threshold t in Fig. 4.2(a)). A ROC curve is a plot of FAR(t) against FRR(t) for various decision thresholds.

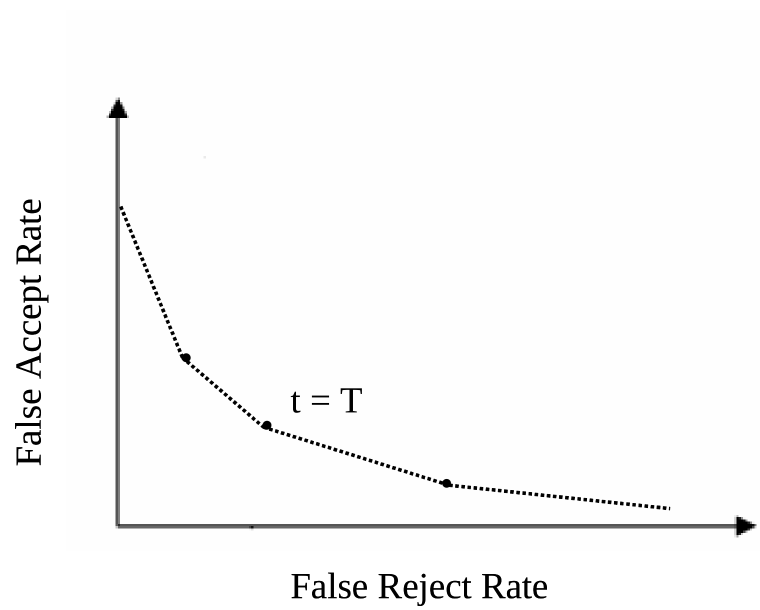
4.2.2 Changeability

Changeability means degree of deformation for transformed information according to original information. If there are striking differences between the transformed data and the original data, then the original information is better protected. For analysis, we used normalized eigencoefficient distribution to comply with the original appearance-based method and the applied proposed method.

We also determined the degree of overlap by two distance distribution points which were genuine versus before and after transformations. Fig. 4.3. show genuine and imposter elements of normalized distance distribution and normalized distance of the original eigencoefficients versus the transformed eigencoefficients by the proposed method for the same image. We defined the latter distribution as ‘pseudo genuine distribution’. Also, we determined the threshold



(a)



(b)

Figure 4.2: The distance distributions: (a) genuine and imposter distribution, (b) a receiver operation curve (ROC).

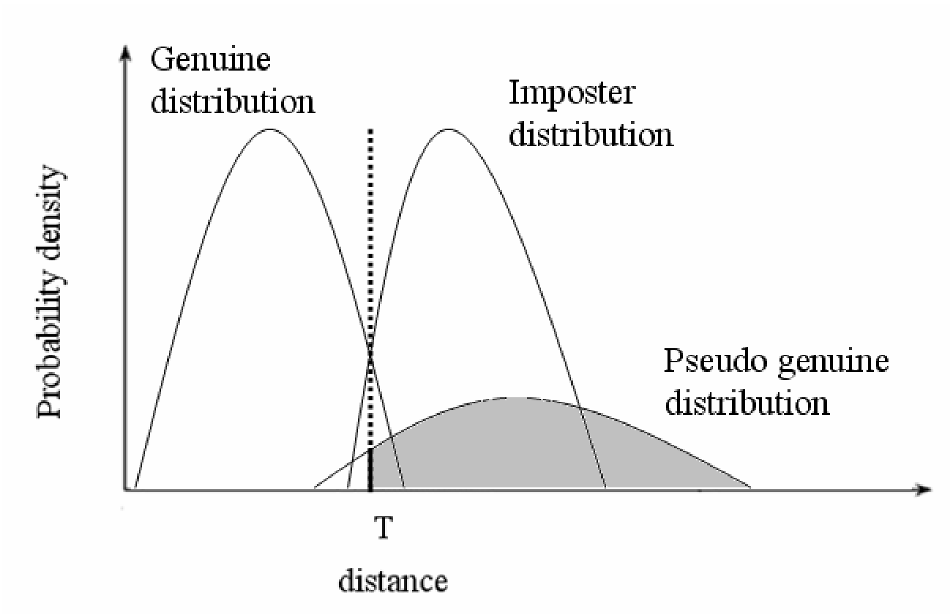


Figure 4.3: The distance distributions: genuine, imposter, and pseudo genuine distribution.

t as the EER point obtained by genuine and imposter distribution. If the distance of the threshold t and the pseudo genuine distribution was further to the right, the transformation before and after was more different. This is because the same image of the before and after transformation was classified as an imposter. The difference value means changeability by transformation. The degree of overlap using the distribution of threshold t and the pseudo genuine element showed a specific changeability value.

4.2.3 Reproducibility

Changeable biometric systems use change because the number of biometrics is insufficient. Therefore, the transform functions can be created indefinitely and the number of possible changed templates must be unlimited or numerous. This is called reproducibility. For analysis of reproducibility, we calculated a number of cases.

4.3 Experimental Results

4.3.1 Matching performance

We examined how the recognition rate varied when the number of dimensions changed from 300 to 10. Within this framework, we compared performance using PCA, ICAI(ICA architecture I), NMF and the proposed method. The experimental results of the proposed method were found for multiple instances for each simulation because the scrambling function for the coefficients was a randomly changing function. Therefore we conducted a total of 100 experiments for each case, and used the Euclidian distance as a measurement of dissimilarity.

Fig. 4.4and Fig. 4.5 show the EER results when, firstly, the PCA coefficient vector and the ICAI coefficient vector, and secondly, the PCA coefficient vector and the NMF coefficient vector were used for verification, and when the transformed coefficient vectors were used for verification, as the number of coefficient dimension varied. These experimental results show that the EER of the proposed method did not degrade significantly when using any of the conventional PCA,

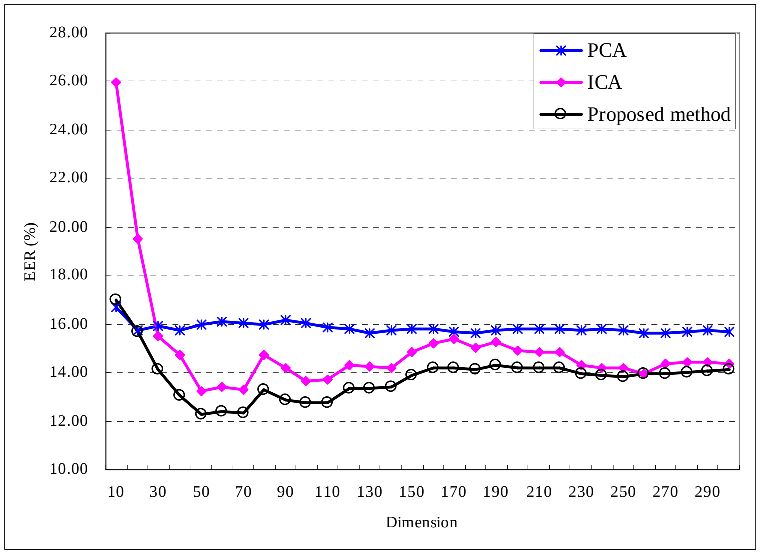


Figure 4.4: Recognition performance of PCA, ICAI and proposed method in varying dimensions for the AR Face database.

ICAI, or NMF based methods.

4.3.2 Changeability

To establish the performance of the proposed method and its changeability, we then confirmed the eigencoefficients. Fig. 4.6 and Fig. 4.7 show the distribution of the eigencoefficients before and after using the proposed method. The original face information was deformed when using the proposed method. Therefore, the original face information was protected from an attacker because it is different from the transformed eigencoefficients in the database.

The changeability value given by the number of 40 eigenfaces is shown in Fig. 4.8 and Fig. 4.9 The results show the genuine and imposter elements of the

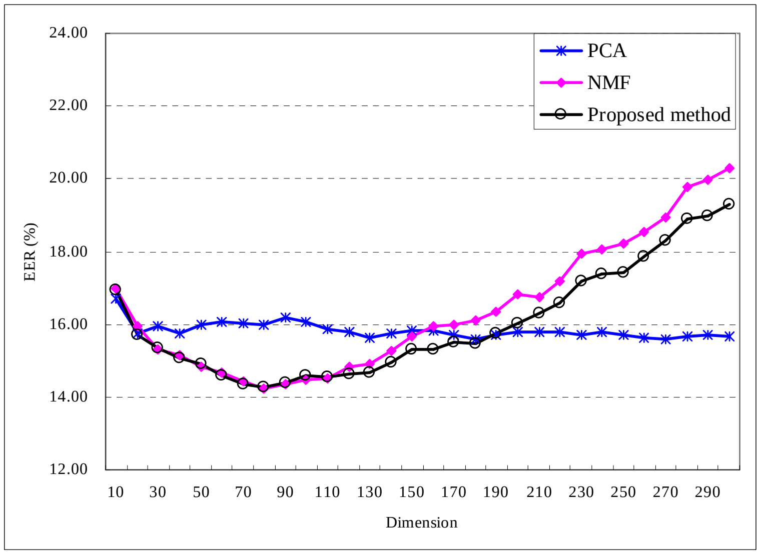
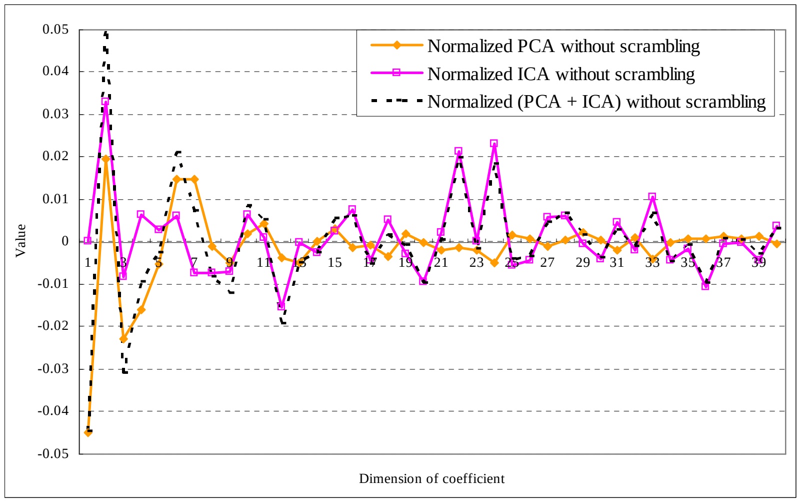


Figure 4.5: Recognition performance of PCA, NMF and proposed method in varying dimensions for the AR Face database.

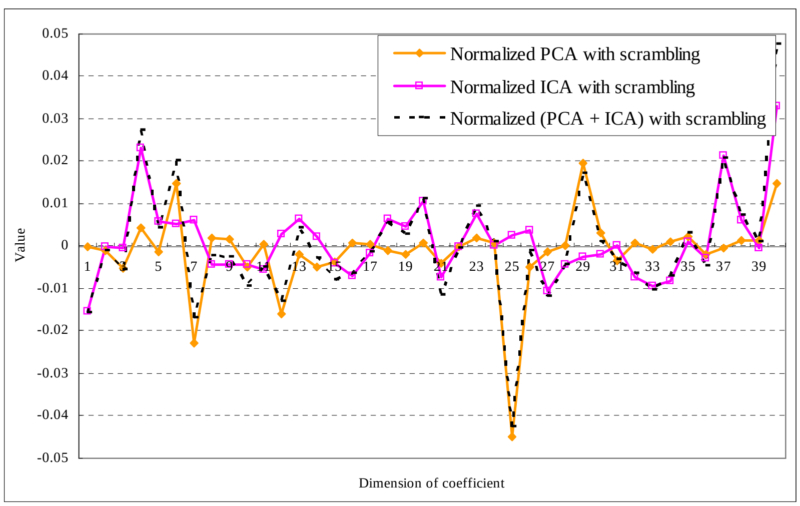
normalized distance distribution to the applied proposed method and the pseudo genuine distribution. We determined the threshold t as the EER point by using the genuine and imposter distribution. All distribution was placed on the right side rather than on threshold t. Namely, the same image of the before and after transformation was classified as an imposter element. These results mean that the changeability for the proposed method was satisfying a good level of changeability.

4.3.3 Reproducibility

Reproducibility was calculated by the number of cases of eigencoefficients produced by the scrambling rule. The scrambling method has large number of cases.

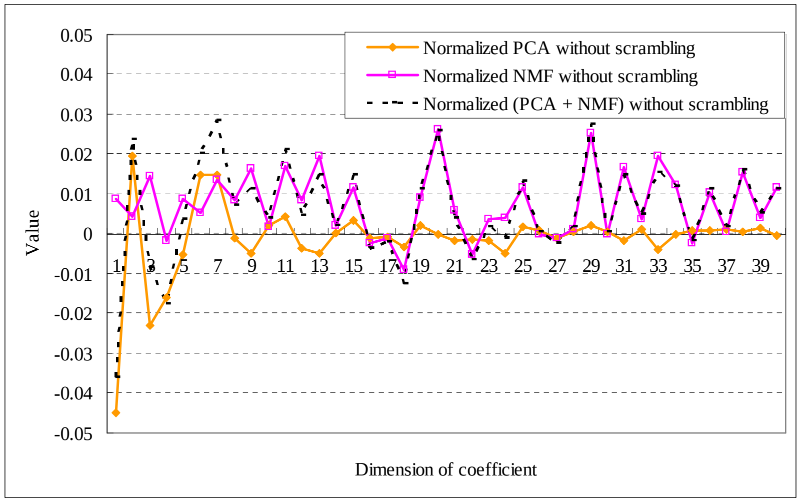


(a)

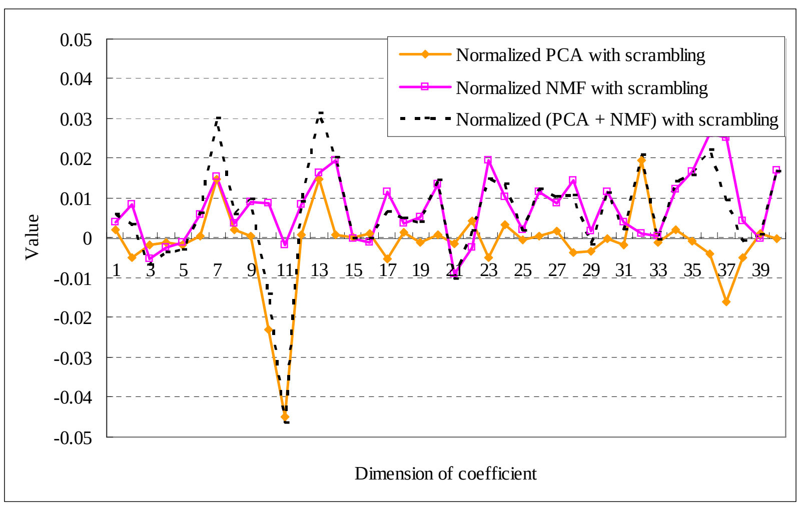


(b)

Figure 4.6: Example of PCA, ICAI and summation PCA and ICAI normalized eigencoefficients. (a) Example of PCA, ICAI and summation PCA and ICAI normalized eigencoefficients without scrambling. (b) Example of PCA, ICAI and summation PCA and ICAI normalized eigencoefficients with scrambling.

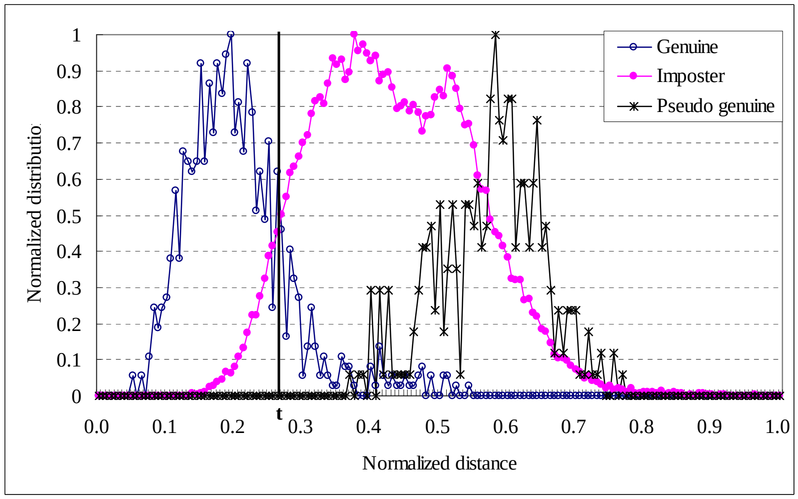


(a)

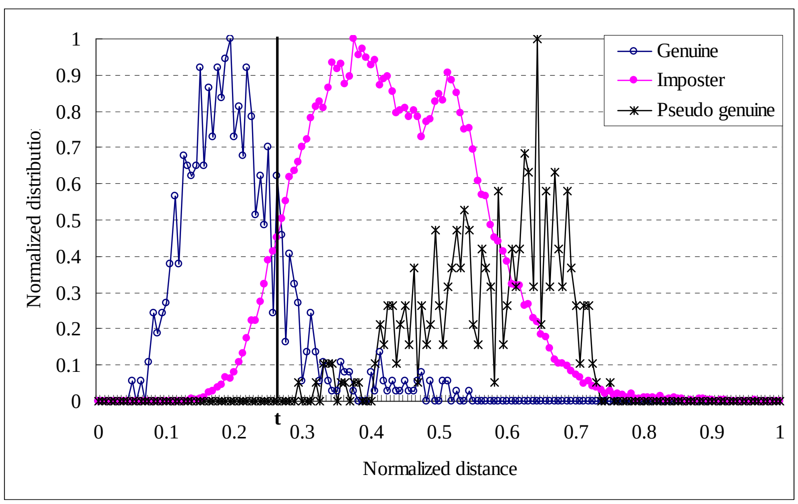


(b)

Figure 4.7: Example of PCA, ICAI and summation PCA and ICAI normalized eigencoefficients. (a) Example of PCA, NMF and summation PCA and NMF normalized eigencoefficients without scrambling. (b) Example of PCA, NMF and summation PCA and NMF normalized eigencoefficients with scrambling.

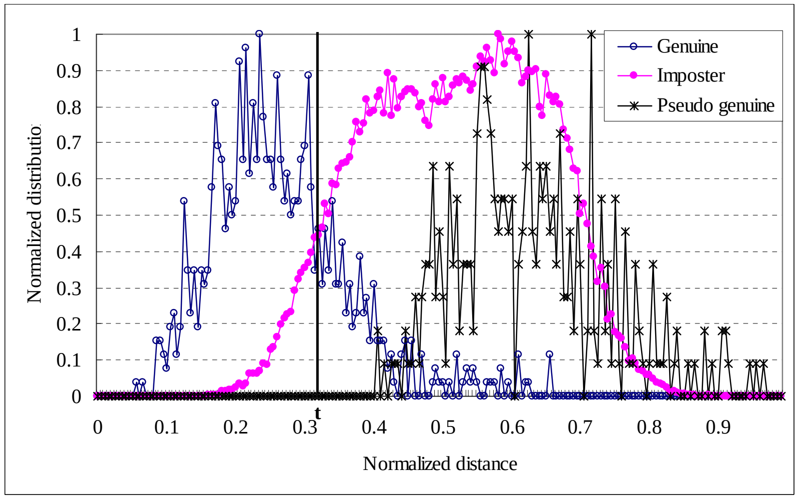


(a)

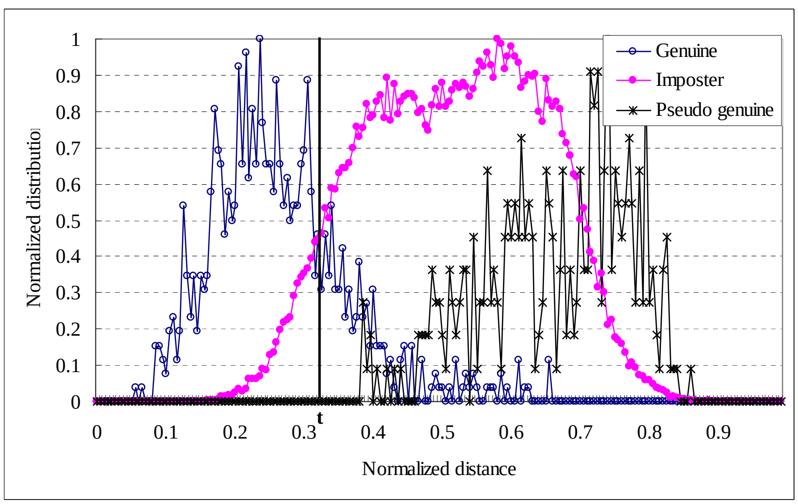


(b)

Figure 4.8: Distribution of genuine, imposter and pseudo genuine elements. (a) PCA, Proposed method using PCA and ICAI. (b) ICAI, Proposed method using PCA and ICAI.



(a)



(b)

Figure 4.9: Distribution of genuine, imposter and pseudo genuine elements. (a) PCA, Proposed method using PCA and NMF. (b) NMF, Proposed method using PCA and NMF.

If number of n was chosen as the dimension of used eigenfaces, the number of cases for an n eigenface scrambling method was $n!$. Here, the number of cases was numerous because the order of each of the PCA and ICAI (or PCA and NMF) vectors was differently scrambled and added. Therefore, the total number of cases for the proposed method was $n! \times n!$ obtained by using a differently randomly scrambled method. For example, if we used 50 eigenfaces (n), we had $50! \times 50! = 9.2502\mathrm{e} + 128$ cases for reproducibility. Therefore, this method contributed to reproducibility, which is good for changeable biometric systems.

Chapter 5

Conclusions

Biometrics is a method of personal authentication. Among its many advantages is the fact that information cannot be stolen, forgotten, or shared. Also, biometric systems provide a greater degree of security compared with traditional authentication methods. However, there are also weak points. One of these problems is the issue of privacy concerning non-revocable biometrics, especially in the case of identity theft. When a biometric template is compromised, it is rendered unusable because biometric data cannot be discarded and reissued. The only remedy is to replace the template with another biometric feature. However, a person has only a limited number of biometric features. Moreover, if biometric templates get stolen, an attacker can attack other authentication systems by using the compromised biometric templates. The key reason for these drawbacks is that biometric information is derived from a person's physical features, and thus, biometrics cannot be as easily changed as password or keys.

Changeable biometrics is an alternative to biometric problems. It uses transformed or distorted biometric data instead of original biometric data for identifying a person. When a set of biometric data is found to be compromised, it can be discarded and a new set can be generated.

In this thesis, we proposed a changeable biometric system for face recognition using an appearance-based approach. The main idea was to scramble the PCA and ICA (or the PCA and NMF) coefficient vectors and find a weighted sum of the two vectors. From experimental results, it is clear that this method can maintain performance comparable to that of conventional methods. By scrambling the order of the coefficients in the transform function, we were able to generate numerous instances of changeable face data. Therefore, the proposed method is characterized by not only resolving a weak point of biometric systems, but also maintaining good performance.

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국 문 요 약

외형기반 기법의 합성에 의한 가변 얼굴 생체인식

이 논문에서는 생체인식을 이용한 개인 인증 시 나타날 수 있는 프라이버시 문제의 해결을 위하여 얼굴인식을 위한 가변 생체인식을 제안한다.

생체인식은 개인의 독특한 생체정보를 사용하여 인증을 하는 방법 중 하나로 신체 정보를 사용하므로 쉽게 도난 당할 수 없다는 점, 휴대의 불편함이 없다는 점, 잊어버리지 않는 다는 점, 공유 할 수 없다는 점 등 많은 장점이 있다. 그러나 생체특성은 그 수가 한정되어 있기 때문에 도난 당하거나 손상을 당했을 경우 변경이 불가능하거나 그 횟수가 매우 제한된다. 가변 생체인식은 이런 생체인식 문제를 해결하기 위한 대안 중 하나이다. 가변 생체인식은 변경 가능한 생체인식 기법으로써 저장된 생체정보에 문제가 발생하면 등록 되어있던 생체정보를 취소하고 다른 생체정보로 변경하여 사용할 수 있음을 의미한다. 가변 생체인식을 위해서는 먼저 변환 함수를 선택하여 생체정보를 변형 시키고, 변형된 생체정보를 실제 시스템을 위한 생체 정보로 사용하게 된다. 이 변환 함수는 사람에 따라 또는 시스템에 따라 다르게 주어지며, 만약 생체정보가 도난을 당했을 경우 기존의 생체정보는 제거를 하고 새로운 변환 함수를 할당 받아 새로운 생체정보를 다시 생성하게 된다. 이때 변경된 함수로 만들어진 생체정보는 이전의 생체정보와 전혀 상관성이 없으며 원본 영상으로 복구하는 것도 불가능하다.

우리는 기존에 알려진 얼굴인식의 방법 가운데 하나인 외형 기반 기법(appea-rance-based method)의 고유계수(eigencoefficient)를 이용하여 가변 생체인식을 구현하는 방법을 제안한다. 먼저 한 영상에서 서로 다른 외형 기반 기법을 이용하여 고유 계수를 추출한다. 추출된 각 고유계수 값의 범위를 평준화(normalization) 통하여 일치시킨다. 평준화 된 각각의 고유계수를 랜덤함수를 이용하여 불규칙하게 순서를 변경한다. 임의적으로 순서가 재배열된 고유계수를 서로 더한다. 이렇게 더해져 생성된 변형 고유계수를 인식에 사용한다. 제안된 얼굴 생체정보 생성 방법은 각각의 고유계수의 순서를 임의로 변경하여 무한한 가변 얼굴 정보를 생성할 수 있도록 하였고 고유계수를 더함으로써 비가역성(non-invertibility)을 만족시키려고 시도했다.

제안된 방법을 이용한 실험 결과 가변 얼굴 생체정보를 사용해도 개인 인증의 성능이 유지됨을 확인 할 수 있었다. 변형된 고유계수들은 원 고유계수들의 값과 매우 다르므로 원 정보의 보호 기능을 가진다. 또한 이 방법은 평준화와 더하기 연산을 거쳤기 때문에 역변환이 불가능하고, 순서 변경을 위한 랜덤함수가 무한하므로 재생산성을 충분히 만족시키며, 사칙 연산만을 이용하므로 계산이 간단하다. 게다가 복원된 영상은 원본과 매우 다르므로 개인 얼굴정보를 보호할 수 있다. 따라서 제안 방법은 가변 생체인식에 매우 적합하다.

핵심되는 말 : 생체인식, 가변 생체인식, 얼굴 인식, 주성분 분석, 독립 성분 분석, 비음수 구속조건을 따른 행렬분해