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Robust Face Recognition System Based on a Multi-Views Face Database

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1. Introduction

Biometry is currently a very active area of research spanning several sub-disciplines such as image processing, pattern recognition, and computer vision. The main goal of biometry is to build systems that can identify people from some observable characteristics such as their face, fingerprints, iris, etc. Facial recognition is the identification of humans by the unique characteristics of their faces. It has become a specialized area within the large field of computer vision. It has attracted a lot of attention because of its potential applications. Indeed, vision systems that automate face recognition process appear to be promising in various fields such as law enforcement applications, secure information systems, multimedia systems, and cognitive sciences.

The interest into face recognition is mainly focused on the identification requirements for secure information systems, multimedia systems, and cognitive sciences. Interest is still on the rise, since face recognition is also seen as an important part of next-generation smart environments (Ekenel & Sankur, 2004).

Different techniques can be used to track and process faces (Yang et al, 2001), e.g., neural networks approaches (Férand et al., 2001, Rowley et al., 1998), eigenfaces (Turk & Pentland, 1991), or Markov chains (Slimane et al., 1999). As the recent DARPA-sponsored vendor test showed, much of the face recognition research uses the public 2-D face databases as the input pattern (Phillips et al., 2003), with a recognition performance that is often sensitive to pose and lighting conditions. One way to override these limitations is to combine modalities: color, depth, 3-D facial surface, etc. (Tsalakanidou et al., 2003, Beumier & Acheroy, 2001, Hehser et al., 2003, Lu et al., 2004, Bowyer et al., 2002). Most 3-D acquisition systems use professional devices such as a traveling camera or a 3-D scanner (Hehser et al., 2003, Lu et al., 2004). Typically, these systems require that the subject remain immobile during several seconds in order to obtain a 3-D scan, and therefore may not be appropriate for some applications such as human expression categorization using movement estimation. Moreover, many applications in the field of human face recognition such as human-computer interfaces, model-based video coding, and security control (Kobayashi, 2001, Yeh & Lee, 1999) need to be high-speed and real-time, for example, passing through customs

quickly while ensuring security. Furthermore, the cost of systems based on sophisticated 3-D scanners can easily make such an approach prohibitive for routine applications.

In order to avoid using expensive and time intensive 3-D acquisition devices, some face recognition systems generate 3-D information from stereo-vision (Wang, et al., 2003). Complex calculations, however, are necessary in order to perform the self-calibration and the 2-D projective transformation (Hartly et al., 2003). Another possible approach is to derive some 3-D information from a set of face images, but without trying to reconstitute the complete 3-D structure of the face (Tsalakanidou et al., 2003; Liu & Chen, 2003).

In this chapter, we describe a new robust face recognition system based on a multi-views face database that derives some 3-D information from a set of face images. We attempt to build an approximately 3-D system for improving the performance of face recognition. Our objective is to provide a basic 3-D system for improving the performance of face recognition. The main goal of this vision system is 1) to minimize the hardware resources, 2) to obtain high success rates of identity verification, and 3) to cope with real-time constraints.

Our acquisition system is composed of five standard cameras, which can take simultaneously five views of a face at different angles (frontal face, right profile, left profile, three-quarter right and three-quarter left). This system was used to build the multi-views face database. For this purpose, 3600 images were collected in a period of 12 months for 10 human subjects (six males and four females).

Research in automatic face recognition dates back to at least the 1960s. Most current face recognition techniques, however, date back only to the appearance-based recognition work of the late 1980s and 1990s (Draper et al., 2003). A number of current face recognition algorithms use face representations found by unsupervised statistical methods. Typically these methods find a set of basis images and represent faces as a linear combination of those images. Principal Component Analysis (PCA) is a popular example of such methods. PCA is used to compute a set of subspace basis vectors (which they called "eigenfaces") for a database of face images, and project the images in the database into the compressed subspace. One characteristic of PCA is that it produces spatially global feature vectors. In other words, the basis vectors produced by PCA are non-zero for almost all dimensions, implying that a change to a single input pixel will alter every dimension of its subspace projection. There is also a lot of interest in techniques that create spatially localized feature vectors, in the hopes that they might be less susceptible to occlusion and would implement recognition by parts. The most common method for generating spatially localized features is to apply Independent Component Analysis (ICA) in order to produce basis vectors that are statistically independent.

The basis images found by PCA depend only on pair-wise relationships between pixels in the image database. In a task such as face recognition, in which important information may be contained in the high-order relationships among pixels, it seems reasonable to expect that better basis images may be found by methods sensitive to these high order statistics (Bartlett et al., 2002). Compared to PCA, ICA decorrelates high-order statistics from the training signals, while PCA decorrelates up to second-order statistics only. On the other hand, ICA basis vectors are more spatially local than the PCA basis vectors, and local features (such as edges, sparse coding, and wavelet) give better face representations (Hyvarinen, 1999). This property is particularly useful for face recognition. As the human face is a non-rigid object, local representation of faces will reduce the sensitivity of the face variations due to different facial expressions, small occlusions, and pose variations. That means some independent components are less sensitive under such variations (Hyvarinen & Oja, 2000).

Using the multi-views database, we address the problem of face recognition by evaluating the two methods PCA and ICA and comparing their relative performance. We explore the issues of subspace selection, algorithm comparison, and multi-views face recognition performance. In order to make full use of the multi-views property, we also propose a strategy of majority voting among the five views, which can improve the recognition rate. Experimental results show that ICA is a promising method among the many possible face recognition methods, and that the ICA algorithm with majority-voting is currently the best choice for our purposes.

The rest of this chapter is organized as following: Section 2 describes the hardware acquisition system, the acquisition software and the multi-views face database. Section 3 gives a brief introduction to PCA and ICA, and especially the ICA algorithms. Experimental results are discussed in Section 4, and conclusions are drawn in Section 5.

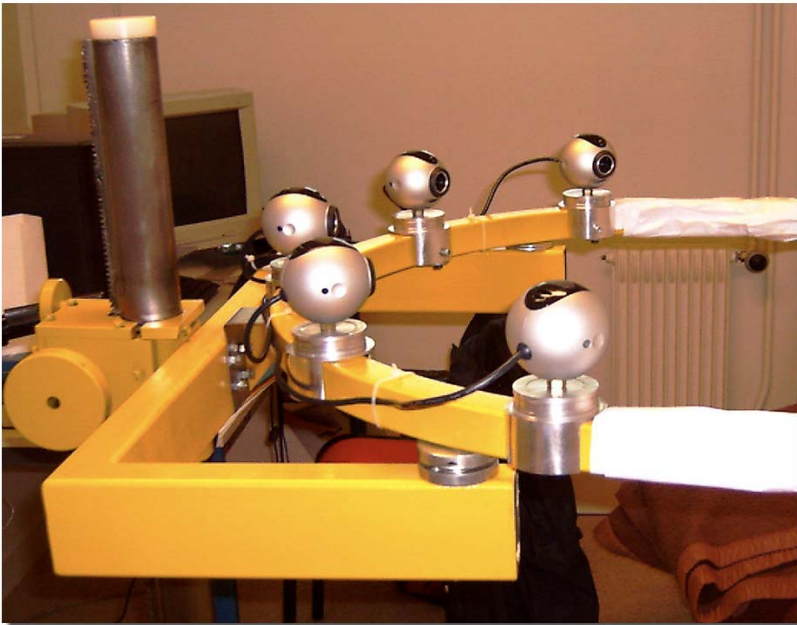


Fig. 1. Acquisition system with the five Logitech cameras fixed on their support

2. Acquisition and database system presentation

Our acquisition system is composed of five Logitech 4000 USB cameras with a maximal resolution of 640×480 pixels. The parameters of each camera can be adjusted independently. Each camera is fixed on a height-adjustable sliding support in order to adapt the camera position to each individual, as depicted on Fig. 1.

The human subject sits in front of the acquisition system, directly facing the central camera. A specific acquisition program has been developed in order to simultaneously grab images from the 5 cameras. The five collected images are stored into the PC hard disk with a frame data rate of 20×5 images per second. As an example, a software screenshot is presented on the Fig. 2.

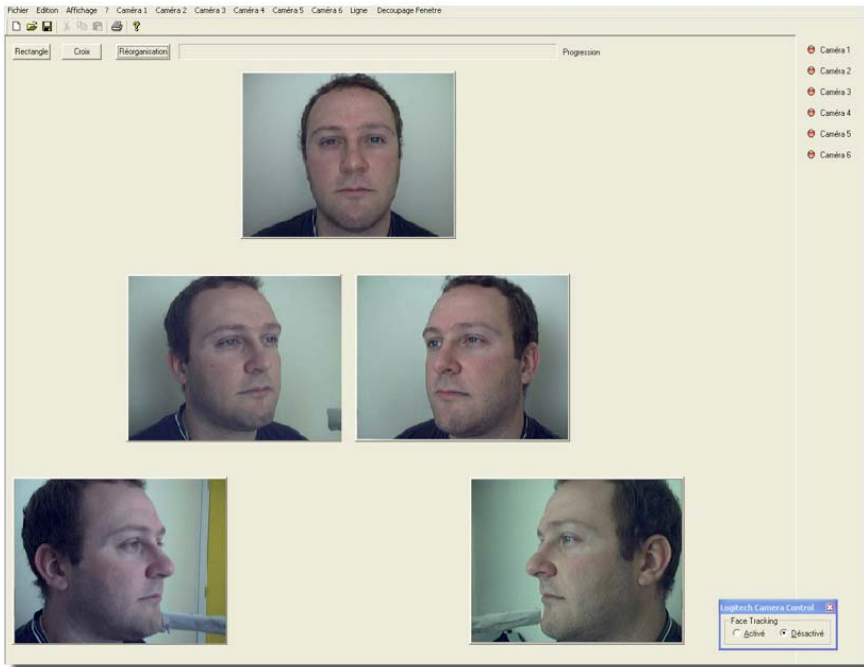


Fig. 2. Example of five images collected from a subject by the acquisition software.

The multi-views face database was built using the described acquisition system of 5 views. This database collected 3600 images taken in a period of 12 months for 10 human subjects (six males and four females). The rate of acquisition is 6 times per subject and 5 views for every subject at each occasion. The hairstyle and the facial expression of the subjects are different in every acquisition. The five views for each subject were made at the same time but in different orientations. **Face**, **ProfR**, **ProfL**, **TQR** and **TQL**, indicate respectively the frontal face, profile right, profile left, three-quarter right and three-quarter left images.

The Fig. 3 shows some typical images stored in the face database.

This database can also be expressed as following:

1. Total of 3600 different images (5 orientations \times 10 people \times 6 acquisitions \times 12 months),
2. Total of 720 visages in each orientation (10 people \times 6 acquisitions \times 12 months),
3. Total of 360 images for each person (5 orientations \times 6 acquisitions \times 12 months).

3. Algorithm description: PCA and ICA

3.1 Principal component analysis

Over the past 25 years, several face recognition techniques have been proposed, motivated by the increasing number of real-world applications and also by the interest in modelling human cognition. One of the most versatile approaches is derived from the statistical technique called Principal Component Analysis (PCA) adapted to face images (Valentin et al., 1994; Abdi, 1988). In the context of face detection and identification, the use of PCA was first proposed by Kirby and Sirovich. They showed that PCA is an optimal

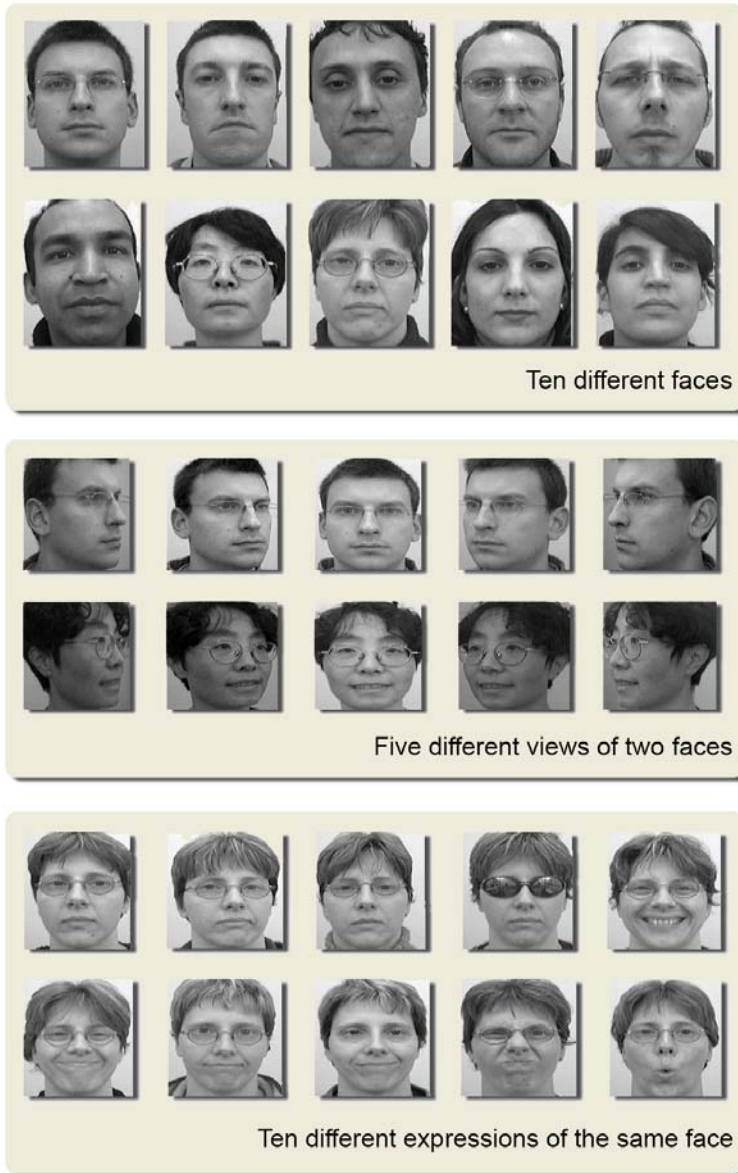


Fig. 3. Different views of the face database: the ten subjects (top), the five views of two subjects (middle), and different expressions of the frontal view of one subject (bottom).

compression scheme that minimizes the mean squared error between the original images and their reconstructions for any given level of compression (Sirovich & Kirby, 1987; Kirby & Sirovich, 1990). Turk & Pentland (1991) popularized the use of PCA for face recognition. PCA is based on the idea that face recognition can be accomplished with a small set of

features that best approximates the set of known facial images. Application of PCA for face recognition proceeds by first performing PCA on a set of training images of known human faces. From this analysis, a set of principal components is obtained, and the projection of the test faces on these components is used in order to compute distances between test faces and the training faces. These distances, in turn, are used to make predictions about the test faces. Consider the $D \times K$ -dimensional face data matrix X , where D represents the number of pixels of the face images and K the total number of images under consideration. XX^T is then the sample covariance matrix for the training images, and the principal components of the covariance matrix are computed by solving the following equation:

$$R^T(XX^T)R = \Lambda \quad (1)$$

where Λ is the diagonal matrix of eigenvalues and R is the matrix of orthonormal eigenvectors. Geometrically, R is a rotation matrix that rotates the original coordinate system onto the eigenvectors, where the eigenvector associated with the largest eigenvalue is the axis of maximum variance; the eigenvector associated with the second largest eigenvalue is the orthogonal axis with the second maximum variance, etc. Typically, only the M eigenvectors associated with the M largest eigenvalues are used to define the subspace, where M is the desired subspace dimensionality.

3.2 Independent component analysis

Independent Component Analysis (ICA) is a statistical signal processing technique. It is very closely related to the method called Blind Source Separation (BSS) or Blind Signal Separation. The basic idea of ICA is to represent a set of random variables using basis functions, where the components are statistically independent or as independent as possible. Let s be the vector of unknown source signals and x be the vector of observed mixtures. If A is the unknown mixing matrix, then the mixing model is written as: $x = As$. It is assumed that the source signals are independent of each other and the mixing matrix A is invertible. Based on these assumptions and the observed mixtures, ICA algorithms try to find the mixing matrix A or the separating matrix W such that $u = Wx = WAs$ is an estimation of the independent source signals (Cardoso, 1997).

Technically, independence can be defined by the probability densities. Signals are statistically independent when:

$$f_u(u) = \prod_i f_{u_i}(u_i) \quad (2)$$

where f_u is the probability density function of u . It is equivalent to say that the vector u is uniformly distributed. Unfortunately, there may not be any matrix W that fully satisfies the independence condition, and there is no closed form expression to find W . Instead, there are several algorithms that iteratively approximate W so as to indirectly maximize independence.

Since it is difficult to maximize directly the independence condition above, all common ICA algorithms recast the problem in order to iteratively optimize a smooth function whose global optima occurs when the output vectors u are independent. For example, the algorithm of InfoMax (Bell & Sejnowski, 1995) relies on the observation that independence is maximized when the entropy $H(u)$ is maximized, where:

$$H(u) = - \int f_u(u) \log f_u(u) du \quad (3)$$

The algorithm of InfoMax performs gradient ascent on the elements so as to maximize $H(u)$ (Sirovich & Kirby, 1987). It gets its name from the observation that maximizing $H(u)$ also maximizes the mutual information between the input and the output vectors.

The algorithm of FastICA is arguably the most general, maximizing:

$$J(y) \approx c [E\{G(y)\} - E\{G(v)\}]^2 \quad (4)$$

where G is a non-quadratic function, v is a Gaussian random variable, and c is any positive constant, since it can be shown that maximizing any function of this form will also maximize independence (Hyvarinen, 1999).

InfoMax and FastICA all maximize functions with the same global optima. As a result, the two algorithms should converge to the same solution for any given data set. In practice, the different formulations of the independence constraint are designed to enable different approximation techniques, and the algorithms find different solutions because of differences among these techniques. Limited empirical studies suggest that the differences in performance between the algorithms are minor and depend on the data set (Draper et al., 2003).

4. Experiments and discussions

4.1 Experimental setup

We carried out experiments on the multi-views face database. Again there are 10 individuals, each having 360 images taken simultaneously at five orientations, with different expressions, different hairstyles, and at different times, making a total of 3600 images (see Section 2). For each individual in the set, we have three experimental schemes. First, we choose one visage from each acquisition to compose the training sets, all the visages (10 people) selected are aligned in rows in the training matrix, one visage per row. The remaining five visages for each acquisition are used for testing purposes. We call this scheme (1, 5) or "scheme1". Thereby the training matrix has 120 rows, and the testing matrix has 600 rows. The experiments are performed on five views respectively. In the second scheme, we select two visages in each acquisition as training sets, and the left four visages are used for testing. So the training matrix has 240 rows and there are 480 rows in the testing matrix. This scheme is (2, 4) or "scheme2". The third scheme gets three visages in each acquisition as training sets and the others as testing sets. This is (3, 3) or "scheme3". Note that the training and testing sets were randomly chosen.

Based on these three schemes, we perform the experiments on two ICA algorithms (InfoMax and FastICA) and PCA according to only one criterion: recognition rate. The purpose is to verify and compare the performance of ICA and PCA on our multi-views face database.

Face recognition performance is evaluated by a nearest neighbor algorithm, using cosines as the similarity measure. Since ICA basis vectors are not mutually orthogonal, the cosine distance measure is often used to retrieve images in the ICA subspaces (Bartlett, 2001).

4.2 Experimental results

The experimental results presented in this section are composed of three parts. The first part analyses the relationship between subspace dimensions and the recognition rate. The second

part gives a brief comparison of the three algorithms as applied to a face recognition task. Finally we will report systematically the multi-views performance.

We carry out the experiments using the publicly available MATLAB code written by Tony Bell and Marian Stewart Bartlett and revised in 2003 (InfoMax) and realized by Hugo Gavert, Jarmo Hurri, Jaakko Sareal, and Aapo Hyvarinen, version 2005 (FastICA).

When using ICA in facial identity tasks, we usually perform PCA as a preprocessing, and then load the principal component eigenvectors into rows of input matrix and run ICA on it. The problem that we first meet is the selection of subspace dimensions. We need not use all possible eigenvectors, since in PCA only the M eigenvectors associated with the M largest eigenvalues are used to define the subspace, where M is the desired subspace dimensionality.

We chose the subspace dimensions in proportion to the maximum in different schemes and performed the experiments using two ICA algorithms on our multi-views database. Fig. 4 gives one result of FastICA algorithm using Face images on the three schemes. By the way, although not presented here, we also tested this using the InfoMax algorithm, and the result is similar.

In the Fig. 4, $D1, D2, D3, D4, D5, D6$ presents respectively six selected dimensions. For scheme1, there are 120 images in the training set, so the maximum dimension is 120, $D1-D6$ are 20-120, i.e. recognition rate were measured for subspace dimensionalities starting at 20 and increasing by 20 dimensions up to a total of 120. For scheme2, there are 240 images in training set, thereby, $D1-D6$ changed from 40 to 240 increasing by 40 dimensions. For scheme3, there are 360 images in training set, and $D1-D6$ varied from 60 to 360 increasing by 60 dimensions.

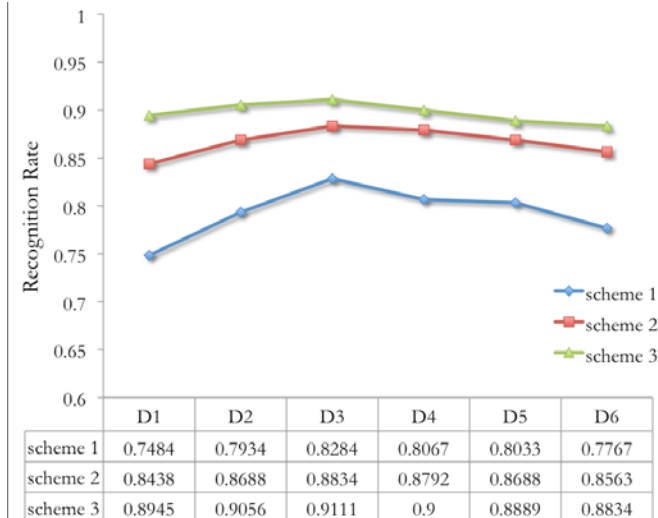


Fig. 4. Relationship between recognition rate and subspace dimensions.

It can be observed from this figure that the desired subspace dimension occurs in the half of the maximum. So, the subspace dimensions we used later are all at the half value of the maximum. Selecting subspace dimensions can simplify and reduce the computation process, which is useful for our future real time application.

After deciding the number of subspace dimensions, it is also interesting to compare the performance of the three face representation algorithms. These experiments were performed on our multi-views database. The results using frontal view are shown in Fig. 5.

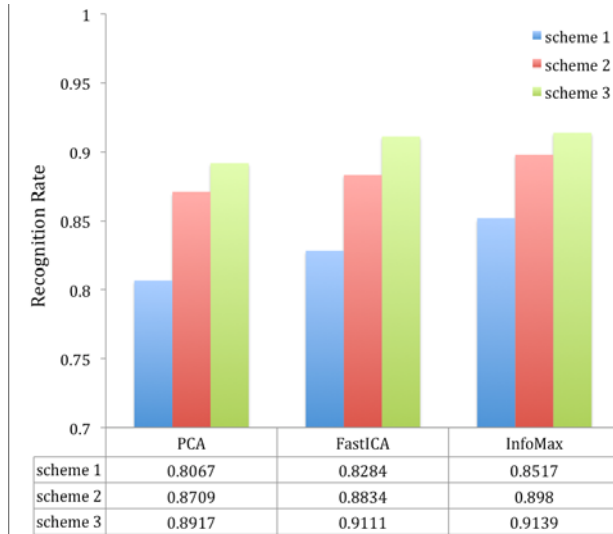


Fig. 5. Comparison of the three algorithms PCA, FastICA, and InfoMax.

4.3 Multi-views system performances

In order to fully explore our multi-views database, we also perform the majority-voting procedure among the five views. Fig. 6, Fig. 7 and Table 1 present the experimental results of this part.

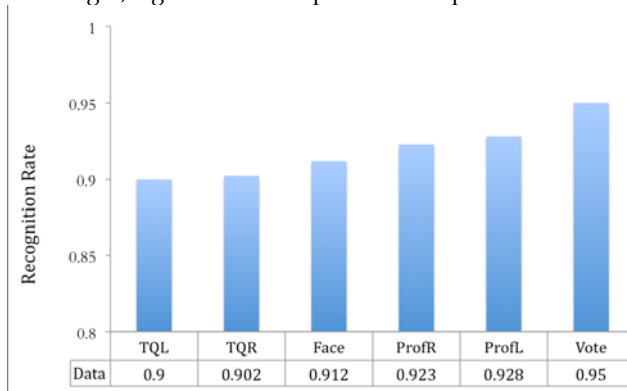


Fig. 6. Multi-views performance using the FastICA algorithm.

Fig. 6 gives results of multi-views face recognition performance comparison, using the FastICA algorithm as an example. Fig. 7 illustrates “VOTE” and “Face” performance for three algorithms. The multi-views face recognition rates for PCA, InfoMax, and FastICA increase respectively by 5.35%, 5.56%, and 5.53% in comparison with frontal face recognition.

In Table 1, **Face**, **ProfR**, **ProfL**, **TQR** and **TQL** indicate respectively the frontal face, profile right, profile left, three-quarter right and three-quarter left images. **VOTE** presents the results of the majority-voting procedure. (1, 5), (2, 4), and (3, 3) express respectively the number of training and testing sets which we have presented before. We performed several tests for each case and the results in the table are the averaged results.

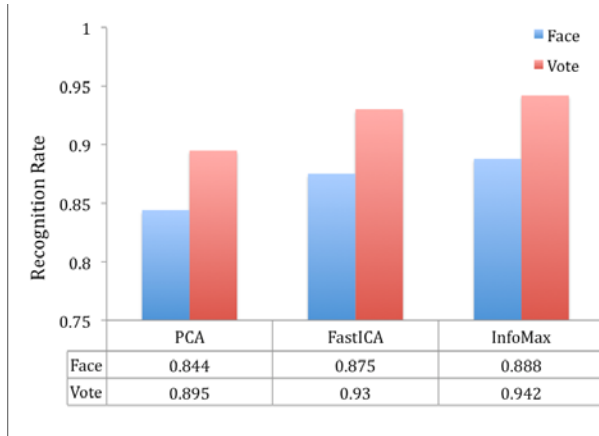


Fig. 7. Face and VOTE performance.

| Algorithms | InfoMax | | | FastICA | | | PCA | | |
|------------|---------|--------|--------|---------|--------|--------|--------|--------|--------|
| | (1,5) | (2,4) | (3,3) | (1,5) | (2,4) | (3,3) | (1,5) | (2,4) | (3,3) |
| Face | 0.8517 | 0.8980 | 0.9139 | 0.8284 | 0.8834 | 0.9111 | 0.8067 | 0.8709 | 0.8917 |
| ProfR | 0.9000 | 0.9313 | 0.9417 | 0.8450 | 0.8923 | 0.9222 | 0.8650 | 0.8958 | 0.9167 |
| ProfL | 0.9017 | 0.9334 | 0.9333 | 0.8683 | 0.9208 | 0.9278 | 0.8600 | 0.9125 | 0.9167 |
| TQR | 0.8484 | 0.8833 | 0.9361 | 0.8334 | 0.8480 | 0.9028 | 0.8250 | 0.8438 | 0.8750 |
| TQL | 0.8688 | 0.8915 | 0.9111 | 0.8483 | 0.8792 | 0.9000 | 0.8284 | 0.8500 | 0.8611 |
| VOTE | 0.9234 | 0.9479 | 0.9584 | 0.9084 | 0.9313 | 0.9500 | 0.8334 | 0.8875 | 0.9389 |

Table 1. Recognition rates for ICA and PCA using the multi-views face database

One can observe from Table 1 that, no matter which view and algorithm we use, the recognition rate always improves as the number of training samples is increased, and it is very interesting that the best performance occurs in **ProfR** or **ProfL**, i.e. the right profile or left profile images, not in **Face**, i.e. the frontal face images. On our opinion, the profile images maybe have more information than frontal face images.

Our results are accordance with the Draper's (Draper et al, 2003) on the FERET face data set that the relative performance of PCA and ICA depends on the task statement, the ICA architecture, the ICA algorithm, and (for PCA) the subspace distance metric, and for the facial identity task, ICA performs well than PCA.

5. Conclusion

In this chapter, we proposed a new face image acquisition system and multi-views face database. Face recognition using PCA and ICA were discussed. We evaluated the performance of ICA according to the recognition rate on this new multi-views face database. We explored the issues of subspace selection, algorithm comparison, and multi-views performance. We also proposed a strategy in order to improve the recognition performance, which performs the majority-voting using five views of each face. Our results are, in

accordance with most other literature that ICA is an efficient method in the task of face recognition, especially in face images with different orientations.

Moreover, based on our multi-views face database, we have the following conclusions:

1. For face recognition task, the algorithms based on statistic analysis method, such as FastICA, InfoMax, and PCA, InfoMax gives the best performance.
2. The desired subspace dimension occurs in the half of the maximum according to our experiments. Selection of subspace dimensions can simplify and reduce the computation process.
3. For every individual, different views have different recognition results. In our system, among five views, the highest recognition rate occurs in **ProfR** or **ProfL**, i.e the profile images, not in **Face**, i.e. the frontal face images. This is very interesting and we think that this is because of the profile images give more face features than frontal images.
4. Majority-voting procedure is a good method for improving the face recognition performance.

Our future work will focus on the multi-views face recognition application in real time systems. We will explore the new methods recently introduced in some literature, such as ensemble learning for independent component analysis using Random Independent Subspace (RIS) in Cheng et al. (2006), Kernel ICA algorithm in Yang et al. (2005), and Common Face method by using Common Vector Approach (CVP) introduced in He et al. (2006). We also will use more information fusion methods to obtain high recognition performance. Our purpose is to study an efficient and simple algorithm for later hardware implementation.

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