# Biometric Recognition of 3D Faces and Expressions

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*Abstract:* -Biometric recognition is the research field which pursues the association of a person's identity with the biological characteristics or the behavioral characteristics of that person. Face recognition is preferred by many researchers in biometrics because of its noninvasiveness and its naturalness. In this paper, face recognition using 3D scans is explored. Comparing with 2D face recognition, which uses intensity images to recognize a person, 3D face recognition has the advantage of being independent of environment illumination and subject orientation. However, expression variations of the subjects will change the corresponding 3D scans and thus have a negative impact on 3D face recognition algorithms which assume that the 3D faces are rigid surfaces. In this paper, this issue is also addressed by a proposed framework which incorporates the expressions variation of incoming faces. To test the proposed method, a database containing 30 subjects and 120 3D scans (60 neutral scans and 60 smiling scans) was built. The results proved that incorporating the 3D expression variation into the previous algorithm which treats the face as a rigid surface yields important improvements in the performance of the system.

*Key-Words:* - face recognition, biometrics, 2D, 3D, range image, PCA, subspace, SVM, LDA

## 1 Introduction

Biometrics is a specific area of bioengineering. It pursues the recognition of a person through something the person has, i.e., the biological characteristics or something the person produces, i.e., behavioral characteristics. Examples of the former include finger print, iris, retina, palm print, face, DNA, etc. Examples of the latter include voice, handwriting, gait, signature, etc. Biometrics is used for identification or authentication in border control, e-commerce, ATM machine access control, crowd surveillance, etc. In recent years, biometrics gained more and more attention for its potential application in anti-terrorism.

Among the different modalities used in biometrics, the face is considered to be the most transparent one. It requires minimum cooperation from the subject. In some application scenarios, like crowd surveillance, face recognition probably is the only feasible modality to use. Face recognition is also the natural way used by human beings in daily life. Therefore, face recognition has attracted many researchers from different disciplines, such as image processing, pattern recognition, computer vision, and neural networks. Face recognition scenarios can be classified into the following two:

- **Face verification** ("Am I who I say I am?") is a one-to-one match that compares a query face image against a gallery face image whose identity is being claimed. (The gallery face images are the images which have been stored in the database.)
- **Face identification** ("Who am I?") is a one-to-many matching process that compares a query face image against all the gallery images in a face database to determine the identity of the query face. In the identification task, we assume that through some other methods we know that the person is in the database. The identification of the query image is done by locating the image in the database that has the highest similarity with the query image. In this paper, the face identification problem was addressed.

Most of the face recognition attempts that have been made until recently use 2D intensity images as the data format for processing. Varying levels of success have been achieved in 2D face recognition research. Detailed and comprehensive surveys can be found in [1, 2]. 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 [3], 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 actually the face surface is deformed by different expressions of the subject. Therefore, systems that treat the face as a rigid surface are prone to fail when dealing with faces with expressions. The involvement of facial expression has become an important challenge in 3D face recognition systems. In this paper, we propose an approach to tackle the expression challenge in 3D face recognition. Because the deformation of the face surface is always associated with a specific expression, an integrated expression recognition and face recognition system is proposed. In section 2, a model of the relationship between expression and face recognition is introduced. Based on this model, a framework of integrated expression recognition and face recognition is proposed. Section 3 explains the acquisition of the experimental data used and the preprocessing performed. Section 4 outlines our approach to 3D face expression recognition. Section 5 explains the process used for 3D face recognition. Section 6 describes the experiments performed and the results obtained. Section 7 presents our discussion and conclusion.

## 2 Relationships between Expression Recognition and Face Recognition

From the psychological point of view, it is still not known whether facial expression recognition information directly impacts the face recognition process in human beings. Some models suggest there is no relationship between face recognition and facial expression recognition [4]. Other models support the opinion that a connection exists between the two processes [5].

One of the experiments that support the existence of the connection between facial expression recognition and face recognition was reported in [6]. The authors found that people are slower in identifying happy and angry faces than they are in identifying faces with neutral expression. Also, in [7] experiments show that people are slower in identifying pictures of familiar faces when they exhibit uncommon facial expressions.

Our proposed framework is based on the assumption that the identification of the facial expression of a query face will aid an automated face recognition system to achieve its goal. The incoming 3D range image is firstly processed by an expression recognition system to find the most appropriate expression label for it. The expression label could be one of the six prototypical expressions of the faces, which are happiness, sadness, anger, fear, surprise and disgust [8]. In addition, the face could also be labeled as 'neutral'. Therefore, the output of the expression recognition system will be one of the seven expressions. Our framework proposes that a different face recognition approach be used for each type of expression. If the expression label assigned is "neutral", then the incoming 3D range image is directly passed to a neutral expression face recognition system, which uses the features of the probe image to match those of the gallery images and get the closest match. If the expression label determined 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 by modeling the variations of the face features between the neutral face and the corresponding expressional face. Because recognition through modeling is a more complex process than the direct matching for the neutral face, our framework aligns with the view that people will be slower in identifying happy and angry faces than they will be in identifying faces with neutral expression. Figure 1 shows a simplified version of this framework, it only deals with happy (smiling) expressions in addition to neutral expression. Smiling is the most common (non-neutral) expression displayed by people in public. Accordingly, the framework includes three modules: Expression Recognition Module, Neutral Face Recognition Module and Smiling Face Recognition Module.

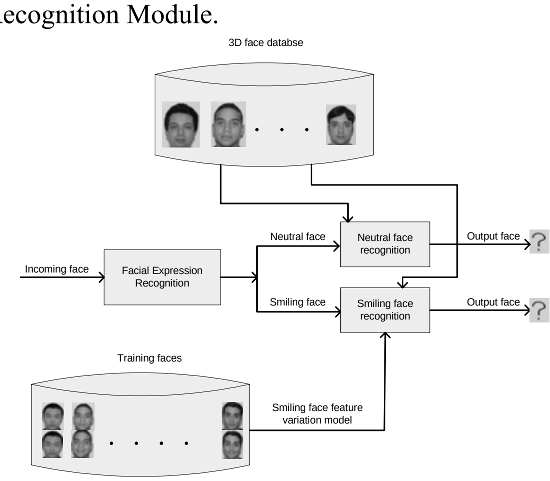


Figure1 Simplified framework of 3D face recognition

## 3 Data Acquisition and Preprocessing

To test the idea proposed in this model, a database, which includes 30 subjects, was built. In this database, we test the different processing of the two most common expressions, i.e., smiling versus neutral. 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. [9]. The resulting database contains 60 3D neutral scans and 60 3D smiling scans of 30 subjects. 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 2.5 mm(e.g., Fig 2), trilinear interpolation was used [11]. 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. The left image in Figure 2 shows an example of the 3D scans obtained using this scanner, the right image is the preprocessed 2.5D range image used in the algorithm.

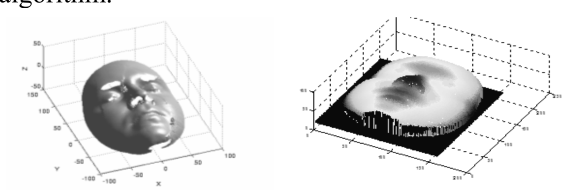

Figure 2 3D surface (left) and mesh plot of the converted range image (right)

## 4 Expression Recognition

Facial expressions constitute a basic mode of nonverbal communication among people. In [8], Ekman and Friesen proposed six primary emotions. Each possesses a distinctive content together with a unique facial expression. They seem to be universal across human ethnicities and cultures. These six emotions are happiness, sadness, fear, disgust, surprise and anger. Together with the neutral expression, they also form the seven basic prototypical facial expressions.

Automatic facial expression recognition has gained more and more attention recently. It has various potential applications for improved intelligence in human computer interfaces, image compression and synthetic face animation. As in face recognition, most contemporary facial expression systems use two-dimensional 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 our experiment, we aim to recognize social smiles, which were posed by each subject. Smiling 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”. So, the most distinctive features associated with the smile are the bulging of the cheek muscle and the uplift of the corner of the mouth, as shown in Figure 3.

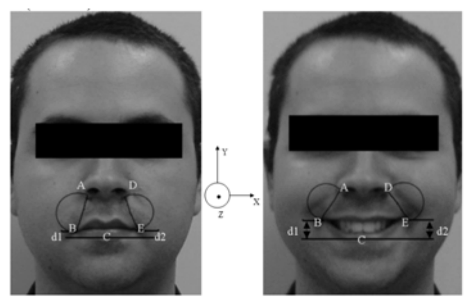


Figure 3 Illustration of features of a smiling face

The following steps are followed to extract six representative features for the smiling expression:

1. An algorithm is developed to obtain the coordinates of five characteristic points A, B, C, D and E in the face range image as shown in Figure 3. 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.
2. The first feature is the width of the mouth, BE, normalized by the length of AD. Obviously, while smiling the mouth becomes wider. The first feature is represented by *mw*.
3. The second feature is the depth of the mouth (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. This second feature is represented by *md*.
4. The third feature is 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 and represented by *lc*.

5. The fourth feature is the angle of AB and DE with the central vertical profile, represented by *ag*.
6. The last two features are extracted from the semicircular areas shown, which are defined by using AB and DE as diameters. The histograms of the range (Z coordinates) of all the points within these two semicircles are calculated.

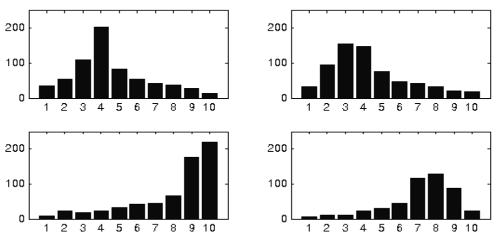

Figure 4 Histogram of range of cheeks (L &R) for neutral (top row), and smiling (bottom row) face

Figure 4 shows the histograms for the smiling and the neutral faces of the subject in Figure 3. 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 two figures in the second row are the histograms of the range values for the left cheek and right cheek of 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*.

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

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

In summary, six features, i.e. *mw*, *md*, *lc*, *ag, hr* and *hm,* are extracted from each face for the purpose of expression recognition.

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). It has been widely used in many applications such as in [10]. Also in [11], you can find an introduction to software which can helps you learn SVM. For our work, Libsvm [12] was used to implement a suitable 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[13]. Therefore, for neutral face recognition, the same method as in [14] is used: the results of central vertical profile matching and contour matching are combined. But the combination method in this work is different from the method in [14]. The combination of the two classifiers improves the overall performance significantly. The final image selected is based on the sum of the two voting scores. The voting score is the inverse of the rank for a classifier. The image with the highest score in the gallery will be chosen as the matching face for the probe image.

$$Score = \frac{1}{rank_{classifier1}} + \frac{1}{rank_{classifier2}} \qquad (3)$$

## 5.2 Smiling Face Recognition

For the recognition of smiling faces we have adopted the probabilistic subspace method proposed by B. Moghaddam et al. [15, 16]. It is an unsupervised technique for visual learning, which is based on density estimation in high dimensional spaces created through eigen decomposition. Using the probabilistic subspace method, a multi-class classification problem can be converted into a binary classification problem.

Let $\Delta$ represents the difference between two vectors in a high dimensional subspace.

$$\Delta = I1 - I2 \qquad (4)$$

$\Delta$ belongs to the intrapersonal space in the high dimensional subspace if I1 and I2 are two different instances of the same subject; $\Delta$ 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,

$$S(\Delta) = P(\Omega_I \mid \Delta) = \frac{P(\Delta \mid \Omega_I)P(\Omega_I)}{P(\Delta \mid \Omega_I)P(\Omega_I) + P(\Delta \mid \Omega_E)P(\Omega_E)} \qquad (5)$$

$P(\Delta | \Omega_I)$ and $P(\Delta | \Omega_E)$ 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 $P(\Omega_I | \Delta)$ is greater than $P(\Omega_E | \Delta)$, the two images are considered to be different instances of the same subject, otherwise, they belong to two subjects.

Another method based only on $\Omega_I$ can be used to simplify the computation. This maximum-likelihood (ML) similarity measure ignores extrapersonal variations.

$$S^{'}(\Delta) = P(\Delta | \Omega_I) \qquad (6)$$

In [14], it was found that the $\Omega_I$ density in (6) carries greater weight in modeling the posterior similarity used for MAP recognition. The extrapersonal $\Omega_E$ ,on the other hand serves a secondary role and its accurate modeling is less critical. By dropping the $\Omega_E$ likelihood in favor of an ML similarity, the results typically suffer only a minor deficit in accuracy as compared to $S(\Delta)$. In this paper, this simplified Bayes rule was used.

**Subspace density estimation**

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 [12, 13] 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 5.

$F$ is spanned by the first M (M<<N) eigen vectors corresponding to the largest M eigen values of principal component decomposition results of all the vectors in vector space of $R^N$.

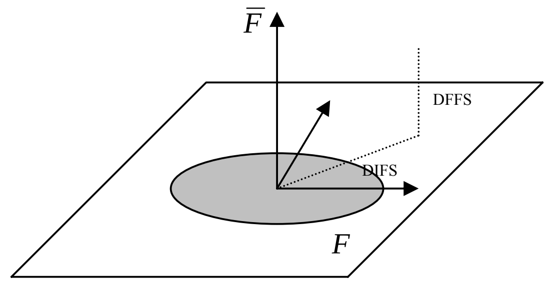


Figure 5 The principal subspace $F$ and its orthogonal complement $\overline{F}$ for a Gaussian density

As derived in [14], the complete likelihood estimate can be written as the product of two independent marginal Gaussian densities,

$$\hat{P}(\Delta | \Omega) = \left[ \frac{\exp\left( -\frac{1}{2} \sum_{i=1}^{M} \frac{y_i{}^2}{\lambda_i} \right)}{(2\pi)^{\frac{M}{2}} \prod_{i=1}^{M} \lambda_i{}^{1/2}} \right] \left[ \frac{\exp\left( -\frac{\varepsilon^2(\Delta)}{2\rho} \right)}{2\pi\rho^{(N-M)/2}} \right] = P_F(\Delta | \Omega) \hat{P}_{\overline{F}}(\Delta | \Omega; \rho) \qquad (7)$$

where $P_F(\Delta | \Omega)$ is the true marginal density in $F$ , $\hat{P}_{\overline{F}}(\Delta | \Omega; \rho)$ 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 [14], the optimal value for $\rho$ is the average of the $\overline{F}$ eigen values:

$$\rho = \frac{1}{N-M} \sum_{i=M+1}^{N} \lambda_i \qquad (8)$$

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. Down sampling is achieved by simply taking one point every 10 points in the central vertical profile and the contour. The dimension of difference in feature space is set to be 8, which contains approximately 97% of the total variance. The dimension of difference from feature space is chosen to be 4.

The results of central vertical profile matching and contour matching are combined. Here also the combination of the two classifiers improves the performance. The final similarity score for the probe image is a voting score also defined in Equation 3. The image with the largest score in the gallery will be chosen as the matching face for the probe face.

# 6 Experiments and Results

In order to evaluate the performance of the suggested framework, one gallery and three probe databases were created. 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, (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. Two classifiers are used. One is the linear discriminant classifier; the other is a support vector machine classifier. The results are shown in Table 1.

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, the leave-one-out cross validation is used to verify the performance of the smiling face recognition module alone.

2.1 Neutral face recognition: probe set 1. (Neutral face recognition module used.)

2.2 Neutral face recognition: probe set 2. (Neutral face recognition module used.)

2.3 Smiling face recognition: probe set 2. (Smiling face recognition module used.)

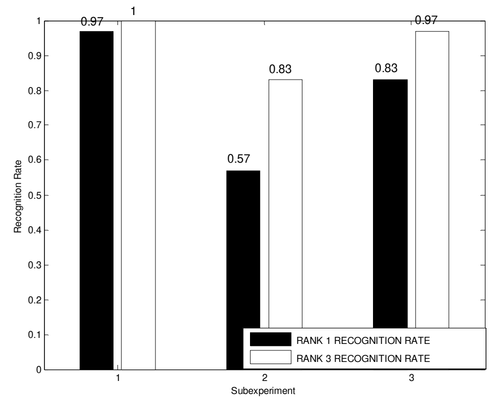


Figure 6 Results of Experiment 2 (three sub-experiments)

From Figure 6, it can be seen that when the incoming faces are all neutral, the algorithm which treats all the faces as neutral achieves a very high rank-one recognition rate (97%). On the other hand, if the incoming faces are smiling, then the neutral face recognition algorithm does not perform well, only 57% rank-one recognition rate is obtained. In contrast, when the smiling face recognition algorithm is used to deal with smiling faces, the recognition rate can be as high as 83%.

**Experiment 3: Testing a practical scenario**

These sub-experiments emulate 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. In 3.2 the expression recognition is performed with the linear discriminant classifier, while in 3.3 it is implemented through the support vector machine approach.

3.1 Neutral face recognition module used alone: probe set 3 is used

3.2 Integrated expression and face recognition: probe set 3 is used. (Linear discriminant classifier for expression recognition.)

3.3 Integrated expression and face recognition: probe set 3 is used. (Support vector machine for expression recognition.)

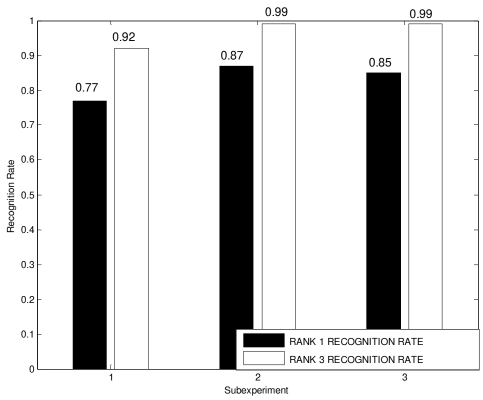


Figure 7 Results of Experiment 3 (three sub-experiments)

It can been seen in Figure 7 that if the incoming faces include both neutral faces and smiling faces, the recognition rate can be improved about 10 percent by using the integrated framework proposed here.

# 7 Discussion and Conclusion

Experiment 1 was aimed at determining the level of performance of the Facial Expression Recognition Module, by itself. Using the leave-one-out cross validation approach, 30 different tests were carried out (Each using 29 x 2 neutral faces and 29 x 2 smiling faces for training). The average success rate in identifying the expressions of the face belonging to the subject not used for training, in each case, was 90.8% with LDA and 92.5% when SVM was used. This confirms the capability of this module to successfully sort these two types of faces (neutral vs. smiling). Both algorithms were applied on the six facial features obtained from the range images (*mw*, *md*, *lc*, *ag, hr* and *hm*). Using these features, the actual choice of algorithm used to separate neutral from smiling faces did not seem to be critical.

Experiment two was carried out to test one of the basic assumptions behind the framework proposed (Figure 1). That is, a system meant to recognize neutral faces may be successful with faces that are indeed neutral, but may have much less success when dealing with faces displaying an expression, e.g., smiling faces. This differentiation was confirmed by the high rank-one recognition (97%) achieved by the Neutral Face Recognition Module for neutral faces (probe set 1) in sub-experiment 1, which was in strong contrast with the much lower rank-one recognition rate (57%) achieved by this same module for smiling faces (probe set 2), in sub-experiment 2. On the other hand, in the third sub-experiment we confirmed that a module that has been specifically developed for the identification of individuals from smiling probe images (probe set 2) is clearly more successful in this task (83% rank-one recognition).

Finally, Experiment 3 was meant to simulate a more practical scenario, in which the generation of probe images does not control the expression of the subject. Therefore for all three sub-experiments in Experiment 3 we used the comprehensive probe set 3, including one neutral range image and one smiling range image from each of the subjects. In the first sub-experiment we observe the kind of results that could be expected when these 60 probe images are processed by a "standard" Neutral Face Recognition Module alone, which is similar to several of the contemporary approaches used for 3D face recognition. Unfortunately, with a mix of neutral and smiling faces this simple system only achieves a 77% rank-one face recognition (much lower than the 97% obtained for probe set 1, made up of just neutral faces, in Experiment 2). This result highlights the need to account for the possibility of a non-neutral expression in 3D face recognition systems. On the other hand, in sub-experiments two and three we apply the same mixed set of images (Probe set 3) through the complete process depicted in our proposed framework (Figure 1). That is, every incoming image is first sorted by the Facial Expression Recognition Module and accordingly routed to either the Neutral Face Recognition Module or the Smiling Face Recognition Module, where the identity of the subject is estimated. The right-most four columns in Figure 6 show that, whether using the linear discriminant analyzer or the support vector machine for the initial expression sorting, the rank-one face recognition levels achieved by the overall system are higher (87%, 85%).

In reviewing the results described above, 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.

The work reported in this paper represents an attempt to acknowledge and account for the presence of expression on 3D face images, towards their improved identification. The method introduced here is computationally efficient. Furthermore, this method also yields as a secondary result the information of the expression found in the faces. Based on these findings we believe that the acknowledgement of the impact of expression on 3D face recognition and the development of systems that account for it, such as the framework introduced here, will be keys to future enhancements in the field of 3D Automatic Face Recognition.

## 8 Acknowledgement

This work was sponsored by NSF grants IIS-0308155, CNS-0520811, HRD-0317692 and CNS-0426125. Mr. Chao Li is the recipient of an FIU Dissertation Year Research Fellowship.

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