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Discriminant Subspace Analysis for Uncertain Situation in Facial Recognition

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1. Introduction

Facial analysis and recognition have received substential attention from researchers in biometrics, pattern recognition, and computer vision communities. They have a large number of applications, such as security, communication, and entertainment. Although a great deal of efforts has been devoted to automated face recognition systems, it still remains a challenging uncertainty problem. This is because human facial appearance has potentially of very large intra-subject variations of head pose, illumination, facial expression, occlusion due to other objects or accessories, facial hair and aging. These misleading variations may cause classifiers to degrade generalization performance.

It is important for face recognition systems to employ an effective feature extraction scheme to enhance separability between pattern classes which should maintain and enhance features of the input data that make distinct pattern classes separable (Jan, 2004). In general, there exist a number of different feature extraction methods. The most common feature extraction methods are subspace analysis methods such as principle component analysis (PCA) (Kirby & Sirovich, 1990) (Jolliffe, 1986) (Turk & Pentland, 1991b), kernel principle component analysis (KPCA) (Schölkopf et al., 1998) (Kim et al., 2002) (all of which extract the most informative features and reduce the feature dimensionality), Fisher's linear discriminant analysis (FLD) (Duda et al., 2000) (Belhumeur et al., 1997), and kernel Fisher's discriminant analysis (KFLD) (Mika et al., 1999) (Scholkopf & Smola, 2002) (which discriminate different patterns; that is, they minimize the intra-class pattern compactness while enhancing the extra-class separability). The discriminant analysis is necessary because the patterns may overlap in decision space.

Recently, Lu et al. (Lu et al., 2003) stated that PCA and LDA are the most widely used conventional tools for dimensionality reduction and feature extraction in the appearancebased face recognition. However, because facial features are naturally non-linear and the inherent linear nature of PCA and LDA, there are some limitations when applying these methods to the facial data distribution (Bichsel & Pentland, 1994) (Lu et al., 2003). To overcome such problems, nonlinear methods can be applied to better construct the most discriminative subspace.

In real world applications, overlapping classes and various environmental variations can significantly impact face recognition accuracy and robustness. Such misleading information make Machine Learning difficult in modelling facial data. According to Adini et al. (Adini et al., 1997), it is desirable to have a recognition system which is able to recognize a face insensitive to these within-personal variations.

Source: Recent Advances in Face Recognition, Book edited by: Kresimir Delac, Mislav Grgic and Marian Stewart Bartlett, ISBN 978-953-7619-34-3, pp. 236, December 2008, I-Tech, Vienna, Austria However, in (Adini et al., 1997), the authors mainly focused their empirical experiments on variations due to changes in illumination. They stated that within-personal variation is larger than between-personal separation. These variations between images of the same individual faces make difficult machine learning. Therefore, in a facial recognition system if the extracted input data contains misleading information (ambiguous regions), classifiers may produce a degraded classification performance (Jan, 2004). Specifically, in this chapter, we will mainly focus our empirical experiments on variations due to changes in facial expression that are less emphasized in (Adini et al., 1997) and deal with the impact of facial expression changes as individuals deform/express their faces either naturally or deliberately in a real-time face recognition system. As Adini et al. (Adini et al., 1997) stated that a facial recognition system should recognize a face insensitive to these within-personal variations. Limited success is reported for face recognition systems that are invariant of facial expression changes (Liu et al., 2002b) (Liu et al., 2003) (Martinez, 2000) (Martinez, 2002) (Seow et al., 2003) (Chen & Lovell, 2004). Our earlier research on a facial expression invariant system demonstrated its challenging nature (Tsai et al., 2005) (Tsai & Jan, 2005). If the number of individuals is increased (along with their varying facial expressions), the facial data will largely overlap. Thus, the variations of individual facial expressions will increase the range of uncertainty. This makes classification difficult.

The aim of this chapter was first to address the issue of within-personal variations due to facial expression changes. We then used a kernel-based discriminant analysis technique to reduce the uncertainty (overlapping) in the feature subspace applied before learning so as to improve classification rates. This chapter also examined other linear and nonlinear techniques (PCA, FLD, and KPCA) for comparison. Their transformation effects on a subsequent classification performances were then tested in combination with learning algorithms (multi-layered perceptron neural networks (MLPNNs), radial basis function neural networks (RBFNNs), and support vector machines (SVMs)). The algorithms were then applied to face database with facial expression changes. We found that the transformation of kernel-based discriminant analysis had a beneficial effect to the classification performance. The experimental results indicates that non-linear discrimininant analysis method may robustly deal with the uncertainty problem. It appears that a facial recognition system may be robust to facial expressio changes, and thus be applicable.

The structure of this chapter is as follows: First, we provide a concise overview of the facial expression analysis. Second, we discuss the expression variant problem in facial recognition. Third, we introduce a concise overview of the subspace feature extraction methods. Then, in the final part of this chapter, we analyse different subspace transformation methods and their transformation capabilities. We finally present the results of the experiments and discuss them from several aspects, focusing on the advantages and disadvantages of each subspace feature extraction method.

2. Facial expression analysis

Human faces contain abundant information of human facial behaviors (Cohn et al., 1999). According to Johansson's point-light display experiment (Johansson, 1973) (Johansson, 1976), facial expressions can be described by the movements of points that belong to the facial features such as eye brows, eyes, nose, mouth and chin and analyzed by the relationships between those features in movements (Pantic & Rothkrantz, 2000b). Hence,

point-based visual properties of facial expressions can then be used for facial gesture analysis. We present a literature review regarding facial expression analysis in the following subsections.

2.1 Facial muscle analysis

Facial features such as eyes, eyebrows, mouth, facial lines and bulges will change human facial appearances when their facial muscles are contracted. The contracted muscles will deform those features temporarily and the change of the muscular movements can only last for a few seconds (Fasel & Luettin, 2003) (Pantic & Rothkrantz, 2004). Those facial muscles include frontalis, corrugator, procerus, depressor supercilli, orbicularis oculi, levator labii superioris, nasalis, zygomatic minor, zygomatic major, caninus, depressor labii, buccinator, orbicularis oris, masseter, depressor labii, mentalis, triangularis, platysman, and risorius. Readers who are interested in the anatomy of facial muscles can refer to dataface website¹ for rigorous exposition.

2.2 Action Units (AUs)

The FACS is called Facial Action Coding system, which is used to describe facial movements/motions/actions of facial muscles in behavior science (Ekman & Friesen, 1975) (Donato et al., 1999) (Essa & Pentland, 1997). This system is based on action units (Aus). Each AU represents some facial movement. For example, AU1 stands for upward pull of the inner portion of the eyebrows. There are 44 AUs in total. Different sets of combinations of AUs accur in different facial expression categories; for example, the combination of 'surprise' consists of AUs1+2. In Figure 1, it shows the upper facial muscles that correspond to action units 1,2,4,6 and 7.



Fig. 1. The corresponding action units to the upper facial muscle (Donato et al., 1999).

Moreover, those action units can also be used to detect subtle changes of facial expression (Pantic & Rothkrantz, 2004, Tian et al., 2001). The Automatic Facial Analysis (AFA) system

¹ http://face-and-emotion.com/dataface/general/homepage.jsp

(Tian et al., 2001) and FACS+ (Essa & Pentland, 1997) were developed to improve FACS system (Ekman & Friesen, 1975).

2.3 Facial expression data extraction

Detection of feature points of a still image is very important in facial expression analysis because by knowing which expression the current image is and which facial muscle actions produce such an expression (Pantic & Rothkrantz, 2004, Vukadinovic & Pantic, 2005). There are three types of face representation for analyzing facial expressions (Donato et al., 1999). They are template-based (holistic), feature-based (analytic), and hybrid (analytic to holistic) methods (Pantic & Rothkrantz, 2000a). See Figure 7.2 and literature (Pantic & Rothkrantz, 2004) (Cootes et al., 1998) (Huang & Huang, 1997) (Kobayashi & Hara, 1992) (Valstar & Pantic, 2006) (Cohn et al., 1998) (Lyons et al., 1998) (Zhang et al., 1998). Interested readers can refer to those references for rigorous explanations.



Fig. 2. Different ways of detecting facial fiducial points (Cootes et al., 1998) (Huang & Huang, 1997) (Kobayashi & Hara, 1992) (Pantic & Rothkrantz, 2004) (Valstar & Pantic, 2006) (Cohn et al., 1998) (Lyons et al., 1998) (Zhang et al., 1998) .

2.4 Facial model

About 55% of human communication relies on facial expressions. Facial expressions; however, are the normative units of the non-verbal communication (Pantic & Rothkrantz, 2000b). There are prototypic (Six basic emotional expressions: sadness, happiness, anger, disgust, fear and surprise) and non-prototypic (blended emotional expression) expressions (Ekman & Friesen, 1975, Pantic & Rothkrantz, 2000b). In addition, *facial fiducial points* are the special facial points such as the corners of the eyes, corners of the eyebrows, and the tip of the chin etc. (Vukadinovic & Pantic, 2005). Examples using facial feature points are (Pantic & Rothkrantz, 2004) which used 19 fiducial feature points and (Vukadinovic & Pantic, 2005) (Valstar & Pantic, 2006) which used 20 fiducial feature points as in Figure 3.

The frontal-view face model is composed of 30 features (F1-F30, please see (Pantic & Rothkrantz, 2000b)), which are defined by a set of 20 facial fiducial points. For example, F3 is the distance between point A and E and F18 is the distance between point C and point M etc. (See Table 1 (Right) for some examples). These points are illustrated in Figure 3 and described in Table 1 (Right).



Fig. 3. Twenty Facial fiducial points (Pantic & Rothkrantz, 2004).

Point	Point Description	Eastura	Fastura description
1 Viin	1 our Description	Feature	reature description
A	Left eye outer corner, stable point	F1	Angle BAD
Al	Right eye outer corner, stable point	F2	Angle B1A1D1
B	Left eye inner corner, stable point	F3	Distance AE
B1	Right eye inner corner, stable point	F4	Distance A1E1
С	The medial point between left and right nostril centers	F5	Distance cF, c is the centre of AB
D	Left eyebrow inner corner, non-stable	F6	Distance c1F1, c1 is the centre of A1B1
DI	Right eyebrow inner corner, non-stable	F7	Distance cG
E	Left eyebrow outer corner, non-stable	F8	Distance c1G1
El	Right eyebrow outer corner, non-stable	F9	Distance FG
F	Top of the left eye, non-stable	F10	Distance F1G1
Fl	Top of the right eye, non-stable	F11	Distance CK, C is 0.5HH1 (f0)
G	Bottom of the left eye, non-stable	F12	Distance IB
GI	Bottom of the right eye, non-stable	F13	Distance JB1
K	Top of the upper lip, non-stable	F14	Distance CI
L	Bottom of the lower lip, non-stable	F15	Distance CJ
I	Left corner of the mouth, non-stable	F16	Distance IJ
J	Right corner of the mouth, non-stable	F17	Distance KL
М	Tip of the chin, non-stable	 F18	Distance CM

Table 1. (Left) Facial fiducial point description of the frontal-view model; (Right) Some examples of the features of the frontal-view model (Pantic & Rothkrantz, 2000b).

3. Related work in expression invariant facial recognition

The facial expression variation problem not only exist in facial recognition but also in any multimedia databases that require image retrieval. The recognition performance of facial recognition system that trained with only neural faces will drop if there are facial expression variations in the appearance of facial images. Image retrieval from multimedia databases

requires semantic queries to help a user to obtain or to manipulate data without knowing its detailed syntactic structure. An emerging technology in this area is the image-based query from a user's input. In particular, in the context of facial images, it is of interest to retrieve information based on faces. There are many research have been conducted to tackle pose or illumination problems. However, little work has been conducted to tackle expressions. When images of the databases appear at different facial expressions, most currently available face recognition approaches encounter the expression-invariant problem in which neutral faces are difficult to recognize.

For example, (Liu et al., 2002b) (Liu et al., 2003), a quantified statistical facial asymmetry method under 2D facial expression changes (called AsymFaces) was used for person identification. PCA was then applied to AsymFaces for dimension reduction. AsymFaces were claimed to be invariant to facial expression changes. In (Martinez, 2000) (Martinez, 2002), a local and probabilistic weighting method that weights the local areas of facial features independently, which are less sensitive to expression changes. In (Seow et al., 2003), a learning algorithm based on L2-norm approximation was proposed and applied to face expression variant database so as to evaluate the problem of facial expression changes for face recognition. In (Chen & Lovell, 2004), an adaptive principle component analysis (APCA) method was used to deal with one sample problem under both illumination and facial expression changes simultaneously. APCA method was applied to 2D face images after applying standard PCA method in order to construct a subspace for image representation and to improve class separability. A Bayes classifier was then used for classification.

However, their apperance-based approaches still suffer from high dimensionality problem; that is to say, this problem will require expensive computation and increase the sparse data distribution. Our earlier research (Tsai et al., 2005) (Tsai & Jan, 2005) used seventeen Euclidean distance-based facial features of multiple training images in each class and applied subspace model analysis to develop a facial recognition system that was tolerant to facial expression changes. The dimensionality of the Euclidean distance-based facial features was reduced greatly compared to the appearance-based approaches. Our previous work also demonstrated its challenging nature. If the number of individuals is increased (along with their varying facial expressions), the facial data will largely overlap. That is, the variations of individual facial expressions will increase the range of uncertainty. This makes classification difficult. Therefore, the extensive work of our previous research in this chapter aimed to reduce the uncertainty (overlapping) in the feature subspace applied before learning so as to improve the classification rates.

4. An overview of subspace analysis in feature extraction

Feature extraction in subspace analysis aims to transform a multidimensional feature space of initial objects to be classified (data points) into a reduced low dimensional feature space before executing a learning algorithm so as to improve classification performance and to reduce the dimensionality of the data. That is, the initial data feature set is transformed into another transformed feature set so as to yield a more efficient and faster classification. The approach of subspace analysis methods can be either linear or nonlinear. We then discuss these methods in the following sections. Our aim is to help the reader gain a unified view of these feature extraction methods and get some ideas about their usage.

4.1 Linear-based suspace analysis

Subspace analysis methods are the processes of projecting high dimensional data to a lower dimensional subspace which are used for visualization or dimensionality reduction in pattern recognition applications. Subspace Analysis methods such as Principle Component Analysis (PCA) and Fisher's Linear Discriminant (FLD) analysis are used for the extraction of low-dimensional forms consisted of statistically uncorrelated or independent variables which is crucial in machine learning that tends to simplify tasks such as regression, classification, and density estimation.

4.1.1 Principle Component Analysis (PCA)

PCA is a classical feature extraction and data representation technique also known as Karhunen-Loeve Expansion. It is a linear method that projects the high-dimensional data onto a lower dimensional space. It seeks a weight projection that best represents the data, which is called principle components. It has been used in the areas of pattern recognition and computer vision. Sirovich and Kirby (1987 and 1990) first used PCA to efficiently represent pictures of human faces. Turk and Pentland presented the well-known Eigenfaces methods for face recognition in 1991 (Turk & Pentland, 1991a) (Turk, 2001). However, its main limitation is that it does not consider class separability.

Let a face image X_i be a two-dimensional $m \times m$ array of intensity values, an image may also be considered as a vector of dimension x^2 . Denote the training set of n face images by $X = (X_1, X_2, ..., X_n) \subset R^{m^2 \times n}$, and we assume that each image belongs to one of c classes.

Define the covariance matrix as follows (Bishop, 1995) (Duda et al., 2000):

$$\Sigma = \frac{1}{n} \sum_{i=1}^{n} (X_i - \overline{X}) (X_i - \overline{X})^T = \Phi \Phi^T$$
(1)

where $\Phi = (\Phi_1, \Phi_2, ..., \Phi_n) \subset \Re^{m^2 \times n}$ and $\overline{X} = (1/n) \sum_{i=1}^n X_i$. Then, the eigenvalues and eigenvectors of the covariance Σ are calculated. Let $U = (U_1, U_2, ..., U_r) \subset \Re^{m^2 \times n}(r < n)$ be the *r* eigenvectors corresponding to the *r* largest eigenvalues. Thus, for a set of original face images $X \subset \Re^{m^2 \times n}$, their corresponding eigenface-based feature $Y \subset \Re^{r \times n}$ can be obtained by projecting *X* onto the eigen-based feature space as follows:

 $Y = U^T X$ ⁽²⁾

4.1.2 Linear Discriminant Analysis (LDA)

While PCA is unsupervised method that constructs the face space without using the face class (category) information, the LDA aims to find an "optimal" way to represent the face vector space to maximize the discrimination between different face classes. Exploiting the class information can be helpful to the identification tasks.

FLD is also a linear projection of discriminant analysis. It is not just the choice of discriminant itself but the choice of dimensionality reduction. Therefore, it is a specific

choice of direction for projection of the data right down to one dimension. Its objective is to preserve the class discriminatory information as much as possible while reducing the dimensionality from original *n* dimension space into (c-1) dimension space in order to classify *c* classes of objects. Therefore, if the data is linearly separable, the results of FLD will be globally optimal because of its linear transformation which maximizes the ratio of the determinant of the between-class scatter matrix of the projected samples to the determinant of the with-class scatter matrix of the projected samples (Bishop, 1995) (Duda et al., 2000).

However, its limitations include "the separability criterion is not directly related to the classification accuracy in the output space" and "if the distributions are significantly non-Gaussian, the LDA projections will not be able to preserve any complex structure of the data, which may be needed for classification" (Lotlikar & Kothari, 2000).

Let a face image X_i be a two-dimensional $m \times m$ array of intensity values, an image may also be considered as a vector of dimension x^2 . Denote the training set of n face images by $X = (X_1, X_2, ..., X_n) \subset \mathbb{R}^{m^2 \times n}$, and we assume that each image belongs to one of c classes. Define the between-class scatter and the within-class scatter matrices as follows:

$$S_B = \sum_{i=1}^{c} n^i (\overline{X}^i - \overline{X}) (\overline{X}^i - \overline{X})^i$$
(3)

$$S_{W} = \sum_{i=1}^{C} \sum_{X_{k} \in X_{i}} (X_{k} - \overline{X}^{i}) (X_{k} - \overline{X}^{i})^{T}$$
(4)

where $\overline{X} = (1/n)\sum_{j=1}^{n} X_{j}$ is the mean image of input vectors, and $\overline{X}^{i} = (1/n^{i})\sum_{j=1}^{n^{i}} X_{j}^{i}$ is the mean image of the *ith* class, n^{i} is the number of samples in the *ith* class and c is the number of classes. Therefore, If S_{W} is nonsingular, the optimal projection W_{opt} is chosen as the matrix with orthonormal columns which maximizes the ratio of the determinant of the between-class scatter matrix of the projected input samples to the determinant of the withclass scatter matrix of the projected input samples. The optimal projection W_{opt} is defined as follows:

$$W_{opt} = \arg \max_{W} \frac{\left| W^{T} S_{B} W \right|}{\left| W^{T} S_{W} W \right|} = \left[W_{1}, W_{2}, ..., W_{m} \right]$$
(5)

where $\{W_i \mid i = 1, 2, ..., c-1\}$ is the set of generalized eigenvectors of S_B and S_W corresponding to the c-1 largest generalized eigenvalues $\{\lambda_i \mid i = 1, 2, ..., c-1\}$, i.e.,

$$S_W^{-1}S_BW = \lambda_i W \tag{6}$$

Thereby, the feature vectors Z for any probe face images X in the most discriminant subspace can be calculated as follows:

$$Z = W_{opt}^T \cdot X \tag{7}$$

4.2 Non-linear subspace analysis

The combination of subspace analysis methods with NN-based classifiers is to reduce the dimensionality of input data so as to reducing the NN structure and computational complexity; hence increasing the classification accuracy. KPCA and KFLD are kernel-based PCA and FLD subspace analysis methods. These two kernel-based methods are ideal to use in nonlinearly complex real-world problems. They firstly nonlinearly map the input data into some high dimensional feature space F by using kernel functions, and secondly apply the PCA and FLD methods in the mapped feature space (Schölkopf et al., 1998) (Mika et al., 1999). Some further details of KPCA and KFDA in face recognition are provided in (Yang et al., 2000) (Liu et al., 2002a) (Kim et al., 2002) (Yang, 2002).

4.2.1 Kernel principle component analysis

Given a set of centered input data $X = \{x_k\} \Big|_{k=1,...,n,k \in \mathbb{R}^{d \times n}}$, where *n* the number of input data is, *d* is the number of dimensions, the input data is projected onto a high dimensional feature space *F* by nonlinear kernel mapping $\Phi: X \in \mathbb{R}^{d \times n} \to f \in F$, in which the mapped data $\Phi(x_k)$ is centered as $\sum_{k=1}^{N} \Phi(x_k) = 0$. In the feature space *F*, the estimate of the covariance matrix of the mapped data $\Phi(x_k)$ is defined as:

$$C^{\Phi} = \frac{1}{n} \sum_{k=1}^{n} \Phi(x_{k}) \Phi(x_{k})^{T}$$
(8)

and the eigenvalues and eigenvectors of the covariance matrix C^{Φ} is calculated as

$$\lambda w^{\Phi} = C^{\Phi} w^{\Phi} \tag{9}$$

where eigen-values $\lambda \ge 0$ and eigenvectors $w^{\Phi} \in F \setminus \{0\}$. As $C^{\Phi}w^{\Phi} = \frac{1}{n} \sum_{k=1}^{n} (\Phi(x_{k}) \cdot w^{\Phi}) \Phi(x_{k})$, all solutions w^{Φ} with $\lambda \ne 0$ must lie in the span of $\Phi(x_{1}), ..., \Phi(x_{N})$; hence, equation **Error! Reference source not found.** is equivalent to

$$\lambda(\Phi(x_k) \cdot w^{\Phi}) = (\Phi(x_k) \cdot C^{\Phi} w^{\Phi}) \ \forall k = 1, ..., n$$
(10)

The expansion of w^{Φ} is formed as

$$w^{\Phi} = \sum_{i=1}^{n} \alpha_i \Phi(x_i) \tag{11}$$

where any solution $\{\alpha_i | i=1...n\}$ must lie in the span of all samples in *F*.

Combining (10) and (11), and also defining an $n \times n$ matrix K by $k_{ij} = (\Phi(x_i)\Phi(x_j))$, which produces an eigenvalue problem, is defined as

$$M\lambda k\alpha = k^2 \alpha \equiv M\lambda \alpha = k\alpha \tag{12}$$

Now, we can solve the eigenvalue problem (12) in *F* by finding the *r* largest leading eigenvectors $\{\alpha_i | i = 1, 2, ..., r\}$ of $M\lambda$ corresponding to *r* largest eigenvalues $\{\lambda_i | i = 1, 2, ..., r\}$. Finally, we can project $\Phi(x)$ to a lower dimensional subspace spanned by eigenvectors w^{Φ} , i.e.

$$w^{\Phi}\Phi(x) = \sum_{i=1}^{n} \alpha_i k(x_i, x)$$
(13)

, which is the nonlinear principle component corresponding to Φ .

4.2.2 Kernel fisher's linear discriminant analysis

Let the centered input data $X = \bigcup_{i=1}^{C} x_{n_i}^i$ be samples from *c* classes with total samples $n = \sum_{i=1}^{C} n_i$, where each class has n_i samples. The input data is projected into an implicit

feature space *F* by nonlinear kernel mapping $\Phi : x \in \mathbb{R}^{d \times n} \to f \in F$. The kernel functions such as Gaussian RBF or polynomial is used to compute the dot products of the training patterns in some feature space *F*, instead of computing Φ explicitly. We then compute Fisher's linear discriminant in *F*. Let Φ be a non-linear mapping to *F*, we need to find the vector $w^{\Phi} \in F$ which maximizes

$$J(w^{\Phi}) = \frac{(w^{\Phi})^{T} S_{B}^{\Phi} w^{\Phi}}{(w^{\Phi})^{T} S_{W}^{\Phi} w^{\Phi}}$$
(14)

so as to find the linear discriminant in *F*. We define between-class scatter matrix S_B^{Φ} and within-class scatter matrix S_W^{Φ} in the feature space *F* as

$$S_B^{\Phi} = \frac{1}{c(c-1)} \sum_{i=1}^{C} \sum_{j=1}^{C} (u_i^{\Phi} - u_j^{\Phi}) (u_i^{\Phi} - u_j^{\Phi})^T$$
(15)

$$S_W^{\Phi} = \frac{1}{c} \sum_{i=1}^{c} \frac{1}{ni} \sum_{j=1}^{n_i} (\Phi(x_j^i) - u_i^{\Phi}) (\Phi(x_j^i) - u_i^{\Phi})^T$$
(16)

where $u_i^{\Phi} = \frac{1}{n_i} \sum_{j=1}^{n_i} \Phi(x_j^i)$ denotes the sample mean of class *i* in *F*. Therefore, any solution $\{\alpha_i | i=1...n\}$ must lie in the span of all samples in *F*. The expansion of w^{Φ} is formed as

$$v^{\Phi} = \sum_{i=1}^{n} \alpha_i \Phi(x_i) \tag{17}$$

by (17) and u_i^{Φ} , we write the projection of u_i^{Φ} onto w^{Φ} as

$$((w^{\Phi})^{T} \cdot u_{i}^{\Phi}) = \frac{1}{n_{i}} \sum_{j=1}^{n} \sum_{k=1}^{n_{i}} \alpha_{jk}(x_{j}, x_{k}^{i}) = \alpha^{T} U_{i}$$
(18)

where $(U_i)_j = \frac{1}{n_i} \sum_{k=1}^{n_i} k(x_j, x_k^i)$, and the dot products is replaced by the kernel function. Therefore, it follows that

$$(w^{\Phi})^{T} S_{B}^{\Phi} w^{\Phi} = \alpha^{T} M B \alpha$$

$$(w^{\Phi})^{T} S_{W}^{\Phi} w^{\Phi} = \alpha^{T} N W \alpha$$
(19)
(20)

where $M_B = \frac{1}{c(c-1)} \sum_{i=1}^{C} \sum_{j=1}^{C} (m_i - m_j)(m_i - m_j)^T$ and $N_W = \frac{1}{c} \sum_{i=1}^{C} \frac{1}{n_i} \sum_{j=1}^{n_i} (\xi_j - m_i)(\xi_j - m_i)^T$ with $\xi_j = \sum_{j=1}^{n_i} k(x_n, x_j)^T$.

We then replace N_W with $N_W + \mu I$ for numerical issues and regularization(Mika et al., 1999). Thus, combining (19) and (20), we can choose the (c-1) optimal projection α_{opt} , which maximize the Fisher's linear discriminant in F by

$$J(\alpha) = \frac{\alpha^T M_B \alpha}{\alpha^T N_W \alpha}$$
(21)

The optimal projection α_{opt} is defined as finding the (c-1) leading eigenvectors $\{\alpha_i | i = 1, 2, ..., c-1\}$ of $Nw^{-1}M_B$ corresponding to the (c-1) largest eigenvalues $\{\lambda_i | i = 1, 2, ..., c-1\}$, i.e

$$Nw^{-1}M_B\alpha_i = \lambda_i\alpha_i \tag{22}$$

Finally, we can project $\Phi(x)$ to a lower dimensional subspace spanned by eigenvectors w^{Φ} , i.e.

$$\left(\left(w^{\Phi}\right)^{T} \cdot \Phi(x)\right) = \sum_{i=1}^{n} \alpha_{ik}(x_{i}, x)$$
(23)

5. Experiments

Experiments will consist of comparing the face recognition rates under varying expressions for different types of classifiers. In the following sections, we discuss the analyses of different feature extractors.

5.1 Facial expression database and performance evaluation

One of the databases of facial expression images used in this chapter is the Japanese Female Facial Expression (JAFFE) database². This database is used for facial expression analysis and

² http://www.kasrl.org/jaffe.html

recognition (Lyons et al., 1998) (Zhang et al., 1998) (Lyons et al., 1999). It contains 213 grayscale images of 6 facial expressions (happiness, sadness, surprise, anger, disgust, fear) plus one neutral face posed by 10 Japanese women. Each woman posed for two, three or four examples of each of the six basic facial expressions and a neutral face. Each individual pose is for various extents of facial expression changes. Some individuals pose similar facial expression changes, while others pose different ones. Also, some individuals have slight pose variations when they pose facial expressions. The size of each image is 256x256, resulting in an input dimensionality of d = 65536. Figure 4 displays the sample images in the database.

Moreover, we will conduct the hold-out procedure for our performance evaluation; that is, a certain amount of data is used for training and the remaining is used for testing. That is, one-third of the data for testing and two-thirds for training.



Fig. 4. Facial Expression Images from JAFFE database.

5.2 Geometric feature-based analysis

Features in facial images include eyes, nose, mouth, and chin. In facial recognition, geometric properties and relations such as areas, distances and angles between the features are selected as the descriptors of faces for recognition. Therefore, the geometric attributes provide benefits in data reduction and less sensitivity to variations in illumination, viewpoint, and expressions. Ivancevic et al. (Ivancevic et al., 2003) stated that, there are

about 80 landmark points on a human face Figure 5, and the number of points chosen is application-dependant. However, some authors used more than 80 facai points.

For example, Cootes et al. (Cootes et al., 1998) used 122 landmark points, Huang and Huang (Huang & Huang, 1997) used 90 facial feature points, Kobayashi and Hara (Kobayashi & Hara, 1992) used 30 facial characteristic points, Pantic and Rothkrantz (Pantic & Rothkrantz, 2004) used 19 facial fiducial points, Valstar and Pantic (Valstar & Pantic, 2006) used 20 facial fiducial points, Cohn et al. (Cohn et al., 1998) used 46 fiducial points, and Zhang et al. (Zhang et al., 1998) used 34 fidicial points.

Therefore, based on works in feature point tracking(Cohn et al., 1999, Cohn et al., 1998), action units recognition for facial expression analysis (Tian et al., 2001) (Valstar & Pantic, 2006) (Donato et al., 1999) (Essa & Pentland, 1997) (Pantic & Rothkrantz, 2004) (Tian et al., 2001), review papers in facial expression analysis (Fasel & Luettin, 2003) (Pantic & Rothkrantz, 2000b) (Pantic & Rothkrantz, 2000a), and the aforementioned works, we manually selected 18 fiducial characteristic points on each of the images for representing the original 17 Euclidean distance-based facial features superimposed on the subject's face image in Figure 6 Fig. 6. The 18 fiducial points on the subject's face image in the database. Note that we chose 'a' as the base point because that point does not move when changing expressions. These features are marked as F1, F2 ... F17 (See Table 2). Hence, these facial features provided certain discriminative information when individuals change expressions.



Fig. 5. Pre-selected facial features in the sample of 80 facial images from the test database



Fig. 6. The 18 fiducial points on the subject's face image in the database.

Features	F1	F2	F3	F4	F5	F6	F7	F8	F9
Distances	a_b	a_c	A_d	a_e	a_f	a_g	a_h	a_i	a_j
Features	F10	F11	F12	F13	F14	F15	F16	F17	
Distances	a_k	a_l	A_m	a_n	a_o	a_p	a_q	a_r	

Table 2. The original 17 pre-selected facial feature distances

5.3 Subspace tranformation analysis

The input facial features were normalized to have zero mean and unit variance so as to improve the performance of proposed methods. Figure 7 displays the first two components of the original 17 facial features (dimensions) of three and ten individuals respectively. Each shape symbol stands for each individual's name (e.g. KA, MK or NM etc.). The figure shows the nonlinear nature of image distribution and the increased overlapping problem of intrapersonal variations under facial expression changes.



Fig. 7. (Left) First two components of 17 facial features of 3. (Right) 10 individuals after normalization.

Hence, these normalized input data were used for KPCA and KFLD subspace analysis methods. The Gaussian kernel $k(x, y) = \exp(-\|x - y\|^2 / 2\sigma^2)$ was used for the following analyses, where σ is Gaussian width. We will examine the impacts of KPCA and KFLD in the following subsections.

5.3.1 Linear-based subspace analysis results

In PCA-based Subspace Analysis, the original normalized 17 facial features of 3 and 10 individuals were reduced to 2 and 9 features after using PCA as shown in Figure 9 (Left) and Figure 9 (Right), respectively.

Figure 9 (Left) demonstrates that the original 17 facial features of three individuals were complex and non-separable after PCA. The result of this extraction thereby provided some insight to the original structure of feature distribution. However, Figure 9 (Right)

demonstrates that the original facial features of ten individuals became more complex and non-separable after PCA due to the increased number of subjects as shown in Figure 8. Therefore, in some cases, PCA looses discriminant information. FLD promised to retain discriminant information.

In FLDA-based Subspace Analysis, the original normalized 17 facial features of three and ten individuals were reduced to two and nine features after using FLD as shown in Figure 9 (Left) Figure 9 (Left) and Figure 9 (Right), respectively. Figure 9 (Left) shows that the original 17 facial features of three individuals were well clustered after FLD; it was better than PCA for for clustering and classification. Figure 9 (Right) shows that the original features were overlapped due to the more dispersed data distribution as shown in Figure 7 (Right); however, the data distribution is still better than that of the PCA-based subspace of the 10 subjects. Hence, the results are very application-specific. Further classifiers are sometimes necessary to discriminate between these clusters using - MLP and/or RBFNN.



Fig. 8. (Left) Normalized 17 facial features of 3 individuals reduced to 2 features (prince-ple components) after PCA (left). (Right) First two components of PCA-transformed matrix (d = 9).



Fig. 9. (Left) Normalized 17 facial features of 3 individuals reduced to 2 features (c -1) after FLD. (Right) First two components of FLDA-transformed matrix (d = 9)

5.3.2 KPCA-based subspace analysis results

In KPCA-based Subspace Analysis, the normalized input data were reduced to 9 dimensions (c - 1) after using KPCA (same as in PCA). The first two components of the transformed matrix of 10 individuals are shown in Figure 10 (Left). This figure demonstrates that the resultant data distribution was less complex and overlapping than that of PCA (Figure 8(Right)). Clearly, the finding indicates that KPCA still tends to lose discriminant information. KFLD promises to retain discriminant information. In the following subsection, we will examine the results of KFLDA.

In KFLDA-based Subspace Analysis, the normalized input data were reduced to 9 dimensions (c - 1) after using KFLDA (same as in FLDA). The first two components of the transformed matrix of 10 individuals are shown in Figure 10 (Right). This figure shows that the resultant data distribution was well compacted and separated compared to that of FLDA (Figure 9 (Right)). The findings indicate that KFLDA was better than PCA, FLDA and KPCA for classification purpose. Thus, KFLDA can deal with uncertainty problem.

As the transformation results obtained from the above subspace analysis methods, we will use different classifiers to evaluate their transformation capabilities in the following section.



Fig. 10. (Left) First two components of KPCA-transformed matrix ($\sigma = 1$; d = 9). (Right) first two components of KFLD-transformed matrix ($\sigma = 1$; d = 9)

6. Results and discussion

Experiments will consist of comparing the face recognition rates under varying expressions for different types of classifiers. The original normalized facial features were fed to ANN-based classifiers and its results are compared to the results when the outputs of subspace analysis were fed to MLP, RBF or SVM classifiers.

The experimental results are shown in Table 3. Note that we focused on the transformation capability of each extractor instead of each classifier.

It shows that the classification performances of MLP and RBF neural networks were 90.9% and 45.5%, respectively. The classification performances of the PCA-based subspace analysis in sequence with ANNs for 3 individuals were 31.8% for both MLP and RBF models. The results from PCA subspace analysis showed to achieve poor classification

performances. It is because the data distribution for PCA-based subspace provides less discriminative features. The classification performances of the FLD-based subspace analysis in sequence with ANNs for 3 individuals were 100% for both MLP and RBF models. The results used the FLD subspace analysis method were shown to achieve better classification performances. This is due to the data distribution for FLD-based subspace being perfectly separated and each class well-clustered. However, if the number of sample subjects is increased to 10, there is an obvious decrease of performance rates (Please see the averaged classification performances as shown in Table 3) due to the increased complexity of data distribution, which makes the PCA and/or FLD-based subspace analysis method more difficult to extract the informative and/or discriminant information for further classification. Hence, it appears that subspace analysis is crucial in pattern classification because of the importance of selecting optimal feature dimensionality. In summary, the experimental results of linear mapping subspace analyses showed that the existence of large within-class variation under facial expression changes will degrade the classification performance. This degradation is aggravated especially when the number of subjects is increased; and this happens frequently in the real world. Because of the limitation on linear mapping methods, more advanced methods will be employed to deal with the inherent nature of nonlinear data distribution of facial images by using the kernel-based discriminant analysis method.

Extractors	MLP	RBF	SVM	Average				
3 subjects								
None(all)	90.9	45.5	95.5	77.3				
PCA (2)	31.8	31.8	36.4	33.3				
FLD(2)	100	100	100	100				
10 subjects								
None(all)	84.9	42.5	83.6	70.3				
PCA (9)	6.8	21.9	45.6	24.8				
FLD (9)	45.2	63.0	87.7	65.3				
KPCA(9)	75.3	39.7	72.6	62.5				
KFLD(9)	100	100	100	100				

 Table 3. Classification performance of different classifiers (%)

PCA achieved the poorest classification performance. It is due to the data distribution for the PCA-based subspace being in ill-clustered features.

Note too that using the original features also directly returns fairly good classification performances due to the original feature subspace being tighter compact than that of PCA and all the three complex classifiers are powerful for dealing with nonlinear data distribution. PCA is of a linear nature; hence sometimes it is inadequate for non-linear problems. FLDA achieved better classification performance than PCA. It is because the image data distribution for the FLDA-based subspace is much better separated and clustered than that of the PCA-based subspace. However, these two linear mapping methods are incapable of dealing with the nonlinear image data problem adequately. They

are poor in dealing with the uncertainty (overlapping) problem. The uncertainty problem can cause poor generalization in classification. Therefore, we used the two kernel-based nonlinear methods (KPCA and KFLDA) for coping with the aforementioned problem. KPCA achieved much better performance than that of the PCA method, but slightly poorer performance than that of FLDA. It is likely due to the fact that KPCA obtained better salient information than PCA, but less discriminative separability than FLDA. KFLDA achieved the highest performance among all methods considerd here because it obtained the most compact and discriminant subspace. Therefore, the average classification performances of MLP, RBF and SVM classifiers for each feature set have obviously shown that the proposed KFLDA method is the most powerful extractor among all the others.

In concusion, the findings indicate that the use of geometric features of facial behavior might provide individual unique cues to some extent and the proposed method might achieve superior classification performance with reduced feature dimensions. The nonlinear supervised transformation has the tendency to perform better than the linear and nonlinear unsupervised methods. Hence, it appears that face recognition should be robust to facial expression changes and have potential applicability if an automatic measurement of facial features can be employed. However, the main drawback of kernel-based methods is that computing the kernel matrix is very expensive, and the transformation of kernel methods attempts to find the minimum compact within-class variations and the maximum discrimination of between-class separations; whereas it is indirectly avoided the varying changes of data points (Indirect Invariance).

7. Conclusion and future work

The purpose of this research is three fold: (1) to demonstrate that the within-class variation under facial expression changes will increase the uncertain regions for classification; hence, degrades the classification performance, (2) the low-dimensional subspace with enhanced discriminatory power could provide better feature space for classification, and (3) facial behaviors could also be used as another behavioural biometric for human identification and verification.

This experiment attempted to analyze the uncertainty (overlapping) problem in facial recognition under expression changes by using kernel-based subspace analysis methods and ANN-based classifiers so as to provide an insight of possible solutions for the expression variations problem in face recognition. Moreover, we also emphasized the empirical experiments on variations due to changes in facial expression that are less emphasized in (Adini et al., 1997).

Only 17 facial features of 18 fiducial points were selected. The selected features were shown to provide expressive information and demonstrated that facial expression could be used as another behavior biometric. They also showed that the feature dimensionality was reduced greatly compared to appearance-based or image-based feature extraction.

Our proposed non-linear discriminant analysis method dealt very well with the uncertainty (overlapping) due to expression changes. We found that the transformation of kernel-based discriminant analysis has a beneficial effect on the classification performance. The experimental results showed that a face recognition system with optimal design may eventually be developed, which is robust to the problem of facial expression changes.

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

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