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3D Face Registration using Individual Reference Face Shape

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Abstract: ***3D face biometrics has become an important research topic that has seen an enormous growth in the last few decades. The performance of any 3D face recognition system depends on the accurate registration or alignment of facial surfaces. Various registration methods in literature so far use either the one-to-all registration approaches or the average face model (AFM) based approaches for aligning the probe 3D face to gallery faces. In the former approach, each probe face is registered to all faces in the gallery, at a great computational cost. In the latter approach, the AFM calculated from the gallery images is considered as the reference face for aligning all the probe faces. However, the alignment of probe face to the less similar AFM results in the possible loss of discriminatory information. In this paper, an alternative approach that uses individual reference shape for the registration of each probe 3D face is proposed. Here each probe face is aligned to its corresponding, much similar reference face shape that ensures a better registration. Experimental results show that the proposed registration approach provides better alignment than the existing methods and the results are reported using the Bosphorus 3D face database.***

Keywords: 3D face biometrics, 3D face recognition, registration, average face model, Bosphorus 3D face database

1. Introduction

In any 3D face recognition system, the facial surface registration/alignment represents the most important part and the accuracy of the system depends heavily on the quality of alignment. Registration transforms multiple 3D faces to a common coordinate system or to a reference face scan such that an alignment is established between any two faces and one can define similarity between their surfaces. The main applications that rely on surface registration techniques are: 3D surface modeling, model fitting, and face recognition. The various approaches in 3D face modeling, 3D image acquisition and representation has been surveyed in [10].

The facial surface registration methods can be classified into two categories: rigid and non-rigid techniques. The rigid method aligns facial surfaces by rigid transformation, e.g., rotation and translation, while the non-rigid method (e.g. Thin- Plate Spline (TPS) [15]) employs deformations to get a close alignment between surfaces. Iterative Closest Point (ICP) algorithm is the most frequently employed rigid registration approach in 3D face classification applications that establishes a dense correspondence between two point clouds [4].

In any 3D face recognition system, probe faces need to be aligned first to gallery faces for comparison. In most approaches, faces are coarsely aligned initially, either by the set of fiducial points (using their centers of mass), or the nose tip [16], or by fitting a plane to the face and aligning it with that of the camera [1]. In [6], [11] and [12], the given probe face is registered to each gallery face directly, and similarities are computed for classification. However this approach is computationally expensive since it performs N registration operations if there are N gallery faces in the training set.

In the work of Irfanoglu et al. [9] and Gokberk et al. [7], an alternative and fast method was proposed to register faces, where an average face model (AFM) was employed to determine a single point-to-point correspondence. The AFM was generated using the gallery faces, which were already in dense correspondence with it. Thus, a single registration operation is enough to compare a test face to all of the previously registered gallery faces.

In [2], Salah et al. proposed category-specific AFMs based on clustering and cognitive approach. They used ICP and TPS based registrations for defining category-specific AFMs and their results showed that ICP is superior to the faster TPS based method in accuracy. Alyuz et al. [3] employed an adaptively-selected model based registration scheme for occluded face where only the valid non occluded patches of the AFM were utilized. Similar to AFM, generic face model based registration has been proposed in [13] and [14], where these generic 3D face models can be made subject specific by deforming using the feature points extracted from the test faces.

In this paper, we have proposed a simple, fast, and effective registration approach that uses individual reference shape for the registration of any given probe 3D face. The novelty of the approach is that it requires a single registration for comparing a probe face to the entire pre- registered gallery faces. The quality of the proposed registration method has been evaluated under rigid ICP and AFM based registration methods.

The remainder of the paper is structured as follows. In Section 2, the proposed registration method is detailed in a step-by-step procedure together with the face recognition system. The database on which our approach has been tested, the evaluation methods and the comparative results have been described in Section 3. The conclusion is given in Section 4.

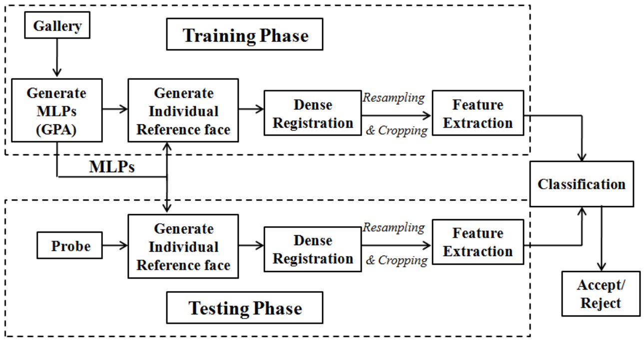


Figure 1: Overall structure of the proposed registration method along with the face recognition system

2. The Proposed 3D Face Registration Method

2.1 Overview of the proposed approach

The framework of the proposed approach is illustrated in Figure 1, which shows the stages of processing for registration and recognition. This approach is targeted to examine the proposed registration method and to verify its accuracy by a 3D face recognition system.

The proposed registration method along with the recognition system consists of two phases: a training phase and a testing phase. Before the training and testing phases, each raw 3D face scan from the gallery and probe faces are preprocessed to remove any imaging artifacts such as spikes, noise and holes. The training process is carried out in the following steps:

(i) Calculate the mean landmark points (MLPs) from the preprocessed training set i.e. the gallery images which represent the main element in the proposed registration approach.
(ii) For each gallery face scan, generate individual reference face shape by aligning its landmark points to the MLPs.
(iii) Register each gallery face scan to their corresponding individual reference face shape to establish dense point-to-point correspondence.
(iv) Resample the depth values of the registered faces on a regular x-y grid and crop the central facial region of required dimension.
(v) Apply the principal components analysis (PCA) on the cropped faces to extract the distinct feature vectors for classification.

The testing phase is implemented in a similar fashion as the training phase (steps (ii) to (v)) that makes use of the mean landmark points (MLPs) to generate individual reference face shapes followed by a dense registration. Finally the features are extracted from the resampled and cropped registered face using PCA. Any given probe face can be identified by calculating the similarity measures between extracted features from the probe and each gallery face using the Nearest-Neighbor classification.

The suggested registration approach has been evaluated using the rigid iterative closest point (ICP), and the AFM based registration methods as followed by Gokberk et al. [7] and Salah et al. [2] are also implemented and a comparative analysis among these approaches has been presented in this paper.

2.2 Determination of Mean Landmark Points (MLPs)

In 3D face scans, landmarks are the key facial points that correspond to the anthropometric locations such as corners of eyes, nose, mouth and tip of nose. Landmarks play an important role in the registration of face scans. The proposed method makes use of the 22 manually located landmark points of each of the gallery faces to generate the mean landmark points (MLPs). Figure 2 depicts a sample 3D face scan with 22 landmarks. Manual landmarks have been used to avoid any errors arising from automatic land marking.

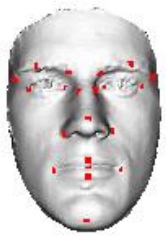


Figure 2: A 3D Face Scan with 22 landmark points

If all of the gallery faces were perfectly frontal and had a same scale with a gaze direction parallel to the z-axis, then a simple averaging would be enough to compute the mean landmark point locations. However, in practice, some of the facial images may have slight rotation and scale variations, which may lead to incorrect mean landmark coordinates. Therefore, it is better to first transform faces into a canonical position using Generalized Procrustes Analysis (GPA) [8] before calculating the MLPs.

The GPA is a rigid shape analysis technique that can be used to align a set of shapes (or set of landmarks) in a least-square sense to their mutual mean by calculating the transformation parameters (e.g., Euclidean or affine). Let $(X_1, X_2, \dots X_N)$ represents the N set of landmarks of the gallery set of size N. The MLPs for the gallery set is calculated using the GPA in the following steps:

Step 1: Select the first shape X_1 (or the landmark points of the first gallery face) to be the approximate mean shape $\overline{X}_m$.

$$\overline{X}_m = X_1 \qquad (1)$$

Step 2: Calculate the centroid $\overline{X}_i$ of each shape (landmark set) X_i , where $\overline{X}_i$ denotes its center point or center of gravity.

$$\overline{X}_i = (\bar{x}, \bar{y}, \bar{z}) = \left(\frac{1}{n} \sum_{j=1}^{n} x_j , \frac{1}{n} \sum_{j=1}^{n} y_j , \frac{1}{n} \sum_{j=1}^{n} z_j \right) \qquad (2)$$

where, n represents the number of points in each shape; in this case n =22. The x coordinate of the centroid is the average of the x coordinates of n landmarks. Similarly the y and z coordinates of the centroid are the average of the y and z coordinates of n landmarks respectively.

Step 3: Translate each shape X_i to the origin (0,0,0) by subtracting its centroid $\overline{X}_i$ from each landmark coordinates. Thus all the landmark sets in the gallery is moved to a common center.

$$\mathbf{X_c} = X_i - \overline{X}_i \qquad (3)$$

where $\mathbf{X_c}$ represents the new coordinates of any shape X_i centered at the origin

Step 4: Scale each shape to unit centroid size, which is the square root of the summed squared distances of each landmark coordinates to its centroid.

$$\mathbf{S}(X_i) = \sqrt{\sum_{j=1}^{n}(x_{ij}-\bar{x}_i)^2 + (y_{ij}-\bar{y}_i)^2 + (z_{ij}-\bar{z}_i)^2} \quad (4)$$

Where $\mathbf{S}(X_i)$ denotes the scaled shape X_i to unit centroid size.

Step 5: Rotate each shape to align with the new approximate mean shape such that the distance between them is minimized.

Step 6: Calculate the new approximate mean from N aligned set of landmarks.

$$\bar{X}_m = \frac{1}{N}\sum_{i=1}^{N} X_i \quad (5)$$

Where $\bar{X}_m$ represents the new approximate mean shape and X_i denotes each set of landmarks in the gallery of size N.

If the calculated approximate mean does not change significantly, convergence is declared; otherwise return to Step 2.Once the convergence is declared in Step 6, the mean shape for the gallery set can be obtained which is considered as the mean landmark points (MLPs) in this paper. The landmark points of two 3D facial scans and their mean landmark points can be seen in Figure 3(a) and (b).

2.3 Generation of Individual Reference Face Shape

In this paper, a novel method of using individual reference face shape has been adopted as opposed to those in [6],[11] and [12] and [2], [7] and [9], for establishing a dense correspondence which is experimentally determined to produce better results. In [6], [11] and [12], each probe face is aligned to all the gallery faces using the one-to-all registration approach for classification. Therefore, N numbers of registrations have to be performed if there are N gallery faces in the training set and leading to high computational cost. In [2], [7] and [9], the Average Face Model (AFM) based approach has been implemented. In these methods the AFM is calculated from the gallery images by aligning the gallery images using either Procrustes Analysis or TPS, which is a time consuming step. Also the probe faces have to be coarsely aligned initially before getting finely aligned to the AFM for better convergence that leads to more computation time.

In order to reduce the above drawbacks to some extent, a novel approach of Registration using Individual Reference Shapes has been proposed. In this method, each face scan (gallery or probe) is registered to its corresponding individual reference face shapes for establishing a point-to-point dense correspondence. The Individual Reference Shape for each scan is generated in the following steps:

Step 1: Alignment of landmark points of each face to MLPs

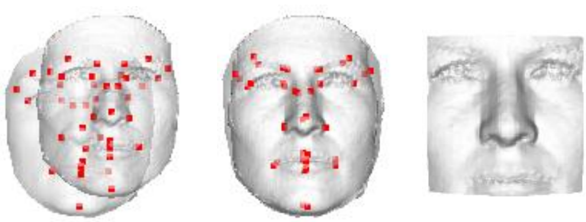
Once the locations of the MLPs are found as explained in Section 2.2, the landmark points of each 3D face is rigidly transformed to these MLPs with the help of Procrustes analysis by calculating the translation and rotation transformation parameters. Thus the transformed or aligned landmark points have similar shapes, orientation and origin.

Step 2: Generation of Individual Reference face shape

For each face scan (gallery or probe), its corresponding Individual reference shape is generated by applying the transformation parameters calculated in previous step to the entire face. After this transformation, each face can be considered as full frontal with the same scale, origin and a gaze direction parallel to the z-axis. The registration of any raw face scan can be performed by simply aligning to its corresponding individual reference face scan.

2.4 Dense Point-to-Point Surface Registration

In this step each source facial scan is densely registered to its target corresponding Individual Reference face shape using the rigid surface registration method i.e. the Iterative Closest Point (ICP) algorithm. ICP iteratively finds the best rotation and translation parameters to align the given face to the reference face. At each iteration, the ICP searches the closest point between the given face and the reference face to establish point wise correspondences between them. A detailed description of ICP can be seen in [4].



(a) (b) (c)

Figure 3: Transparent and overlaid two 3D facial scans with their landmark points.(a) Original 3D face scans, (b) Registered faces, (c) Resampled and cropped facial region

Figure 3 shows an example of two facial scans that are overlaid one over another. Transparency is applied on the face scans and the variations in scaling and orientation are clearly visible in Figure 3 (a).The rigidly aligned face scans using ICP based method are shown in Figure 3 (b).

2.5 Resampling and Cropping of Registered Face Scans

After the faces have been aligned, the 3D points are resampled on a grid of points. Resampling of facial scans helps classification by making the distance measurement more accurate. Besides, resampling lightens the computational burden of comparing the probe with gallery images. It is crucial not to lose precision when going from the 3D domain into the 2D image space.

After the resampling step, the central facial region is cropped and only the points inside the cropped region are retained. The cropped faces are of the same size having exactly same number of pixels which is the primary requirement of applying principal components analysis (PCA) for feature extraction. The cropped facial region of aligned and resampled two transparent facial scans that are overlaid one over the other is shown in Figure 3(c).

3. Experiments

3.1 Database

The accuracy of the proposed registration method has been tested on the Bosphorus 3D face database [15]. The Bosphorus database consists of 4652 3D facial scans of 105 persons with as many as 31 to 54 scans are available per subject. The database includes scans of 60 men and 45 women, in various poses, expressions and occlusions. The majority of the subjects are aged between 25 and 35. The 3D facial data are acquired using Inspeck Mega Capturer II 3D – a commercial Structured-Light based 3D digitizer device. The 3D shape data consists of approximately 35000 point coordinates. After the various operations of alignment, resampling and cropping in Section 2, the original point cloud representation of 3D facial scan with varying number of points, are reduced to a fixed number of densely aligned 100 X 100 =10000 correspondent points which makes the computation much faster.

For our experiments on registration, a subset of the original database has been used. The subjects have been divided into two groups- the gallery set and the probe set. The gallery set comprises of the neutral scans of 105 subjects that are known to the system. The probe set contains 367 facial scans with slight variations in upper and lower facial regions of each subject contained in the gallery set.

3.2 Evaluation based on Face Recognition

In order to assess the quality of the proposed registration method, face recognition system has been employed using Bosphorus 3D face database. After the registration step, the statistical analysis technique has been employed for distinct feature extraction and Principal Component Analysis (PCA), the most popular statistical method has been utilized in this paper. The extracted features from the probe face are then matched to that of the features from each of the gallery faces using the nearest neighbor classification (N-N). The accuracy of the proposed method has been calculated in terms of rank-1 identification rate.

3.3 Experimental Results and Discussion

To comprehensively evaluate the proposed approach and highlight its various aspects, three experiments (E1, E2 and E3) have been designed and a comparative performance analysis has been provided. Experiment E1 implements the idea of the individual reference face shape using ICP based registration technique whereas experiments E2 and E3 implement the average face model (AFM) based approaches as adopted in [2 and 7].

Experiment E1 follows the same procedure as given in section 2.2 and 2.3 for calculating the MLPs and the individual reference face shape. The ICP based registration method is used for iteratively registering each face scan to its corresponding reference face shape. The PCA is then applied to extract the distinct features from the resampled and cropped aligned face scans.Rank-1 identification rate is calculated using N-N classification that validates the accuracy of the proposed registration method.

Experiments E2 and E3 is based on the average face model (AFM) as proposed by Gokberk et al. [7] and Salah et al.[2].In E2 the MLPs are first calculated using GPA and the landmark points of all the gallery faces are transformed to it. The final average landmark locations are obtained by averaging the transformed landmarks. Each training face is then transformed to these landmarks with the help of Procrustes analysis followed by resampling at regular x-y grid. Consequently, the average face model can be computed by averaging the z-depth values of the training faces at regular (x,y) positions. Once the AFM is computed, the gallery and probe faces are registered to AFM in two phases-coarse and fine which can be seen in detail in [7].The accuracy of registration is then evaluated using PCA and the identification process.

In E3, the AFM is generated by first calculating the MLPs using the GPA. TPS deformation is computed for the training faces, which warps the landmarks of each face to the MLPs perfectly and interpolates the rest of the points. The AFM is then computed by averaging the z-depth values of the training faces at regular (x,y) positions, and the gallery and probe faces are registered to AFM similar to E2.

Table 1 illustrates the rank-1 identification rates achieved by the three experiments (E1 to E3) on the subset of Bosphorus 3D face database, thereby comparing the registration based on the individual reference face shape and AFM based methods.

Table 1 Comparison of Rank-1 Identification Performances

Experiments	*Methods*	*Rank-1 Accuracy (%)*
E1	Proposed Reg.(using ICP)	**98.36**
E2	AFM based Reg.(using Procrustes + ICP)	86.37
E3	AFM based Reg.(using TPS+ICP)	87.46

E1 employing the MLPs and individual reference face shape for registration using ICP performs best, yielding a higher rank-1 identification accuracy of 98.36%, is denoted by the boldface figure. On the other hand, E2 and E3 implementing the AFM based registration shows lesser identification rates. The proposed registration method is efficient since the reference face is more similar to the probe face which ensures a better registration whereas in AFM based registration, alignment is done using less similar mean face. Thus, individual reference face shape approach ensures that the dense correspondence will be established between points that have better structural correspondence. Besides, the probe face will be deformed less, and discriminatory information will not be lost in case of much similar reference face. Also, a single registration is enough for comparing a probe face to the entire pre-registered gallery faces which greatly reduces the computation time.

4. Conclusion

The proposed registration method has been evaluated under manual landmarking. For real time 3D face recognition, the computational requirements of the algorithms must be taken into consideration. The much slower ICP method is viable only if the registration is speeded up through the use of much similar individual reference face shape. The accuracy of the proposed registration method is demonstrated through the face recognition system. The experimental results show that the proposed method using ICP is superior to the AFM based registration methods in identification accuracy. However, the AFM based registration method shows similar processing time as the proposed method for the same experimental protocol. Thus by examining the results obtained on the subset of Bosphorus 3D face database, it could be concluded that the rigid registration using individual reference face shape outperforms the other methods since the deformation of each face will be minimized in case of rigid registration and much similar individual reference face.

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