A Framework for the Recognition of 3D Faces and Expressions

Chao Li, Armando Barreto
Electrical & Computer Engineering Department
Florida International University
10555 West Flagler, Miami, FL 33174

ABSTRACT

Face recognition technology has been a focus both in academia and industry for the last couple of years because of its wide potential applications and its importance to meet the security needs of today's world. Most of the systems developed are based on 2D face recognition technology, which uses pictures for data processing. With the development of 3D imaging technology, 3D face recognition emerges as an alternative to overcome the difficulties inherent with 2D face recognition, i.e. sensitivity to illumination conditions and positions of a subject. But 3D face recognition still needs to tackle the problem of deformation of facial geometry that results from the expression changes of a subject. To deal with this issue, a 3D face recognition framework is proposed in this paper. It is composed of three subsystems: an expression recognition system, a system for the identification of faces with expression, and neutral face recognition system. A system for the recognition of faces with one type of expression (happiness) and neutral faces was implemented and tested on a database of 30 subjects. The results proved the feasibility of this framework.

Keywords: face recognition, biometrics, 2D, 3D, range, expression recognition, subspace, PCA, SVM, LDA

1. INTRODCTION

Among the many different biometric technologies, face recognition is a particularly compelling biometric approach because it is the one used every day by nearly everyone as the primary means for recognition of other humans. Most of the face recognition attempts that have been made until recently use 2D intensity images captured by photographic cameras as the data format for processing. This kind of research is called 2D face recognition. Although 2D face recognition has achieved considerable success, certain problems still exist. Because the 2D face images used not only depend on the face of a subject, but also depend on the imaging factors, such as the environmental illumination and the orientation of the subject. These two sources of variability in the face image often make the 2D face recognition system fail. That is the reason why 3D face recognition is believed to have an advantage over 2D face recognition.

With the development of 3D imaging technology, more and more attention has been directed to 3D face recognition. In [1], Bowyer et al. provide a survey of 3D face recognition technology. Most of the 3D face recognition systems treat the 3D face surface as a rigid surface. But, in fact, a face surface can be deformed by different expressions of the subject. In [2], experiments using Iterative Closest Point (ICP) and Principal Component Analysis (PCA) methods were performed on the recognition of faces with expressions. The authors found that expression changes do cause performance to deteriorate in all the methods they studied.

Therefore, the involvement of facial expression has become a big challenge in 3D face recognition systems. In this paper, we tackle the expression challenge in 3D face recognition from a point of view different from the methods that have been proposed. Because the deformation of a face surface is always associated with specific expressions, an integrated expression recognition and face recognition system is proposed. In section 2, the relationship between expression and face recognition is explained. Based on this, an integrated framework of expression recognition and face recognition system is proposed. In section 3, the acquisition of the data which is used in the experiments is described.

The expression recognition method and 3D face recognition methods are discussed separately in section 4 and section 5. Designed experiments and the results are reported in section 6. Finally, discussion and conclusion are given in section 7.

2. EXPRESSION RECOGNITION AND FACE RECOGNITION

Psychologists still disagree on whether or not facial expression recognition information aids the recognition of faces by human beings. One of the experiments that support the existence of the connection between facial expression recognition and face recognition was reported in [3]. The authors found that people are slower in identifying happy and angry faces than they are in identifying faces with neutral expression.

The proposed framework is based on the above findings. At the front end of the system, there is an expression recognition module, which tag expression labels to the incoming faces according to their displayed expressions. The expression labels include the six prototypical expressions of faces, which are happiness, sadness, anger, fear, surprise and disgust [4], plus the neutral expression. Therefore, the output of the expression recognition system will be one of these seven options. If the incoming 3D face range image is labeled as "neutral", it is routed to the neutral expression face recognition module, which uses the features of the probe image to directly match those of the gallery images, which are all neutral instances of all enrolled subjects, to get the closest match. If the label assigned to the incoming face is other than neutral expression, then for each of the six prototypical expressions, a separate face recognition subsystem should be used. The system will find the right face through modeling the variations of the face features between the neutral face and the face with corresponding expressions. Since the recognition through modeling is a more complex process than the direct matching for the neutral face and takes more time computationally, this framework is congruent with the experimental findings that have showed that people are slower in identifying happy and angry faces than they are in identifying faces with neutral expression[3]. Fig 1 illustrates a simplified version of the proposed framework, in which only one expression (happiness), plus neutral expression is processed. In this paper, the experiments below are designed to test the feasibility of this simplified version of the proposed framework.

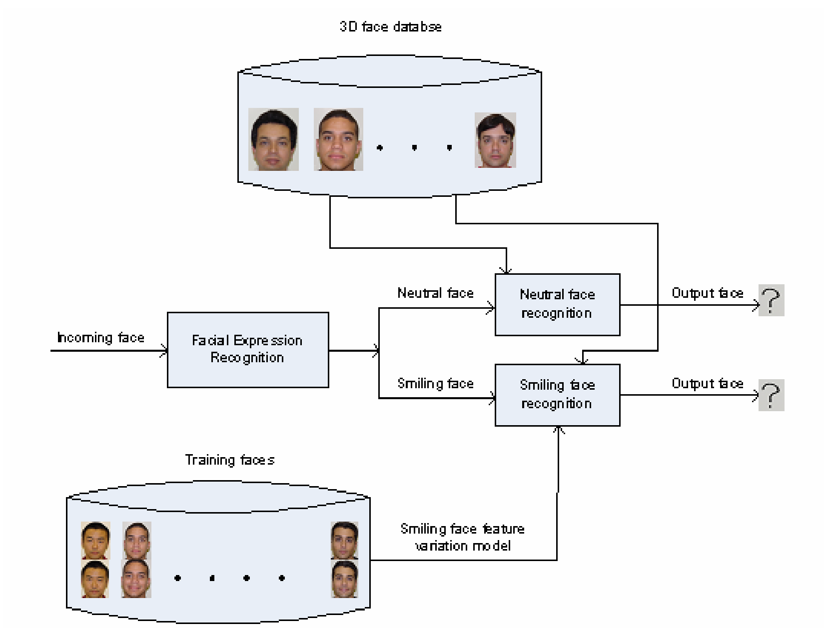

Figure 1 Simplified framework of 3D face expression

3. DATA ACQUISITION

To test the proposed framework, a database, which includes 30 subjects, was built. This database contains instances of the most common expressions, i.e., smiling (happiness) and neutral expression. Each subject participated in two sessions of the data acquisition process, which took place in two different days. In each session, two 3D scans were acquired. One was a neutral expression; the other was a happy (smiling) expression. The 3D scanner used was a Fastscan 3D scanner from Polhemus Inc. [5]. The accuracy of this scanner is specified as 1mm. The resulting database contains 60 3D neutral scans and 60 3D smiling scans of 30 subjects. Figure 2 shows an example of the 3D scans obtained using this scanner.

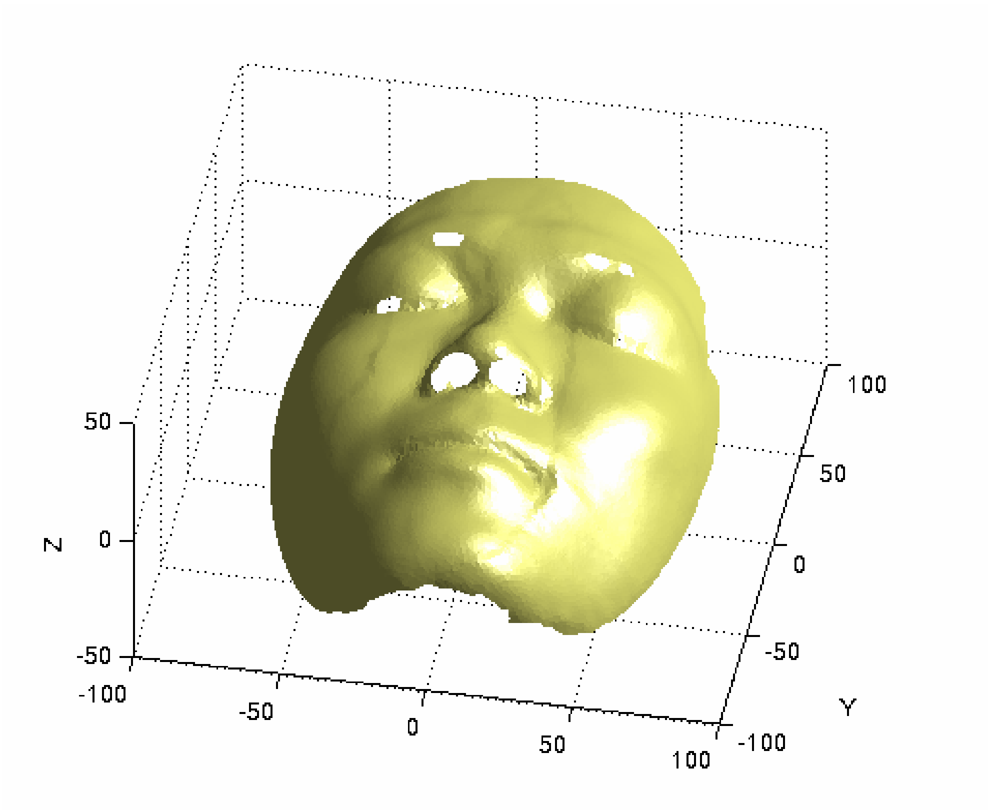

Figure 2 3D face surface acquired by the 3D scanner

In 3D face recognition, registration is a key pre-processing step. It may be crucial to the efficiency of matching methods. In our experiment, a method based on the symmetric property of the face is used to register the face image. In converting the 3D scan from triangulated mesh format to a range image with a sampling interval of 2.5mm (e.g., Fig 2), trilinear interpolation was used[6]. Unavoidably, the scanning process will result in face surfaces containing unwanted holes, especially in the area covered by dark hair, such as the eye brows. To circumvent this problem, the cubic spline interpolation method was used to patch the holes. An example of the resulting 2.5D range image is shown in Fig 3.

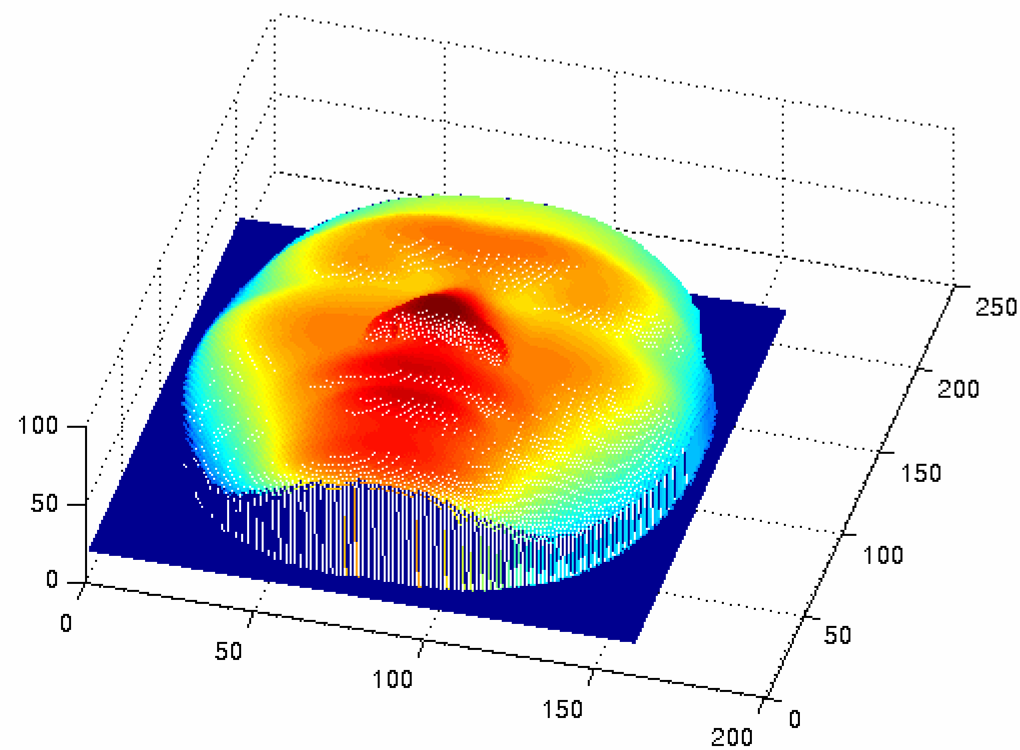

Figure 3 Mesh plot of the converted range image

4. EXPRESSION RECOGNITION

Facial expression of the face is a basic mode of nonverbal communication among people. The facial expression of another person is often the basis on which we form significant opinions on such characteristics as friendliness, trustworthiness, and status. The facial expressions convey information about emotion, mood and ideas. In [4], Ekman and Friesen proposed six primary emotions. They seem to be universal across human ethnicities and cultures. Each possesses a distinctive content together with a unique facial expression. These prototypical emotional displays are also referred to as basic emotions. These six emotions are happiness, sadness, fear, disgust, surprise and anger. Together with the neutral expression, these expressions form the seven basic prototypical facial expressions.

Facial expressions are generated by contractions of facial muscles, which result in temporally deformed facial features such as eye lids, eye brows, nose, lips and skin textures, often revealed by wrinkles and bulges. Typical changes of muscular activities for spontaneous expressions are brief, usually between 250ms and 5s. Three stages have been defined for each expression, which are onset (attack), apex (sustain) and offset (relaxation). In contrast to these spontaneous expressions, posed or deliberate expressions can be found very commonly in social interactions. These expressions typically last longer than spontaneous expressions.

Automatic facial expression recognition has gained more and more attention recently. As in face recognition, most contemporary facial expression systems use 2D images or videos as data format. Logically, the same 2D shortcomings will hamper 2D expression recognition, (i.e., 2D formats are dependent on the pose of the subjects and on the illumination of the environment). In this respect this paper fills the gap by proposing a facial expression system that uses 3D images or range images, which are invariant with respect to illumination and subject orientation. 3D range images have the advantage of invariance with respect to subject alignment and illumination. In addition, the deformed features resulting from expressions are easy to extract from 3D range images.

In our experiment, we aim to recognize social smiles, which were posed by each subject. Smiling is the easiest of all expressions to find in photographs and is readily produced by people on demand. It is generated by contraction of the zygomatic major muscle. This muscle lifts the corner of the mouth obliquely upwards and laterally producing a characteristic "smiling expression" (See Fig 4). So, the most distinctive features associated with the smile are the bulge of the cheek muscle and the uplift of the corner of the mouth. Six features are extracted from each range image to describe the bulge of the cheek and the shape of the mouth associated with a smile.

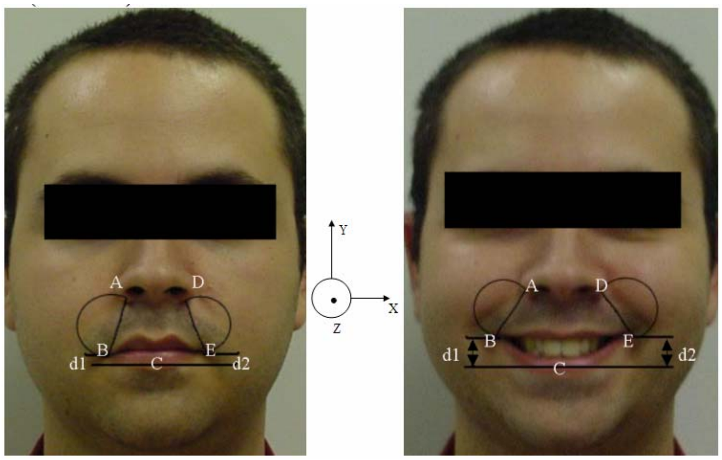

Figure 4 Illustration of the features of a smiling face versus a neutral face

Our procedure to determine if a face is displaying a smiling expression entails:

- Obtain the coordinates of five characteristic points A, B, C, D and E in the face range image as shown in Figure 4. A and D are at the extreme points of the base of the nose. B and E are the points defined by the corners of the mouth. C is in the middle of the lower lip.
- Determine feature "*mw",* the width of the mouth, BE, normalized by the length of AD. Obviously, while smiling the mouth becomes wider.
- Determine feature "*md",* as the difference between the Z coordinates of points BC and EC, normalized by the height of the nose to capture the fact that the smiling expression pulls back the mouth.
- Determine feature "*lc",* as the uplift of the corner of the mouth, compared with the middle of the lower lip d1 and d2, as shown in the figure, normalized by the difference of the Y coordinates of points AB and DE, respectively.
- Determine feature "*ag",* as the angle of AB and DE with the central vertical profile.
- Extract features *"hr"* and *"hm"* from the semicircular areas shown, which are defined by using AB and DE as diameters. The process to define these features is described below.

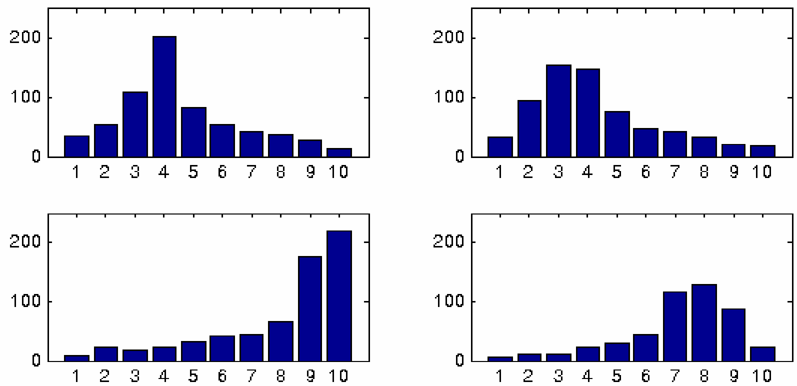

Figure 5 Histogram of Z coordinates in the semicircle area of cheeks for neutral and smiling face

Figure 5 shows the histograms (Z coordinates) for the smiling and the neutral faces of the subject in Figure 4, within the semicircular areas outlined. The two figures in the first row are the histograms of the range values for the left cheek and right cheek of the neutral face image. The second row shows the corresponding histograms for the smiling face image.

From the above figures, we can see that the range histograms of the neutral and smiling expressions are different. The smiling face tends to have large values at the high end of the histogram because of the bulge of the cheek muscle. On the other hand, a neutral face has large values at the low end of the histogram distribution. Therefore two features can be obtained from the histogram: one is called the 'histogram ratio', represented by *hr*, the other is called the 'histogram maximum', represented by *hm*.

$$hr = \frac{h6 + h7 + h8 + h9 + h10}{h1 + h2 + h3 + h4 + h5} \tag{1}$$

$$hm = i\,; \qquad i = \arg\{\max(h(i)\} \tag{2}$$

- After the features have been extracted, this becomes a general classification problem. Two pattern classification methods are applied to recognize the expression of the incoming faces. The first method used is a linear discriminant (LDA) classifier, which seeks the best set of features to separate the classes. The other method used is a support vector machine (SVM). For our work, Libsvm [7] was used to implement a suitable support vector machine.

LDA

LDA tries to find the subspace that best discriminates different classes by maximizing the between-class scatter matrix S_b, while minimizing the within-class scatter matrix S_w in the projective subspace.

$$S_w = \sum_{i=1}^{L} \sum_{\vec{x}_k \in X_i} (\vec{x}_k - \vec{m}_i)(\vec{x}_k - \vec{m}_i)^T \tag{3}$$

$$S_b = \sum_{i=1}^{L} n_i (\vec{m}_i - \vec{m})(\vec{m}_i - \vec{m})^T \quad (4)$$

Where $\vec{m}_i$ is the mean vector for the individual class X_i, and n_i is the number of samples in class X_i, $\vec{m}$ is the mean vector of all the samples. L is the number of classes. The LDA subspace is spanned by a set of vectors W, satisfying

$$W = \arg\max \left| \frac{W^T S_b W}{W^T S_w W} \right| \quad (5)$$

SVM

Support vector machine is a relatively new technology for classification. It relies on preprocessing the data to represent patterns in a high dimension, typically much higher than the original feature space. With an appropriate nonlinear mapping to a sufficiently high dimension, data from two categories can always be separated by a hyperplane. In our research, the Libsvm program package [7] was used to implement the support vector machine.

5. 3D FACE RECOGNITION

5.1 Neutral face recognition

In our earlier research work, we have found that the central vertical profile and the contour are both discriminant features for every person[6]. Therefore, for neutral face recognition, the same method as in [8] is used: the results of central vertical profile matching and contour matching are combined. The difference is in this paper voting score method instead of the method of using the product of the ranks of the two classifiers is used. The definition of the voting score is defined in Equation 3. The combination of the two classifiers improves the overall performance significantly. The final voting score is the sum of the inverse of the ranks for the two classifiers (based on the central vertical profile and contour). The image with the highest voting score in the gallery will be chosen as the matching face for the probe image.

$$Score = \frac{1}{rank_{classifier1}} + \frac{1}{rank_{classifier2}} \quad (6)$$

5.2 Smiling face recognition

For the recognition of smiling faces we have adopted the probabilistic subspace method proposed by B. Moghaddam et al. [9, 10]. It is an unsupervised technique for visual learning, which is based on density estimation in high dimensional spaces using an eigen decomposition. The probability density is used to formulate a maximum-likelihood estimation framework for visual search, target detection and automatic object recognition. Using the probabilistic subspace method, a multi-class classification problem can be converted into a binary classification problem. In the following, it is explained in more details.

Let Δ represents the difference between two vectors in a high dimensional subspace.

$$\Delta = I1 - I2 \quad (7)$$

Δ belongs to the intrapersonal space in the high dimensional subspace if I1 and I2 are two different instances of the same subject; Δ belongs to the interpersonal or extrapersonal space if I1 and I2 are instances from different subjects. $S(\Delta)$ is defined as the similarity between I1 and I2. Using Bayes Rule,

$$S(\Delta) = P(\Omega_I \mid \Delta) = \frac{P(\Delta \mid \Omega_I)P(\Omega_I)}{P(\Delta \mid \Omega_I)P(\Omega_I) + P(\Delta \mid \Omega_E)P(\Omega_E)} \tag{8}$$

$P(\Delta \mid \Omega_I)$ and $P(\Delta \mid \Omega_E)$ are the likelihoods of intrapersonal space and extrapersonal space. The likelihood function can be estimated by traditional means, i.e. maximum likelihood estimation or Parzen window estimation if there are enough data available. In most cases, because of the high dimensionality of the subspace, training data are not sufficient. Subspace density estimation is another choice, which is the case in our experiment. $P(\Omega_I)$ and $P(\Omega_E)$ are *a priori* probabilities for intrapersonal and extrapersonal subspace. Thus, according to the maximum *a posteriori* (MAP) rule, if $P(\Omega_I \mid \Delta)$ is greater than $P(\Omega_E \mid \Delta)$, the two images are considered to be different instances of the same subject, otherwise, they belong to two subjects. Another method based only on Ω_I can be used to simplify the computation. This maximum-likelihood (ML) similarity measure ignores extrapersonal variations.

$$S^{'}(\Delta) = P(\Delta \mid \Omega_I) \tag{9}$$

In [9], it was found that the Ω_I density in (10) carries greater weight in modeling the posterior similarity used for MAP recognition. The extrapersonal Ω_E ,on the other hand serves a secondary role and its accurate modeling is less critical. By dropping the Ω_E likelihood in favor of an ML similarity, the results typically suffer only a minor deficit in accuracy as compared to $S(\Delta)$.

Given the high dimensionality of Δ, traditional methods are not suitable for the purpose of probability density estimation. An efficient subspace density estimation method proposed in [9, 10] was used. The vector space of R^N is divided into two complementary subspaces: DIFS (Difference in Feature Space), F, and DFFS (Difference from Feature Space), $\overline{F}$,as show in the figure. F is spanned by the first M (M<<N) eigen vectors corresponding to the largest M eigen values of principal component decomposition results.

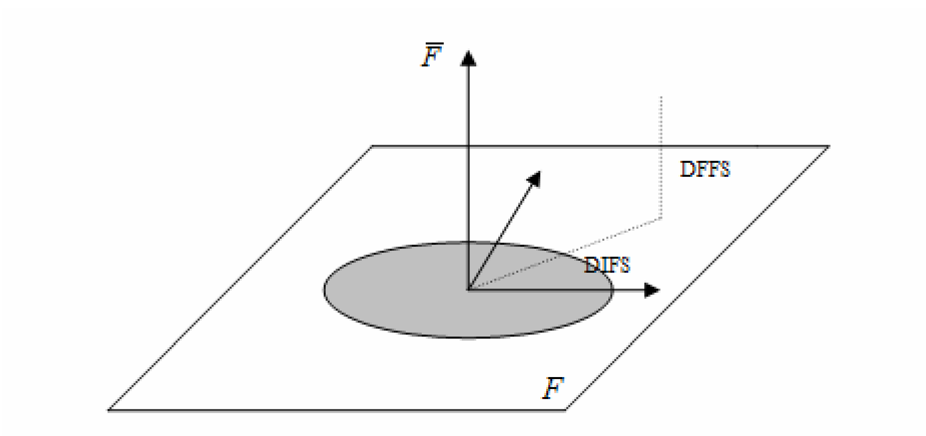

Figure 6 the principal subspace F and its orthogonal complement $\overline{F}$ for a Gaussian density

As derived in[9], the complete likelihood estimate can be written as the product of two independent marginal Gaussian densities

$$\hat{P}(\Delta \mid \Omega) = \left[\frac{\exp\left(-\frac{1}{2} \sum_{i=1}^{M} \frac{y_i^2}{\lambda_i} \right)}{(2\pi)^{\frac{M}{2}} \prod_{i=1}^{M} \lambda_i^{1/2}} \right] \left[\frac{\exp\left(-\frac{\varepsilon^2(\Delta)}{2\rho} \right)}{2\pi\rho^{(N-M)/2}} \right] = P_F(\Delta \mid \Omega) \hat{P}_{\overline{F}}(\Delta \mid \Omega; \rho) \tag{10}$$

where $P_F(\Delta \mid \Omega)$ is the true marginal density in F, $\hat{P}_{\overline{F}}(\Delta \mid \Omega; \rho)$ is the estimated marginal density in the orthogonal complement $\overline{F}$, y_i are the principal components and $\varepsilon^2(\Delta)$ is the PCA residual . From [9], the optimal value for ρ is the average of the $\overline{F}$ eigen values.

$$\rho = \frac{1}{N-M} \sum_{i=M+1}^{N} \lambda_i \tag{11}$$

In the experiment for smiling face recognition, because of the limited number of subjects (30), the central vertical profile and the contour are not used directly as vectors in a high dimensional subspace. Instead, they are down sampled to a dimension of 12 to be used. The down sampling is achieved by getting one point every five points in the vector of central vertical profile and contour. The results of central vertical profile matching and contour matching are combined using voting score method. Here also the combination of the two classifiers improves the performance. The final voting score is defined the same as in the neutral face recognition, i.e., the sum of the inverse of ranks for the two classifiers. The image with the highest voting score in the gallery will be chosen as the matching face for the probe image.

6. EXPERIMENTS AND RESULTS

One gallery and three probe databases are formed for the evaluation of our methods in three experiments. The gallery database has 30 neutral faces, one for each subject, recorded in the first data acquisition session. Three probe sets are formed as follows:

Probe set 1: 30 neutral faces acquired in the second session.
Probe set 2: 30 smiling faces acquired in the second session.
Probe set 3: 60 faces, constituted by probe set 1 and probe set 2.

Experiment 1: Testing the expression recognition module
The leave-one-out cross validation method is used to test the expression recognition classifier. Every time, the faces collected from 29 subjects in both data acquisition sessions are used to train the classifier and the four faces of the remaining subject collected in both sessions are used to test the classifier. The results shown below are the average of the 30 recognition rates. Two classifiers are used. One is the linear discriminant classifier; the other is a support vector machine classifier. They have similar performance of over 90% recognition rate.

Table 1 Expression recognition results

Method	LDA	SVM
Expression recognition rate	90.8%	92.5%

Experiment 2: Testing the neutral and smiling recognition modules separately
In the first two sub experiments, probe faces are directly fed to the neutral face recognition module. In the third sub experiment leave-one-out cross validation is used to verify the performance of the smiling face recognition module. In each cycle, 29 subjects' faces from both acquisition sessions are used for the training and the remaining subject's smiling face from the second session is used as testing face.

2.1 Neutral face recognition: probe set 1 is used. (neutral face recognition module is used)
2.2 Neutral face recognition: probe set 2 is used. (neutral face recognition module is used)
2.3 Smiling face recognition: probe set 2 is used. (smiling face recognition module is used)

The first two columns in Fig 7 are the results for the sub-experiment One. It can be seen when the incoming faces are all neutral, the algorithm which treats all the faces as neutral achieves a very high recognition rate. The rank one recognition rate is 97% and the rank three recognition rate is 100%. On the other hand, if the incoming faces are smiling faces, then the neutral face recognition algorithm does not perform well, obtaining only 57% rank one recognition rate. In contrast, when the smiling face recognition algorithm is used to deal with smiling faces, the rank one recognition rate can be as high as 83%.

Table 2 Results of Experiment 2(three sub-experiments)

	Subexpriemnt1	Subexpriemnt2	Subexpriemnt3
Rank1 recognition rate	86.7%	56.7%	83.3%
Rank3 recognition rate	100%	83.3%	96.7%

Experiment 3: Testing a practical scenario
This experiment emulates a realistic situation in which a mixture of neutral and smiling faces (probe set 3) must be recognized. Sub experiment 1 investigates the performance obtained if the expression recognition front end is bypassed, and the recognition of all the probe faces is attempted with the neutral face recognition module alone. The last two sub experiments implement the full framework shown in Figure 1. (Faces are first sorted according to expression and then routed to the appropriate recognition module.) In 3.2 the expression recognition is performed with the linear discrimant classifier, while in 3.3 it is implemented through the support vector machine approach.

3.1 Neutral face recognition: probe 3 is used. (Probe 3 is treated as neutral faces.)
3.2 Integrated expression and face recognition: probe 3 is used. (Linear discriminate classifier for expression recognition.)
3.3 Integrated expression and face recognition: probe 3 is used. (Support vector machine for expression recognition.)

The results show that if the incoming faces include both neutral faces and smiling faces, the recognition rate can be improved about 10 percent by using the proposed integrated framework compared with the algorithm which treats all the incoming faces as neutral.

Table 3 Results of Experiment 3 (three sub-experiments)

	Subexpriemnt1	Subexpriemnt2	Subexpriemnt3
Rank1 recognition rate	76.7%	86.7%	85%
Rank3 recognition rate	91.7%	98.3%	98.3%

7. DISCUSSION AND CONCLUSION

The results of our experiments confirm the initial assertion that 3D face recognition systems designed under the assumption of face rigidity will be prone to failure in a real-world environment in which the potential presence of a non-neutral facial expression cannot be discarded. While one such system performed satisfactorily for a set of probe faces that had, indeed, neutral expression (86.7 % rank-1 recognition rate), the same system performed poorly when smiling faces of the same set of individuals were presented for recognition (56.7 % rank-1 recognition rate). On the other hand, if the smiling faces are presented for recognition by the module we have proposed for smiling face classification the recognition rate is clearly higher (83.3 % rank-1 recognition). This indicates that there are performance gains to be attained by routing incoming probe faces to expression-matched classifiers. Further, our first experiment showed that this expression sorting is feasible by the means we have proposed, at least within the context of the reduced neutral vs. smiling (only) faces. Under these conditions, both expression recognition modules performed well, achieving over 90% expression recognition success. Our third experiment provided a comprehensive verification of the advantages of the proposed framework over direct use of a “standard” neutral face classifier, with a probe set constituted by equal proportions of neutral and smiling faces (30 samples of each type). The simple neutral classifier achieved only a 76.7 % rank-1 recognition rate, whereas the full-framework classifiers (one using LDA and the other using SVM for expression sorting) achieved 85% or better rank-1 recognition.

In reviewing the results of these experiments, it should be noted that all the experiments involving smiling faces are done using the leave-one-out cross validation method because of the size of the database. Therefore the results displayed are the average, not the best one. For simplicity of implementation, the training samples for the expression recognition system and the smiling face recognition systems are the same faces. In a real application, we would select the training samples to make the best classifier for expression recognition and the identification of faces with a type of expression separately. Considerable performance improvement might be achieved in this way.

Our proposed expression / face recognition framework addresses the need to acknowledge and account for the deformation of the face surface for the purpose of face identification in the context of a more realistic environment, in which the expression of the probe face images cannot be assumed to be constrained to the display of a neutral expression. This would, in fact, be the situation in many potential applications of 3D face recognition. Evidently, the framework implemented here is not yet a general one, as it only involved one expression (smiling) other than the default neutral expression. However, we believe that on key step forward embodied in our proposed approach is the acknowledgement of the need to account for facial expression variations in the design of modern 3D face recognition systems.

8. ACKNOWLEDGEMENTS

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