Intelligent Expression-independent Face Recognition Algorithm

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ABSTRACT
Robotic vision has always been an important topic in robotics research. In this paper an algorithm is proposed to try to endow the robot with the ability to recognize a person by his/her 3D face image. Unlike most previous approaches, this algorithm uses a framework of integrated expression recognition and face recognition to deal with the challenge of expression-independent face recognition. The algorithm is based on the probabilistic methods to model the variation between expressional faces and neutral faces. Experiments were performed on a database of 30 subjects. Each of the subjects contributed two smiling expression images in addition to two neutral expression images. Experimental results proved the feasibility of this framework.

Keywords
3D, face recognition, biometrics, expression recognition, PCA, subspace

1. INTRODUCTION
This paper proposes a framework for robotic recognition of human faces. Human beings have an amazing ability to recognize faces of many different people. We use this ability naturally in our everyday life. For a long time, researchers in robotics have tried to give the same ability to robots. Attempts towards that goal have been made from different perspectives, such as image processing, pattern recognition, neural networks, etc. The challenge of personal identification through faces also belongs to the larger research area of Biometrics, which attempts to associate a person's identity with his/her biological characteristics or behavior characteristics. The former include face, finger print, iris, etc. The latter include gait, speech, signature, etc.

Traditionally, face recognition has been attempted from 2D images acquired by photographic cameras. Numerous approaches have been developed for 2D face recognition, which are summarized in [11, 23] Although significant success has been achieved in 2D face recognition, 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 environmental illumination and orientation of the subject. These two sources of variation in the face images often make the 2D face recognition system fail. In the 2002 Face Recognition Vendor Test (FRVT 2002), which was an independently administered technology evaluation sponsored by the Defense Advanced Research Projects Agency (DARPA), the National Institute of Standards and Technology (NIST) and other agencies, it was found that one of the difficult tasks for modern face recognition systems was recognizing faces in non-frontal images. Most face recognition systems performed well when all of the images were frontal. But as a subject became more and more off angle (both horizontally and vertically), performance decreased. Other tests in FRVT 2002 showed that the variation in the structure of outdoor lighting had a drastic effect on performance. For one system which performed best in strictly controlled indoor environment, verification performance dropped 41 %, from 95% to 54% [22].

With the development of 3D imaging technology during the last decade, 3D scanners have become inexpensive and accurate enough nowadays to be used to acquire the geometry of faces. Therefore 3D face recognition has become a natural alternative to overcome the difficulties in 2D face recognition. Because 3D scanners record the exact geometry of a face, which is invariant with the illumination of the environment and orientation of the subject, these variations in the data acquisition stage are no longer problems in 3D face recognition. A factor which should still be considered is the facial expression, since it changes the geometry of a subject's face. In [7], it was found that there was a noticeable drop in performance when expression variation was introduced, because the algorithm used in that system was based on the assumption that the face is a rigid shape, which was unrealistic. In [5] Bowyer et al., provide a review of the current state-of-art 3D face recognition systems. The authors also list several key challenges in 3D face recognition, and highlight expression independent face recognition as a critical one.

Currently there are only a few algorithms which deal with 3D face recognition with varying expressions. Among them, one is proposed by Bronstein et al. in [7]. This approach is based on geometric invariants introduced in [13]. The key idea of the proposed algorithm is a representation of the facial surface, invariant to isometric deformation, such as those resulting from different expressions and postures of the face. The geometric invariants obtained allow mapping 2D facial texture images into special images that incorporate the 3D geometry of the face. These signature images are then broken-down into their principal components. The authors claim that the algorithm is efficient, accurate and robust to variations in facial expression. Their paper indicates that some experiments were performed using expressional faces, (even including faces with exaggerated expressions, such as puffy cheeks), and shows that those faces were recognized correctly. Another algorithm which deals with

3D expression-varying face recognition was proposed in [10] using the Iterative Closest Point method (ICP), which was initially introduced in [3]. Unlike the previous ICP methods which use all the frontal face surface to register with the faces in the gallery database, this proposed method, which is called 'adaptive rigid multi-region selection method', only uses the parts of the face surface which change least under different expressions. Such areas include the nose tip area, the eye cavity area and the nose bridge area. Curvatures are used to locate these areas. The experiments reported in the paper showed the effectiveness of this method.

In the remainder of this paper, a face and expression recognition framework is proposed, based on important findings from psychology. Using this method, not only the identity but also the expression of a subject can be obtained. Section 2 provides relevant background knowledge and introduces the framework. Section 3 describes the process of acquiring the data used in the verification of the approach. Section 4 describes the methods used for expression recognition. Section 5 outlines the 3D face recognition process used. Section 6 provides the description of the experiments done and the results. In Section 7 our findings are discussed and some concluding statements are made.

2. FACE EXPRESSION AND FACE RECOGNITION FRAMEWORK

2.1 Relationship between expression recognition and face recognition

From a 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 that there is no relationship between face recognition and facial expression recognition [8]. Other models support the opinion that a connection exists between the two processes [15].

One of the experiments that support the existence of the connection between facial expression recognition and face recognition was reported in [14]. The authors found that people are slower in identifying happy and angry faces than they are in identifying faces with neutral expression. Also, in [16] experiments show that people are slower in identifying pictures of familiar faces when they exhibit uncommon facial expressions.

2.2 Proposed framework

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 appropriated expression label for it. The expression label could be one of the six prototypical expressions of faces, which are happiness, sadness, anger, fear, surprise and disgust [12]. 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 labels. Our framework proposes that a different face recognition approach be used for each type of expression. If the expression label determined is neutral expression, then the incoming 3D range image is directly routed to a neutral expression face recognition system, which uses the features of the probe image to match those of the gallery images and finds 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 (from the gallery) and the 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 identification of happy and angry faces is more involved than the identification of faces with neutral expression. Figure 1 shows a simplified version of this framework. It only deals with happy (smiling) expressions in addition to neutral expressions. Since this is an early stage of our research, we decided to test our system with one expression only. The smiling expression was chosen because it is the most common (non-neutral) expression displayed by people in public.

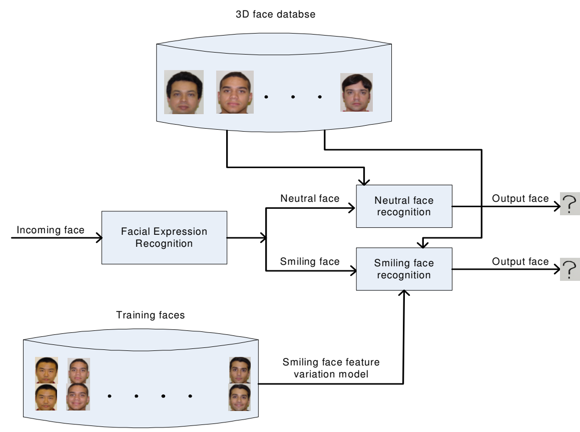

Figure 1. Framework of integrated 3D expression recognition and face recognition

3. DATA ACQUISITION AND PREPROCESSING

3.1 Data acquisition

Unlike 2D face recognition research, for which there are numerous databases available on the Internet, there are only a few 3D face databases available to researchers. Examples are the Biometrics Database from the University of Notre Dame [4] and the University of South Florida Face Database [6]. However, faces included in both databases are mainly neutral faces. Therefore to test the proposed framework, we built a database of our own. In this database, faces with the most common expression i.e., smiling, as well as neutral faces from the same subjects are included. Each subject participated in two data acquisition sessions, which took place in two different days. In each session, two 3D scans were acquired. One was a neutral expression scan; the other was a happy (smiling) expression scan. The 3D scanner used was a Fastscan 3D scanner from Polhemus Inc [24]. 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. In every session in which 3D scans were acquired a 2D color image was also taken of the same subject and same expression, for documentation purposes. Figure 2 and Figure 3 show examples of the 3D scans obtained using this scanner and the corresponding 2D images.

Figure 2. 2D image and 3D scan of a subject with neutral expression

Figure 3. 2D image and 3D scan of a subject with smiling expression

3.2 Preprocessing

For this study, similar preprocessing techniques to those used in [17, 18] were applied to the 3D faces in the FIU 3D database. These included filtering out the noise, registration and patching the holes using cubic spline interpolation. Finally, the 3D scans were converted to range images with a sampling interval of 2.5mm both vertically and horizontally. An example of the resulting range image (sometimes called 2.5D face image) is shown in the following two figures. Figure 4 is the range image of the neutral face in Figure 2 and Figure 5 is the range image of the smiling face in Figure 3.

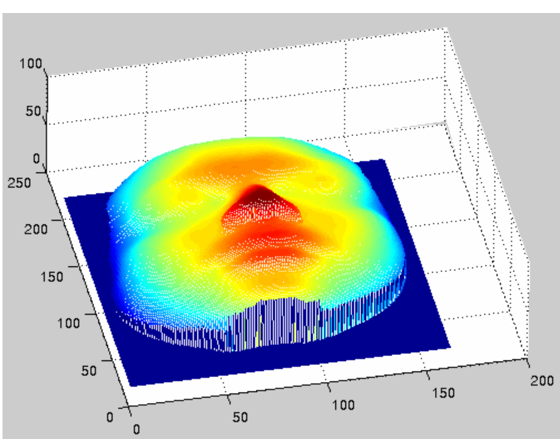

Figure 4. Range image of neutral expression face

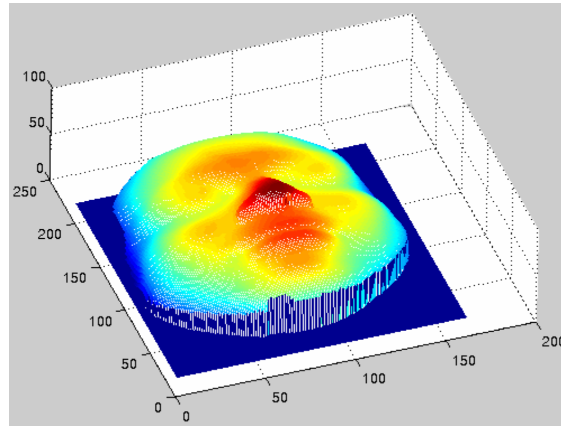

Figure 5. Range image of smiling expression face

4. EXPRESSION RECOGNITION

In [12], Ekman and Friesen proposed six primary emotions. Each possesses a distinctive content together with a unique facial expression. 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. The purpose of facial expression recognition is to categorize the face into one of the six expressions (or state that the face is neutral).

Specifically, in our work, we aim to recognize social smiles, which were posed by each subject. Smiling involves the contraction of the Zygomatic Major muscles, which lift the corners of a mouth obliquely upwards and laterally, producing a characteristic "smiling expression", accompanied by bulging of the cheeks (Figure 6, right panel).

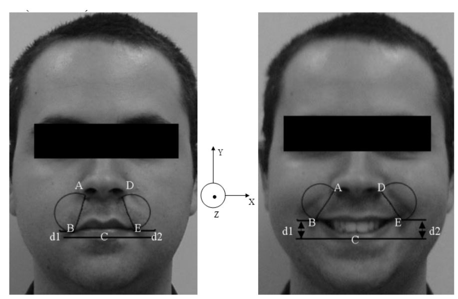

Figure 6. Comparison of neutral face expression and smiling expression (with illustration of feature extraction for expression recognition)

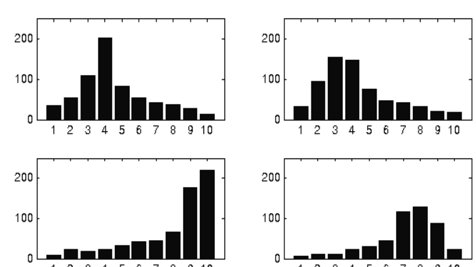

Figure 7. Histogram of range values inside the semicircle area (upper columns are left cheek and right cheek for neutral face, lower columns are left cheek and right cheek for smiling face)

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

- Obtain the coordinates of five characteristic points A, B, C, D and E in the face range image as shown in Figure 6. 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 the feature "*mw*", the width of the mouth, as the distance BE, normalized by the length of AD. Obviously, while smiling the mouth becomes wider.
- Determine the 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 the 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 6, normalized by the difference of the Y coordinates of points AB and DE, respectively.
- Determine the feature "*ag*", as the angle of AB and DE with the central vertical profile.
- Extract the 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 7 shows the histograms of range values (Z coordinates) for the smiling and the neutral faces of the subject in Figure 6, 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* and the other is called the 'histogram maximum', represented by *hm*:

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

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

- 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), which has been successfully used for very diverse pattern classification problems [1, 2]. For our work, Libsvm [9] 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 [18]. Therefore, for neutral face recognition, the same method as in [19] 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 [19]. The combination of the two classifiers improves the overall performance significantly. The final image selected is based on a 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. [20, 21]. 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 Δ represents the difference between two vectors in a high dimensional subspace.

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

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,

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

$P(\Delta \mid \Omega_I)$ 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 the intrapersonal and the extrapersonal subspaces. 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.

$$S^{'}(\Delta) = P(\Delta \mid \Omega_I) \tag{6}$$

In [20], it was found that the Ω_I density in Equation 5 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 $S(\Delta)$. In our work, 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 [20, 21] 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 8.

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 R^N vectors representing the training samples.

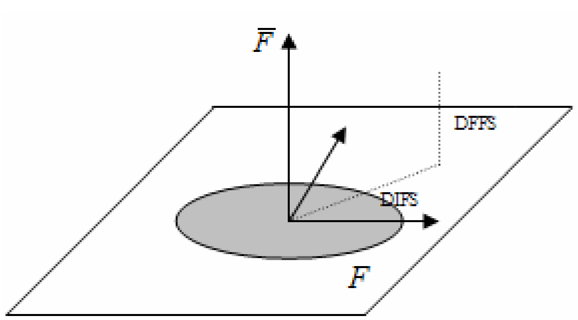

Figure 8. Principal subspace F and its orthogonal complement $\overline{F}$ for a Gaussian density

As derived in [20], the complete likelihood estimate can be written as the product of two independent marginal Gaussian densities,

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

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 [20], the optimal value for ρ is the average of the $\overline{F}$ eigen values:

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

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 22 to be used. Down sampling is achieved by simply taking one point every 5 points in the central vertical profile and the contour. The dimension of difference in feature space is set to be 8, which contains approximately 95% of the total variance. The dimension of difference from feature space is chosen to be 14.

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 of 3D face scans 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, (combination of probe set 1 and probe set 2).

6.1 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 (LDA); the other is a support vector machine classifier (SVM). The results are shown in Table 1.

Table 1 Results of expression recognition

Method	LDA	SVM
Expression recognition rate	90.8%	92.5%

6.2 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.

- Neutral face recognition: Probe Set 1. (Neutral face recognition module used.)
- Neutral face recognition: Probe Set 2. (Neutral face recognition module used.)
- Smiling face recognition: Probe Set 2. (Smiling face recognition module used.)

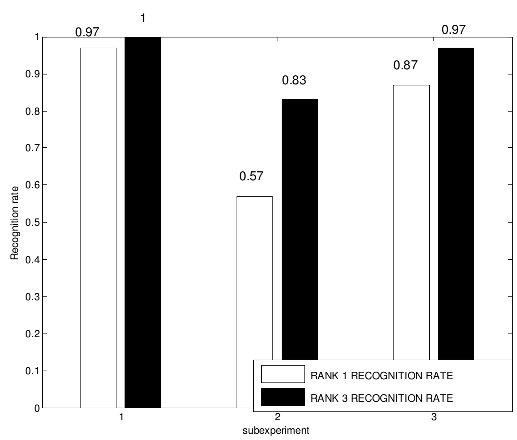

Figure 9. Results of three sub-experiments in Experiment 2

From Figure 9, 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 and 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 87%.

6.3 Experiment 3: Recognition on a mixed probe set

These sub-experiments emulate a realistic situation in which a mixture of neutral and smiling faces (Probe Set 3) must be recognized. (Here it is assumed that smiling and neutral faces have equal probability of presence.) 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 Sub-experiment 2 the expression recognition is performed with the linear discriminant classifier, while in Sub-experiment 3 it is implemented through the support vector machine approach.

- Neutral face recognition module used alone: Probe Set 3 is used.
- Integrated expression and face recognition: Probe Set 3 is used. (Linear discriminant classifier for expression recognition.)
- Integrated expression and face recognition: Probe Set 3 is used. (Support vector machine for expression recognition.)

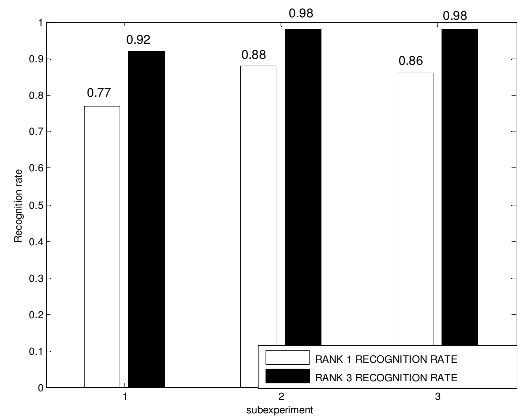

Figure 10. Results of three sub-experiments in Experiment 3

It can been seen in Figure 10 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

The experimental results described in the previous section tend to confirm that an increase in recognition performance can be achieved by acknowledging the possibility that 3D face scans to be identified may come from subjects displaying expressions other than neutral. Implementing a 3D face recognition system that accepts this reality, however, will require a more complex framework. In particular, we have proposed (Figure 1) that the potential presence of non-neutral expressions in the incoming probe faces must be recognized first and that probe faces with different expressions should be recognized through dedicated sub-systems.

The first experiment described in the previous section verified that a Facial Expression Recognition Module can be implemented for the separation of smiling vs. neutral face scans. The separation was performed with two types of classifiers (LDA and SVM), on the bases of six features extracted from the face scans (*mw*, *md*, *lc*, *ag, hr* and *hm*). 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.

The second experiment in our verification process was performed to substantiate our claim that deviations from the assumption of neutrality in the faces to be recognized have a negative impact on the performance of face recognition systems that were developed under that assumption. In the first sub-experiment, neutral faces were recognized by the Neutral Face Recognition Module with a fair degree of success (97% rank-one recognition). However, when smiling faces from the same subjects were processed by the Neutral Face Recognition Module, (Sub-experiment 2) the rank-one recognition rate dropped significantly, to 57%. In contrast, Sub-experiment 3 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 (87% rank-one recognition).

Our third experiment emulates a realistic situation in which a mixture of neutral and smiling probe images have to be recognized against a gallery of (only neutral) known faces. The first sub-experiment here implements the traditional approach that would process all the probe images by a Neutral Face Recognition Module, without distinction, achieving only 77% rank-one recognition. On the other hand sub-experiments 2 and 3 implement our complete propose framework, sorting the probe faces as neutral or smiling and routing them to different recognition modules accordingly. It should be emphasized here that our Smiling Face Recognition Module does not require the availability of a separate gallery of smiling faces, but instead develops matching scores between each incoming (smiling) probe face and neutral faces from the same gallery that is used by the Neutral Face Recognition Module. Two variants of the full framework we proposed were implemented. One used the LDA classifier for expression sorting (Sub-experiment 2), while the other used an SVM for that purpose (Sub-experiment 3). Both versions of the full framework achieved noticeable better performance on this mixed probe set than the Neutral Face Recognition Module alone, recording 88% and 86% rank-one recognition rates, respectively.

Overall, the results from our experimentation support our point of view that approaches for 3D facial recognition will normally be weakened by unrealistic assumptions of face rigidity, particularly when it comes to the probe images, which many times will be collected without full cooperation or even awareness of the subjects. We believe that it might be reasonable to expect that a neutral facial expression can be enforced during the acquisition of gallery scans, as these normally come from situations in which the subject is posed by the operator of the acquisition system, under fairly controlled circumstances (e.g., in the expedition of a motor vehicle license).

The framework proposed works within the constrains listed and has been shown to improved recognition performance for a case in which a mixture of smiling and neutral probe faces have to be recognized.

This work, then, represents an attempt to acknowledge and account for the presence of expression on 3D face images, towards the improved identification of faces by robots. Moreover, the expression recognition results that are obtained as a secondary result of the processing of a probe scan though the framework could have additional utility to further enhance the interaction between the human recognized and a robot, in terms of enabling a more "affectively aware" interaction between the robot and the human, after the recognition process is completed.

8. ACKNOWLEGEMENT

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