General Human Traits Oriented Generic Elastic Model for 3D Face Reconstruction

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Abstract

We propose a *Simplified Generic Elastic Model (S-GEM)* which intends to construct a 3D face from a given 2D face image by making use of a set of general human traits viz., *Gender, Ethnicity and Age (GEA)*. Different from the original GEM model which employs and deforms the mean depth value of 3D sample faces according to a specific 2D input face image, we hypothesise that the variations inherent on the depth information for individuals are significantly mitigated by narrowing down the target information via a selection of specific GEA traits. This is achieved by representing the unknown 3D facial feature points of a 2D input as a Gaussian Mixture Model (GMM) of that of the samples of its own GEA type. It is then further incorporated into a Bayesian framework whereby the 3D face reconstruction is posed as estimating the PCA coefficients of a statistical 3D face model, given the observation of 2D feature points, however, with their respective depth as hidden variables. By making the reasonable assumption that the support area of each component of GMM is small enough, the proposed method is reduced to choose the depth values of the features points of a sample face that is nearest to the 2D input face. Thus the 3D reconstruction is obtained with depth-value augmented feature points rather than the 2D ones in normal PCA statistical model based reconstruction. The proposed method has been tested with the USF 3D face database as well as the FRGC dataset. The experimental results show that the proposed S-GEM has achieved improved reconstruction accuracy, consistency, and the robustness over the conventional PCA based and the GEM (mean-face feature points) reconstruction, and also yields enhanced visual improvements on certain facial features.

1 Introduction

In computer vision, 3D face reconstruction plays an important role in various applications such as face recognition [2, 19], expression recognition [32, 36], gender recognition [27]

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and head pose estimation [18].Various reconstruction techniques such as shape from shading (SFS) [29], shape from silhouettes, structure from motion (SfM) [4, 15, 16] and morphable statistical model (3DMM) which use single or multiple 2D face images are mentioned in the surveys [20, 34, 38]. Most of these techniques define the depth information of the face images based on some components such as image intensity (or illumination) [17, 33] and feature points [37]. The depth information of a 3D object represents the relative surface height of the object from the x and y plane [40].

3D statistical models (eg. 3DMM) and 3D Generic Elastic Models (GEM) [10] are two typical 3D model representations that can be used to represent 3D face models. A 3D statistical model is usually represented by transforming the face model into the vector space using statistical feature extraction techniques such as Principal Component analysis (PCA). A typical example of a statistical model is the 3D morphable model (3DMM) [1]. Initially, a 3D mean face model is computed from a database which consists of 3D face models and important feature points are selected from this mean face. Concurrent to this, face detection and facial feature extraction are also carried out to obtain important 2D feature points [9]. Each of the 2D feature points must have a one-to-one correspondence with a distinct 3D feature point. The 3D face model is expressed as a linear combination of the principal components, which are estimated by minimizing the mean-squared-error between the 3D model feature points and their 2D observations. Generally the PC coefficients are regularised. For example, the Tikhonov regularisation was used to stabilise the PC coefficients in the PCA-based statistical model [23, 25], and distance based regularisation was proposed to determine the optimal regularisation parameter [24].

On the other hand, GEM is a generic depth model representing the mean depth of a set of sample 3D faces, which is directly deformed to obtain the 3D model according to a given input face [10]. Instead of generating an average GEM from the whole database, Jingu Heo and Marios Savvides [11] have proposed a Gender and Ethnicity-specific GEM (GE-GEM) to reconstruct a 3D face model from a single 2D face image. The formation of GE-GEM is performed on a targeted set of face models of the database for a given choice of gender and ethnicity. It has been shown that the depth information is not significantly discriminative between different genders and ethnicity attributes. The face models in the dataset are segregated according to genders (male and female) and ethnicity groups (Asian and Caucasian). For example, while a male Asian 2D face image is computed, the male Asian generic depth model will be chosen in order to estimate the depth information during the process of reconstruction [10, 28].

Both PCA-based and GEM-based models have their own strength and weakness. The former method employs the statistical theory using all sample 3D faces and restricts the reconstructed 3D face models in the subspace formed by the samples. It is therefore produces robust reconstruction results. Nonetheless, as generally only 2D feature points are available from the input image, it tends to lack of control over the depth information of the reconstructed 3D face model. GEM can be considered as a simplified version of the PCA-based methods as far as the deformation of the mean depth is concerned. However, it does not require the reconstructed 3D face be projected onto the 3D face subspace and thus is more flexible though less robust.

In this paper, we propose a 3D reconstruction method to retain the robustness of the PCA-based models and in the meantime to provide control over the depth values of 2D facial feature points. We formulate the reconstruction of the 3D face model of a given 2D face image as a posterior estimation of the PC coefficients Φ given the observations of the 2D facial feature points x_f. The depth value Z of the 2D feature points is expressed as the hidden information. The posterior probability is represented as the marginal distribution of $P(\Phi|x_f)$ integrated over Z. This enables us to explore the possible structure of Z. Specifically, we formulate it as a Gaussian Mixture Model (GMM) of the samples that have the same Gender, Ethnicity, and Age as the given 2D face. By reasonably assuming that the support region of each component in the GMM is small enough, we further simplifies the method to choosing the nearest sample of the given 2D face to obtain the control over the depth information of the 2D feature points. The simplified process is similar to GEM, thus the name of S-GEM. It is worth noting that the final S-GEM model is only a specific implementation of the proposed framework of utilising the hidden depth information of 2D observations. The framework itself warrants novel perspective and can be explored further, which is, however, beyond the scope of this paper and will not be discussed.

Figure 1 demonstrates the overall flow of the proposed approach in 3D face reconstruction. Firstly, the face models in the database are divided into groups according to Gender, Ethnicity and Age (we abbreviate these three criteria as GEA). From the input 2D face image as well as from the 3D face models in the database, a total of 123 feature points are chosen. The 2D feature points of the given face image is matched (the aim is to find the closest match) with the 3D feature points based on the GEA criteria using the Affine Gaussian Mixture Model (A-GMM). The S-GEM is formed by concatenating the Z value of the matched face model with the XY feature points of the the given face. The PCA model of 3D faces is then generated from the USF database [1], and the 3D reconstruction is achieved through the estimation of the PCA coefficients for the given 2D face image. The rest of the paper is structured as follows: Section 2 formulates the proposed method in terms of the PCA modelling, posterior formulation, and the derivation of the S-GEM. Section 3 presents experimental results and discussions. Section 3 finally concludes the paper.

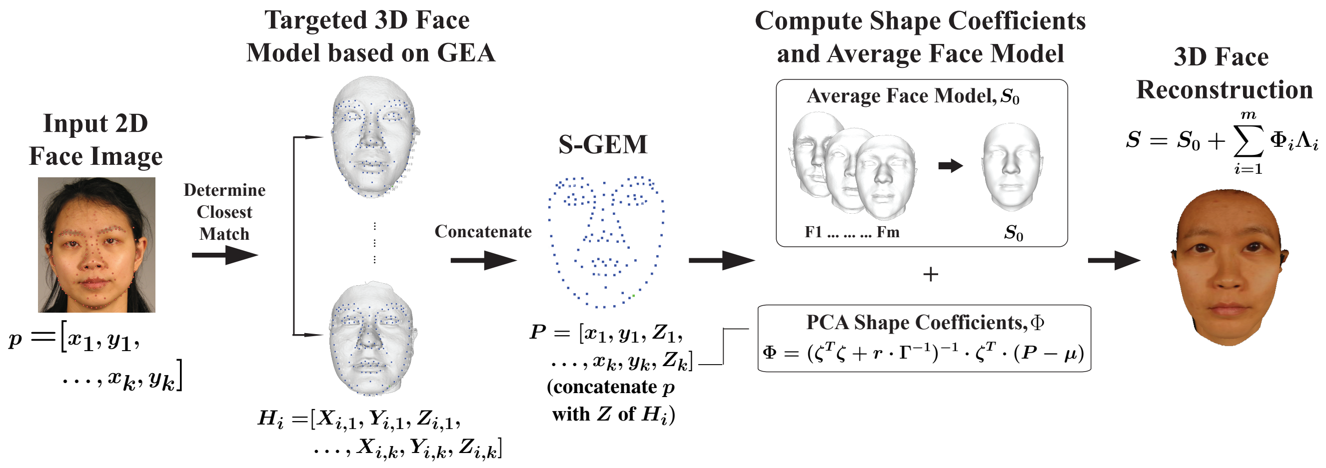


Figure 1: Flow chart of the proposed S-GEM approach

2 3D Face Reconstruction using PCA-based Statistical Model and S-GEM

2.1 PCA-based Statistical Model

The new shape of a face model can be described as:

$$S = S_0 + \sum_{i=1}^{m} \Phi_i \Lambda_i \tag{1}$$

where m is the number of selected 3D face models from the database, S_0 is the mean 3D shape, Λ_i represents the eigenfaces and Φ_i represents the PCA shape coefficients. Φ can be calculated based on the Tikhonov regularisation with the equation below [25]:

$$\Phi = (\zeta^T \zeta + r \cdot \Gamma^{-1})^{-1} \cdot \zeta^T \cdot (p - \mu) \tag{2}$$

where

$$\zeta = \begin{bmatrix} \Lambda_{1,1} & \Lambda_{1,2} & \dots & \Lambda_{1,2k} \\ \Lambda_{2,1} & \Lambda_{2,2} & \dots & \Lambda_{2,2k} \\ \vdots & \dots & \dots & \vdots \\ \Lambda_{m,1} & \Lambda_{m,2} & \dots & \Lambda_{m,2k} \end{bmatrix}, \tag{3}$$

$$\mu = [M_{x,1}, M_{y,1}, \dots, M_{x,k}, M_{y,k}], \tag{4}$$

ζ consists of the Λ of the training samples that corresponds to the 2D feature points, k is the number of selected feature points, M is the mean value of the feature points, Γ is the diagonal matrix consisting of eigenvalues of the covariance matrix (the training samples) and r is the regularisation parameter to balance the fitting error during the reconstruction. ζ and μ are selected based on the feature points. The selected feature points p from the input 2D face image can be represented as:

$$p = [x_1, y_1, \dots, x_k, y_k] \tag{5}$$

2.2 Bayesian Representation of the 3D Face Reconstruction

In this section, a procedure to compute the possible depth values Z_f of the 2D feature points has been described. The Z values pertaining to the depth information of a given 2D face are basically assumed hidden or unknown. Through a Bayesian framework, the posterior distribution of Φ for the given 2D feature points x_f, and its Gender, Ethnicity, and Age (GEA) is represented as the marginal distribution over the hidden variable Z_f.
Basically, the representation is a posteriori distribution that can be defined as:

$$\begin{aligned} P(\Phi|\boldsymbol{x}_f, \Delta) &\propto P(\boldsymbol{x}_f, \Delta|\Phi) \cdot P(\Phi) && (6) \\ &= \sum_{Z_f} P(\boldsymbol{x}_f, Z_f, \Delta|\Phi) \cdot P(\Phi) && (7) \\ &= \sum_{Z_f} P(\Delta|\boldsymbol{x}_f, Z_f, \Phi) \cdot P(\boldsymbol{x}_f, Z_f|\Phi) \cdot P(\Phi) && (8) \end{aligned}$$

where $\boldsymbol{x}_f$ represents the x and y coordinates of the 2D input feature points, Δ represents the corresponding GEA group and Z_f represents the hidden Z values of the 2D input feature points. Also, $\boldsymbol{x}_f$ and Δ are the observed variables in this representation. Φ can be obtained by maximising equation 6, which is a maximum a posteriori (MAP) problem. By integrating Z_f, equation 6 can be expanded into eq. 7 and eq. which represent the marginal distribution over Z_f. Assuming that Φ and Δ are independent, we have

$$P(\Phi|\boldsymbol{x}_f, \Delta) \propto \sum_{Z_f} P(\Delta|\boldsymbol{x}_f, Z_f) \cdot P(\boldsymbol{x}_f, Z_f|\Phi) \cdot P(\Phi) \tag{9}$$

where $P(\Phi)$ and $P(\boldsymbol{x}_f, Z_f|\Phi)$ are:

$$-ln\,P(\Phi) \propto \Phi^T\Gamma^{-1}\Phi \tag{10}$$

$$-ln\,P(\boldsymbol{x}_f, Z_f|\Phi) \propto ||\boldsymbol{X}_f - \mu - \zeta_f\Phi||^2 \tag{11}$$

$\boldsymbol{X}_f = [x_{1,f}, y_{1,f}, Z_{1,f}, \ldots, x_{k,f}, y_{k,f}, Z_{k,f}]$; ζ_f represents the selected eigenfaces that correspond to the features points. Equation 10 represents the prior distribution of the PCA statistical model as described in Section 2.1 whereas equation 11 is the likelihood function of Φ. Based on the Bayesian theory, $P(\Delta|\boldsymbol{x}_f, Z_f)$ can be written as,

$$P(\Delta|\boldsymbol{x}_f, Z_f) = \frac{P(\boldsymbol{x}_f, Z_f|\Delta)P(\Delta)}{\sum P(\boldsymbol{x}_f, Z_f|\Delta)P(\Delta)} \tag{12}$$

Assuming the simplified mixture model for equation 12, we have

$$P(\boldsymbol{x}_f, Z_f|\Delta = \Delta_n) = \sum_{i=1}^{k_n} \frac{1}{k_n} P(\boldsymbol{x}_f, Z_f|H_i) \tag{13}$$

$$= \frac{1}{k_n} \sum_{i=1}^{k_n} \frac{1}{\sqrt{2\pi\sigma^2}}\, exp\left[\frac{-||\boldsymbol{X}_f - H_{i,f}||^2}{2\sigma^2}\right] \tag{14}$$

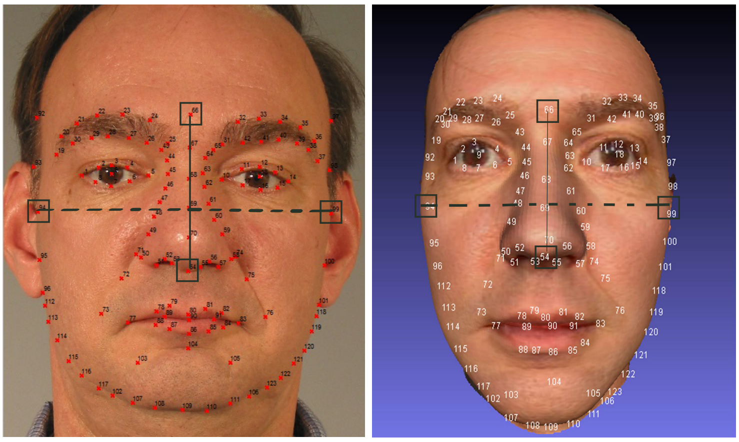
where n is the number of face models that are available in the related GEA, σ represents the variance and k_n is evenly weighted.

From equation 14, if σ is very small and $\boldsymbol{x}_f$ is close to $H_{i,f}$ (one of the samples), then it will maximise the probability $P(\boldsymbol{x}_f, Z_f|\Delta = \Delta_n)$. Otherwise, if the probability is very small, it will cause both $P(\boldsymbol{x}_f, Z_f|\Phi)$ and $P(\Phi)$ to be close as to zero. If $P(\Delta|\boldsymbol{x}_f, Z_f)$ is maximised, then $P(\Phi|\boldsymbol{x}_f, \Delta)$ is also maximised (based on equation 6). Hence, if $P(\Delta|\boldsymbol{x}_f, Z_f)$ is maximised, it follows that the $H_{i,f}$ is the closest pair that matches with the $\boldsymbol{x}_f$. This effectively means that we only need to select $H_{i,f}$ for the given Δ to maximise $P(\Delta|\boldsymbol{x}_f, Z_f)$. In other words, we aim to maximise equation 6.

2.3 Simplified Generic Elastic Model (S-GEM)

In order to select a closest $H_{i,f}$ in equation 14, a simplified generic elastic model (S-GEM) is proposed as follows. Initially, 123 corresponding feature points are manually selected from the 2D face image and the 3D face models as shown in Figure 2. The number of feature points have been increased around the eyes, nose, ears and jawline areas in order to further strengthen the ability of the model to describe the face shapes.

The idea of S-GEM is to integrate the Z values of the selected 3D feature points $H = [X_1, Y_1, Z_1, \ldots, X_k, Y_k, Z_k]$ with the 2D feature points p, so that it may improve the estimation of the unknown shape coefficients. The purpose of this integration is to adopt the Z values (depth information) of the corresponding GEA features and reconstruct the targeted face image accurately. In general, facial features such as the thickness of tissues [7, 26, 30, 31] and facial traits (e.g. nose, mouth and jaw areas) [3, 5, 8, 12, 39] significantly varies between *Gender, Ethnicity, and Age (GEA)*. Hence, it is important to select an appropriate face model from each of the GEA combination groups and reconstruct the targeted face image with the corresponding Z values.



(a) (b)

Figure 2: A typical 2D and its corresponding 3D face model being annotated with feature points. (a) The left image shows the feature points that are being annotated over the 2D face image; (b) The right image shows the feature points that are being annotated over the corresponding 3D face model.

The subjects of the GEA can be grouped into:

1. Male and female (Gender-based).
2. Asian, Caucasian and others (Ethnicity-based).
3. Young and old (Age-based).

The above categories can be represented using a tree structure as shown in Figure 3. In order to construct the S-GEM, 2D-2D rigid point set registration is carried out to determine the closest match between the 2D input feature points (x_f) and the 3D feature points from the GEA (Δ) in order to determine the Z values (hidden variable) which corresponded to equation 13. Before the registration is carried out, the GEA of the 2D input face is defined manually. Depth-first search [35] has been deployed to retrieve the face models of the selected categories from the database based on the proposed tree structure. The determination of GEA may be carried out automatically using the existing techniques, for example, [13, 21, 22]. However, it is beyond the scope of the paper and will not be further discussed. We refer interested readers to the aforementioned articles. Once the face model pertaining to a selected group is obtained, an initial filtration within the group is carried out.

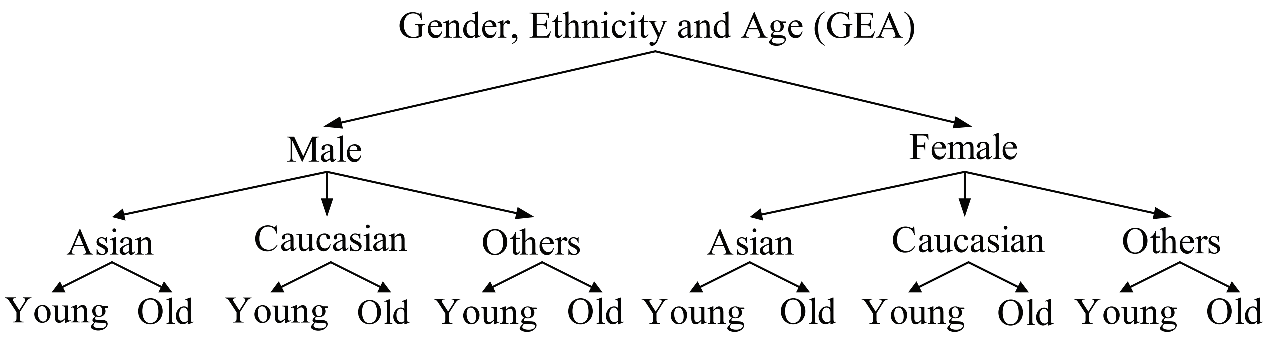


Figure 3: Representation of GEA groups using a tree structure.

The filtration is to eliminate some inappropriate candidates and increase the percentage of selecting the face models which has similar size with that of the given 2D face image. The height of the nose (between point 54 and point 66, plain line) and also the width of the face (between point 94 and point 99, dash line) are utilised to represent the approximate size as shown in Figure 2(a). Affine Gaussian Mixture Model (A-GMM) [14] is chosen to perform rigid point set registration due to its robustness to various initialisation condition for registration. The 2D input feature points g and the 3D feature points from GEA f are represented in terms of corresponding Gaussian mixture distributions and mean square error (MSE) ε is used to calculate the distance between two point sets:

$$\varepsilon = ||f_{A,t} - g||^2 = \int (f_{A,t} - g)^2 d\boldsymbol{x} \tag{15}$$

Finally, the face model with the lowest ε is selected. Once the model H is selected, its Z values are integrated with p to generate new 3D feature points P:

$$P = [x_1, y_1, Z_1, \ldots, x_k, y_k, Z_k] \tag{16}$$

Thus, equation 2 can be re-written as:

$$\Phi = (\zeta^T \zeta + r \cdot \Gamma^{-1})^{-1} \cdot \zeta^T \cdot (P - \mu) \tag{17}$$

where

$$\zeta = \begin{bmatrix} \Lambda_{1,1} & \Lambda_{1,2} & \ldots & \Lambda_{1,3k} \\ \Lambda_{2,1} & \Lambda_{2,2} & \ldots & \Lambda_{2,3k} \\ \vdots & \ldots & \ldots & \vdots \\ \Lambda_{m,1} & \Lambda_{m,2} & \ldots & \Lambda_{m,3k} \end{bmatrix}, \tag{18}$$

$$\mu = [M_{x,1}, M_{y,1}, M_{z,1}, \ldots, M_{x,k}, M_{y,k}, M_{z,k}]. \tag{19}$$

3 Experimental Results and Discussions

We designed the following two sets of experiments to evaluate the performance of the proposed S-GEM method. Firstly, the USF 3D face database [1] was used to evaluate the accuracy of the 3D face reconstruction against the ground truth data. In order to do so, the USF database has been divided into two sets, the training set consisting of 85 randomly chosen 3D faces and the testing set consisting of the rest of 15 3D faces. The training set was used to build a statistical 3D face shape model as depicted in section 2.1. 123 feature points were manually selected for each of the testing faces and the Z coordinates of the feature points were then discarded. The resultant 2D feature points of the testing face were used as the input to reconstruct its corresponding 3D face shape. The reconstruction accuracy was measured with the Mean-Squared-Error between the coordinates of full vertices of the reconstruction and that of the ground truth (see Figure 4). The proposed S-GEM method was compared with the PCA-TR method and a method of utilising the Z-coordinates of the model mean-face feature points (we name it M-GEM). M-GEM is chosen for comparisons

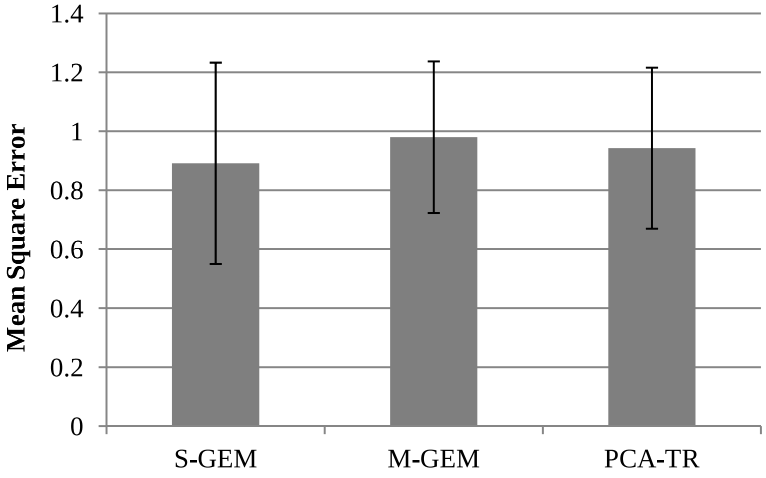


Figure 4: Empirical test of the proposed method (S-GEM), M-GEM and PCA-TR using chosen 15 face models from the USF database. The values in the table are the average MSE and standard deviation of every comparison (between the reconstructed face model and its corresponding original USF face model) and highlighted values shows the lowest MSE values among all three methods.

as it is based on the same principle of the popular GEM model [10], i.e., using the model mean face depth value to represent any individual face depth. The results in Figure 4 shows that the proposed S-GEM method has produced the least MSE out of the three methods in terms of the full 3D face shapes.

The second experiment was designed to evaluate the consistency and robustness of the proposed S-GEM method in reconstructing 3D face shapes from real 2D face images of different individuals with varying conditions. 10 subjects were randomly chosen from the FRGC database for this purpose. Each subject has 10 face images comprising of frontal pose, neutral expression and orthogonal orientation (projection) captured under different operational conditions. 3D faces of these 100 2D face images were reconstructed using the proposed S-GEM method (with the statistical shape model constructed with the 100 USF face data), and were subsequently projected to the model space to obtain their respective model coefficients. 7 reconstructed 3D faces of each individual were randomly chosen to form a training set totaling 70 samples. The rest of the reconstructed 3D faces were regarded as the testing set. The MSE of the model coefficients between each testing 3D face and that of each training face of different groups was calculated and averaged over 100 cross validations (see Table 1). It is evident that the reconstructed 3D faces of the

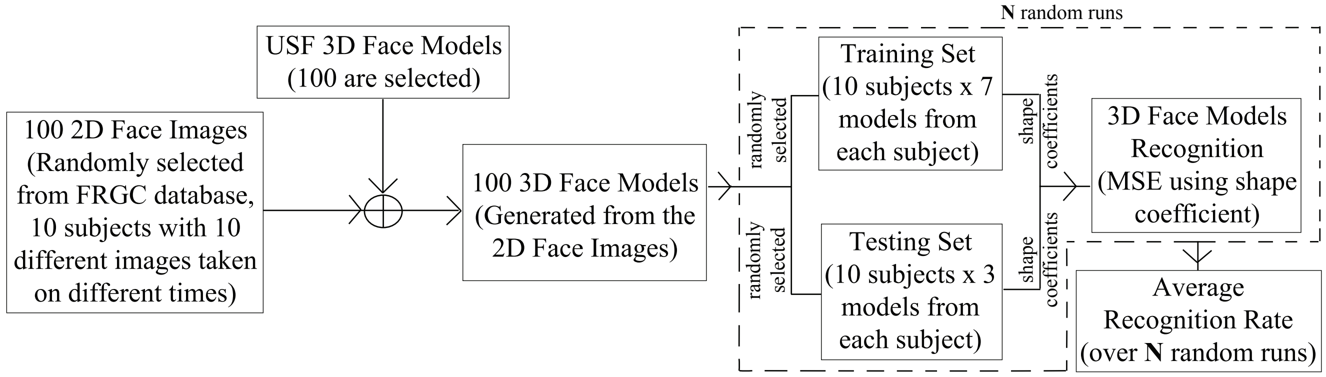


Figure 5: Flow Chart of the experimental evaluations on FRGC data.

Tr \ Ts	1	2	3	4	5	6	7	8	9	10
1	**0.71 ±0.17**	2.54 ±0.12	2.62 ±0.11	3.22 ±0.19	3.61 ±0.25	2.73 ±0.13	1.74 ±0.25	1.99 ±0.29	1.90 ±0.25	2.27 ±0.43
2	2.59 ±0.13	**0.17 ±0.02**	2.19 ±0.08	1.91 ±0.06	2.61 ±0.08	1.68 ±0.08	2.12 ±0.12	1.44 ±0.11	1.26 ±0.05	3.02 ±0.07
3	2.61 ±0.10	2.18 ±0.10	**0.51 ±0.08**	1.59 ±0.08	1.15 ±0.13	1.71 ±0.12	2.13 ±0.14	2.43 ±0.17	2.02 ±0.07	2.71 ±0.14
4	3.17 ±0.32	1.91 ±0.10	1.60 ±0.09	**0.93 ±0.09**	1.39 ±0.11	1.53 ±0.24	2.26 ±0.24	2.47 ±0.25	1.72 ±0.13	2.90 ±0.31
5	3.64 ±0.20	2.59 ±0.15	1.16 ±0.13	1.35 ±0.14	**0.56 ±0.08**	2.25 ±0.11	3.20 ±0.24	3.28 ±0.19	2.11 ±0.10	2.75 ±0.20
6	2.68 ±0.26	1.66 ±0.04	1.71 ±0.11	1.54 ±0.11	2.29 ±0.12	**0.49 ±0.10**	1.75 ±0.19	1.71 ±0.15	2.09 ±0.18	3.20 ±0.25
7	1.86 ±0.48	2.06 ±0.11	2.18 ±0.12	2.31 ±0.16	3.24 ±0.18	1.83 ±0.23	**1.35 ±0.34**	1.86 ±0.12	2.04 ±0.14	3.17 ±0.10
8	2.19 ±0.57	1.49 ±0.16	2.47 ±0.16	2.55 ±0.19	3.34 ±0.21	1.77 ±0.13	1.96 ±0.26	**1.10 ±0.24**	1.65 ±0.43	2.54 ±0.67
9	1.97 ±0.23	1.26 ±0.07	2.01 ±0.07	1.73 ±0.10	2.09 ±0.20	2.13 ±0.16	2.08 ±0.15	1.52 ±0.24	**0.52 ±0.11**	1.46 ±0.16
10	2.38 ±0.56	2.99 ±0.10	2.66 ±0.08	2.97 ±0.15	2.71 ±0.18	3.24 ±0.13	3.15 ±0.28	2.35 ±0.33	1.46 ±0.04	**0.86 ±0.34**

Table 1: Average MSE of the proposed S-GEM approach between the training set (Tr) and the test set (Ts). The highlighted values in the table are showing the lowest MSE values for each row.

same individual are consistent and that of the different individuals are discriminant. The recognition of the testing face based on the label of the closest training face has revealed a 90.6% recognition rate using the proposed S-GEM method, compared to 84.6% of the PCA-TR method. Figure 5 demonstrates the flow of the second experimental evaluations.

Figure 6 shows some examples of the reconstructed 3D faces using the proposed S-GEM approach and the PCA-TR respectively. It is noticeable that the visual quality has improved using the proposed method compared to the PCA-TR. For example, the protrusion of the nose area has been reduced (the nose region of the Figure 6(d)) because the Asian nose had less projected tip and root [6]. The hidden variables that have been integrated into the shape coefficients have effectively controlled the shape of the face models according to its GEA. The outlines of the 3D face shapes have also demonstrated some visual improvements.

4 Conclusion

In this paper, a Simplified Generic Elastic Model (S-GEM) has been proposed to integrate the information of gender, age, ancestry with the statistical model for 3D face reconstruction from a given 2D face image. A hidden variable representing the depth information of the feature points of the given 2D input face image is estimated based on the proposed Bayesian framework, whereby the closest match between the input image and the face models available in the Gender, Ethnicity, and Age (GEA) groups is determined. The experimental results show that the proposed method is more accurate and consistent than the

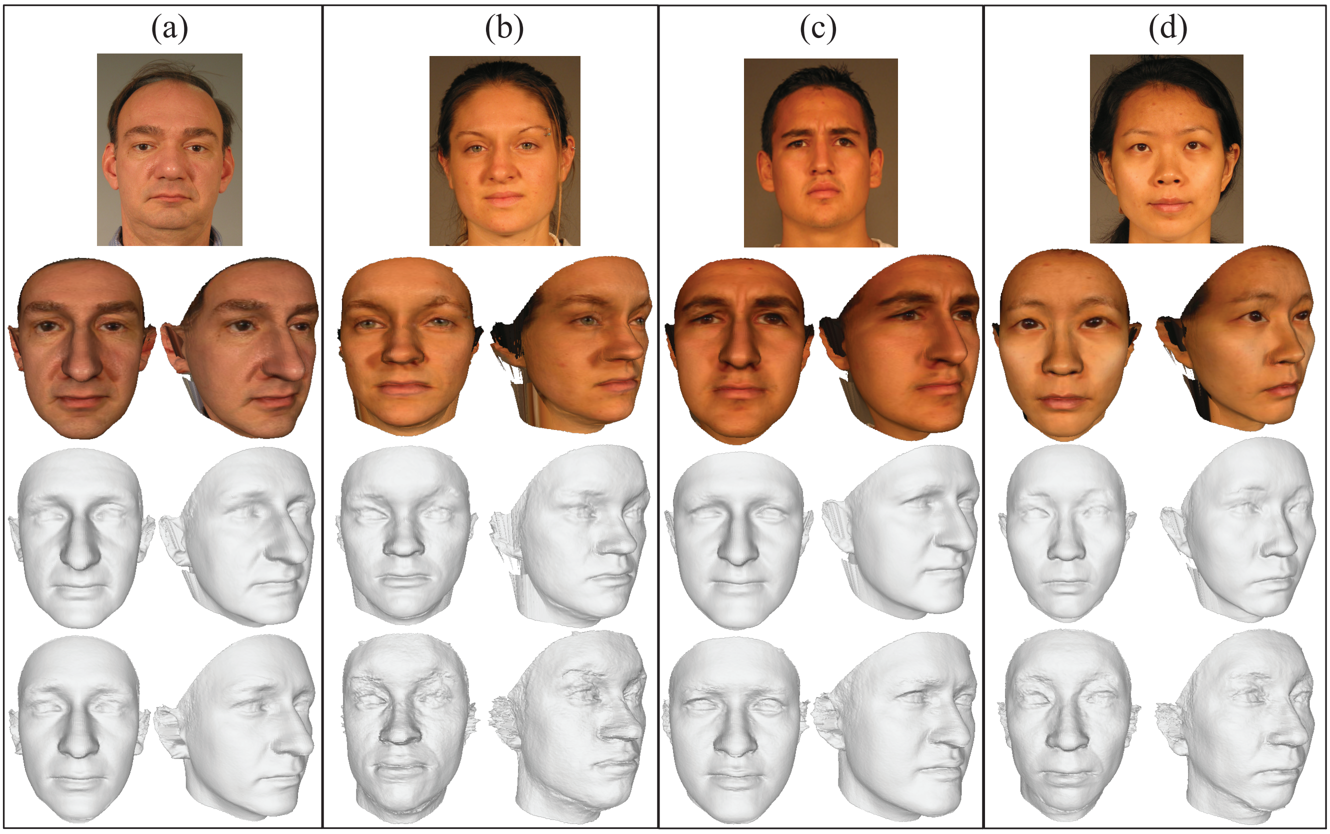


Figure 6: Visual comparisons of the newly reconstructed 3D face models using proposed S-GEM approach (2^{nd} (texture) and 3^{rd} (without texture) row) and PCA-TR (4^{th} (without texture) row). Label: (a) A Caucasian old man; (b) A Caucasian young woman; (c) A young man (Others); (d) An Asian young woman.

PCA-TR method for 3D face reconstruction from single 2D images. However, the proposed method makes the assumption of small variance in building the GEA model and this may be restrictive. Other methods exploiting the hidden depth information of 2D feature points shall be explored in the future.

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