Face Modelling and Tracking from Range Scans

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Abstract

This paper presents an automatic framework for face model and texture reconstruction, facial expression transferring, and face tracking from 3D and 4D range scans. Taking the scale transformation into consideration, an extension of the iterative closest points (ICP) algorithm is introduced to solve the problem of registering a generic face model onto range scans with different sizes. A deformable model derived from thin shells is proposed to faithfully reconstruct face models and textures from range scans. Dense point correspondences are then established across different reconstructed face models so that facial expressions can be easily transferred from one face onto another by the deformation transfer technique. The proposed deformable model is also used to track the facial motion presented in 4D range scans and some preliminary results are obtained.

1 Introduction

Modelling and animating realistic face models is a substantial challenge in computer graphics, especially for facial expressions, because we are so familiar with human faces and very sensitive to "unnatural" subtle changes in faces. Such a challenge has drawn intensive academic and industrial interest in this area [10, 15]. However, creating a convincing facial animation requires a tremendous amount of artistry and manual work, for example, the Digital Emily project [1] took 3 artists, 2 animators and 3 technicians with almost 7 months to create a realistic digital actor. There is a clear need for more automatic techniques to reduce the painstaking work for artists and make reuse of existing data.

One avenue for creating realistic face models is 3D scanning technology [22, 25]. However, starting from a range scan, substantial effort is needed to process the noisy and incomplete surface into a model suitable for analysis and animation. Template-fitting methods are widely used for this purpose to fill holes, reduce the noise level, and capture characteristic features of range scans [2, 22, 25]. In addition, dense point correspondences, which are fundamental requirements in many applications such as morphing and shape analysis, can also be established across models. Generally, template-fitting methods requires users to provide a small set of markers to initially align or warp a template with targets [2, 22, 25]. The process of positioning markers seems to be tedious and error-prone, especially for a large number of range scans.

Synthesis by reusing existing data is one of most desirable features in computer graphics and has recently become popular [16, 18, 24]. Noh and Neumann [24] firstly proposed the concept of *expression cloning*, which is to reuse existing facial expressions to generate new ones on desired targets instead of creating them from scratch. One key problem for expression cloning is how to build good dense correspondences between models.

One way for achieving plausible facial animation is to use the performance of an actor to drive digital characters [1, 22]. There is a vast of body of work on tracking human faces, with applications ranging from motion capture to human-computer interaction [7]. Recently, face tracking for 4D range scans has drawn considerable amount of attention in computer graphics community [22, 23, 25], however, some manual interventions are still involved, such as, identifying a few corresponding feature points on both a template face and range scans.

In this paper, we present a *fully automatic* framework for face modelling and tracking from range scans. This paper makes several specific technical contributions. Firstly, we introduce a *Scaling Iterative Closest Points* (SICP) algorithm to compute optimal alignments between a template face model and range scans with the consideration of the scale problem. Secondly, we propose a deformable model physically based on thin shells to faithfully reconstruct face models and textures from range scans. Furthermore, we combine the deformation transfer technique [18] with dense correspondences established by our deformable model to copy facial expressions from one face onto another. Finally, the proposed deformable model is also capable of tracking facial motions without fast and abrupt deformation in 4D range scans.

In the following section, we review some topics related to our work. In Section 3, we present the technique details of the framework, including alignment, face model and texture reconstruction, facial expression transferring, and face tracking. Results and conclusions are presented in Sections 4 and 5, respectively.

2 Related Work

Modelling and tracking faces is an active research field in computer graphics and computer vision. Here we review three topics most related to our current work: rigid registration, template fitting, expression transferring, face tracking. Other related work is discussed throughout the paper, as appropriate.

Rigid Registration Since the first paper of ICP [3], ICP has been widely used for geometric alignment of 3D models and many variants of ICP have been proposed [17]. Generally, the original ICP can only deal with models with the same scale. To account for the scale problem, Du *et al*. proposed a Iterative Closest Point with Bounded Scale (ICPBS) algorithm which integrated a scale parameter with boundaries into the original ICP algorithm [8], but it's unclear how to determine the upper and lower boundaries of scales that contain the optimal scale.

Template Fitting Due to its great challenge in many research fields, numerous research efforts are devoted to establishing correspondences between different meshes [11]. The template-fitting method [2, 18] deforms a template to a target object to minimise the combining errors of smoothness and fitness between them. Recently, template fitting has become particular popular due to its simplicity and robustness to noisy range data [13, 22]. Our reconstruction method shares the similar idea, but our approach is physically based the elastic deformation of thin shells and derived by variational methods [5].

Expression Transferring Noh and Neumann first proposed the concept of *expression cloning* that facial expressions of one 3D face model were copied onto other face models [24]. The dense point correspondences were established by volume morphing with Radial Basis Functions (RBFs) through dozens of initial corresponding points. Sumner *et al.* [6, 18] generalised the idea to transfer arbitrary nonlinear deformation exhibited by a source triangle mesh onto different target triangle meshes. To build triangle correspondences, they manually specified a small set of initial corresponding feature points and then fitted the source meshes to the target using the template-fitting method. Vlasic *et al.* [21] proposed a method, which used multilinear models for mapping video-recorded performance of one individual to facial animations of another. An example-based approach proposed by Pyun *et al.* [16] clones facial expressions of a source model to a target model while reflecting the characteristic feature of the target model.

Face Tracking There is a vast body of work on tracking the human face, with applications ranging form motion capture to human-computer interaction [7]. Zhang *et al.* [25] presented an automatic offline face tracking method on 3D range data. The resulting facial expression sequences are then used in an interactive face modelling and animation application. Weise *et al.* [22] proposed real-time facial expression tracking with transfer to another person's face. All these methods requires manually labeled feature points for initial warping of the generic template to range scans.

Most of the template-fitting and tracking methods mentioned above require users to manually identify a few corresponding feature points. In contrast, our method does not require any manual interventions. We solve the alignment problem using an extension of the ICP algorithm, which integrates the scale transformation into the original ICP algorithm. We develop our deformable model from thin shells, which hopefully produces more natural and smooth deformation during face model and texture reconstruction and yields good dense correspondences.

3 Face Modelling and Tracking

Since most range scans of human faces are front faces and upright with small rotation angle, in this paper, we assume that the range scans to reconstruct are upright front faces, in which some other unwanted parts (such as hair, neck, shoulder) might also present. Given such a range scan, our goal is to build a new face model with texture to reflect the shape and texture of the range scan from a template face model. For 4D range scans, i.e., a sequence of range scans of a human face performing facial expressions, we want to capture the facial motion using the reconstructed model.

Our method of face model reconstruction consists of two steps: the first step is to find the best alignment between a template face model and a range scan; the second step is to iteratively deform the template model toward the range scan, based on the alignment computed previously, to capture the shape of the range scan.

We preferred triangle meshes for the representation of our models and range scans for efficiency and simplicity. Before elaborating our method, let us introduce some notations used in this paper. A triangle mesh $\mathscr{M}$ consists of a geometrical and a topological component, i.e., $\mathscr{M} = (\mathscr{P}, \mathscr{K})$, where the latter can be represented by a simplicial complex with a set of vertices $\mathscr{V} = \{v_i, 1 \leq i \leq |\mathscr{V}|\}$ ($|\cdot|$ denotes the number of elements in the set), edges $\mathscr{E} = \{e_i \in \mathscr{V} \times \mathscr{V}, 1 \leq i \leq |\mathscr{E}|\}$ and triangles $\mathscr{F} = \{f_i \in \mathscr{V} \times \mathscr{V} \times \mathscr{V}, 1 \leq i \leq |\mathscr{F}|\}$. The geometric embedding of a triangle mesh into $\mathbb{R}^3$ is specified by associating a 3D position $\mathbf{p}_i$ for each vertex $v_i \in \mathscr{V}$: $\mathscr{P} = \{\mathbf{p}_i := \mathbf{p}(v_i) \in \mathbb{R}^3, 1 \leq i \leq |\mathscr{V}|\}$.

3.1 Alignment

In order to reconstruct the surface of a range scan using a template, we need first roughly place the template close to the range scan. Traditionally, this is done by manually specifying a small set of markers [1, 18, 22, 25]. Our method deals with this problem with no manual intervention.

Since the template face model and the range scans of human faces have much similarity in shape, it is intuitive to use the ICP algorithm to compute the initial rigid registrations between them. However, there is a challenge dealing with the scale problem, because the size of the facial region in the range scans is not known a priori and the range scans may also include some unwanted parts.

To deal with the scale problem, we employed an extension version of the ICP algorithm called the Scaling Iterative Closest Points (SICP) algorithm [9], which integrates a scale parameter s to the original ICP equation and iteratively refines the scale from an estimated initial scale until convergence.

Given a template mesh $\mathscr{M}_{\text{template}}$ and a range scan mesh $\mathscr{M}_{\text{scan}}$, the goal of SICP is to find the transformation (scale s, rotation $\mathbf{R} \in \mathbb{R}^{3\times 3}$ and translation $\mathbf{t} \in \mathbb{R}^3$) so that the distance between the registered template mesh $\mathscr{M}'_{\text{template}}$ and $\mathscr{M}_{\text{scan}}$ is as close as possible. Obviously, we should avoid degenerate cases such as $s = 0$ by providing a good initial value for s.

As the original ICP algorithm, SICP is an iterative algorithm, which iteratively refines the registration based on previous registrations until it satisfies a certain termination condition. Let us denote the series of registrations by $\mathscr{T} = \{\mathbf{T}_k = (s_k, \mathbf{R}_k, \mathbf{t}_k), 0 \leq k \leq |\mathscr{T}|\}$. Then the registration process can be formulated mathematically as follows,

$$\mathscr{C}_{k+1} = \{\arg \min_{\mathbf{c} \in \mathscr{M}_{\text{scan}}} d(s_k \mathbf{R}_k \mathbf{p}_i + \mathbf{t}_k, \mathbf{c})\}, \tag{1}$$

$$(s_{k+1}, \mathbf{R}_{k+1}, \mathbf{t}_{k+1}) = \arg\min_{s,\mathbf{R},\mathbf{t}} \sum_{i=1}^{|\mathscr{P}_{\text{template}}|} \|s\mathbf{R}\mathbf{p}_i + \mathbf{t} - \mathbf{c}_i\|^2, \mathbf{c}_i \in \mathscr{C}_k, \tag{2}$$

where $\mathbf{p}_i \in \mathscr{M}_{\text{template}}$, $d(\cdot)$ is a distance function. Equation 1 is to find the corresponding closest points on $\mathscr{M}_{\text{scan}}$ for the points of $\mathscr{M}_{\text{template}}$ and Equation 2 is the absolute orientation problem [12].

As mentioned above, the initial registration state, $s_0, \mathbf{R}_0, \mathbf{t}_0$, is important for the local convergence of SICP. In our examples, we set the initial values as following,

$$s_0 = \frac{\sum_{i=0}^{N} |\mathbf{q}_i - \bar{\mathbf{q}}|/N}{\sum_{i=0}^{M} |\mathbf{p}_i - \bar{\mathbf{p}}|/M}, \quad \mathbf{R}_0 = \mathbf{I}, \quad \mathbf{t}_0 = \bar{\mathbf{q}} - s_0 \mathbf{R}_0 \bar{\mathbf{p}}, \tag{3}$$

where $\bar{\mathbf{p}}$ and $\bar{\mathbf{q}}$ are the centroids of the template and the scan meshes, M and N the number of points of the two meshes, and $\mathbf{I}$ the 3×3 identity matrix. Although SICP has many degenerate cases and does not guarantee the global convergence, our tests show its capability to register the template to range scans with different sizes (see Figures 1 and 5).

3.2 Face Model Reconstruction

Due to the shape diversities between the template face model and range scans, we need further deform the template after the initial rigid registration. There are two criteria that should be considered during the deformation process. One is the regularity that penalises dramatic changes in mesh. Another criterion is the fitting error, which can be formulated as the total distance between corresponding points.

Since the template mesh is a two-manifold surface, the change of the surface can be measured by the change of the first and the second fundamental forms and therefore yields a measure of stretching and bending [19]. Given a two-manifold surface $\mathscr{S}$, after deformation, it becomes $\mathscr{S}'$, we can represent the deformed surface $\mathscr{S}'$ by $\mathbf{p}' = \mathbf{p} + \mathbf{d}$, where $\mathbf{p} \in \mathscr{S}$, $\mathbf{p}' \in \mathscr{S}'$, and $\mathbf{d}$ is the displacement. The minimisation of the physically based elastic energies yields the so-called Euler-Lagrange partial differential equation (PDE) [5]:

$$-k_s \Delta \mathbf{d} + k_b \Delta^2 \mathbf{d} = 0\,, \tag{4}$$

where k_s and k_b are coefficients, Δ and Δ^2 represent the Laplacian and the bi-Laplacian operator, respectively. The Laplacian operator can be extended to triangle meshes to obtain the discrete form of the Laplace-Beltrami operator $\Delta_{\mathscr{M}}$ (refer to [5]). Thus, we can formulate our deformable model as follows,

$$\min_{\mathbf{d}_i} \sum_{i=1}^{M} \| -k_s \Delta_{\mathscr{M}_{\text{template}}} \mathbf{d}_i + k_b \Delta^2_{\mathscr{M}_{\text{template}}} \mathbf{d}_i \|^2 + k_c \sum_{i=1}^{M} w_i \| \mathbf{d}_i - (\mathbf{c}_i - \mathbf{p}_i) \|^2\,, \tag{5}$$

where $\mathbf{p}_i \in \mathscr{P}_{\text{template}}$, $\mathbf{c}_i \in \mathscr{M}_{\text{scan}}$ is the corresponding closest point of $\mathbf{p}_i$, $\mathbf{d}_i$ is the unknown displacement, and k_s, k_b, k_c represent the contribution of stretching, bending and fitting in the total energy, respectively. $w_i = 1$ if the corresponding closest point satisfies a certain compatible conditions, otherwise 0. We employed the similar compatible conditions as [18, 20] to reject pseudo point matching, such as, requiring the angle between two corresponding normals should be greater than 60 degrees, rejecting boundary vertices. The minimization problem can be reformulated as a sparse linear system in terms of least squares [5].

An annealing-like deformation scheme is employed in our experiments. At the initial stage, k_s and k_b are set to relatively large values compared to k_c (In our tests, k_s, k_b and k_c are initially set to 50, 20, 2, respectively). Because at the initial stage we cannot estimate good correspondences between the template and the range scan by the closest points due to the shape diversity and large values of k_s and k_b do not allow dramatic change of the mesh. Then we relax the stiffness of the template face model by gradually decreasing the values of k_s and k_b toward 1.

3.3 Texture Reconstruction

Texture can improve the reality of face models. Thus it is desirable to make the textures available for the reconstructed face models. However, the original range scans usually have holes (missing data). We cannot find all the texture coordinates for the reconstructed face models.

We solve the texture reconstruction problem in the similar way proposed in the previous section, but here we consider the texture coordinates $\mathbf{u}_i \in \mathbb{R}^2$ as the unknown variables and the equation becomes

$$\min_{\mathbf{u}_i} \sum_{i=1}^{M} \| -k_s \Delta_{\mathscr{M}_{\text{template}}} \mathbf{u}_i + k_b \Delta^2_{\mathscr{M}_{\text{template}}} \mathbf{u}_i \|^2 + k_c \sum_{i=1}^{M} w_i \| \mathbf{u}_i - \mathbf{u}'_i \|^2\,, \tag{6}$$

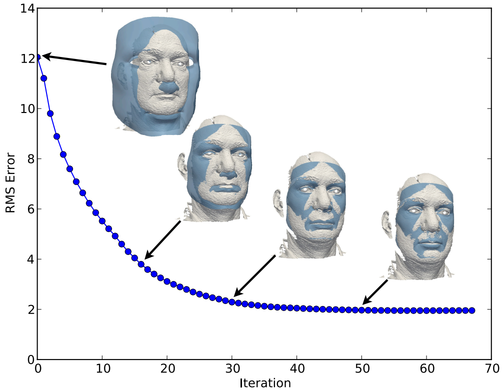

Figure 1: The RMS error of SICP registration. The inset figures show the overlap between the template model and the range scan during the alignment.

where $\mathbf{u}'_i$ is the texture coordinates of the corresponding closest point on the range scan for the point $\mathbf{p}_i$.

When reformulating Equations 5 and 6 in matrix form, we can see that the two equations have the same sparse matrix and only differ in the right hand side. Thus the texture reconstruction can be efficiently solved because the sparse matrix is only factorized once.

3.4 Facial Expression Transferring

After the face model and texture reconstruction, all the reconstructed face models have the same topology as the template one, i.e., the dense point correspondences are automatically established across models. These dense correspondences have numerous applications in many areas such as shape space analysis [2], linear face model [4], morphing. In this paper, to demonstrate the reconstructed face models, textures and the correspondences, we show the facial expression transfer from the generic face model onto various reconstructed face models by using the deformation transfer technique [18]. The results are shown in Figure 6.

3.5 Face Tracking

In this section, we present the procedure of facial expression tracking. Given a sequences of range scans of a human face performing facial expressions, $\mathscr{S} = \{\mathscr{M}^t_{\text{scan}}, t = 0, \ldots, n\}$, without lost of generality, we denote by $\mathscr{M}^0_{\text{scan}}$ the reference neutral range scan. The template face model $\mathscr{M}_{\text{template}}$ is first registered to $\mathscr{M}^0_{\text{scan}}$ using SICP and the aligned template model $\bar{\mathscr{M}}^0_{\text{template}}$ is obtained. Then the deformable model is used to non-rigidly register the initial aligned template $\bar{\mathscr{M}}^0_{\text{template}}$ to $\mathscr{M}^0_{\text{scan}}$, yielding the reconstructed face model $\mathscr{M}^0_{\text{template}}$ for that range scan. For the subsequent range scans, we use the previous deformed template $\mathscr{M}^t_{\text{template}}$

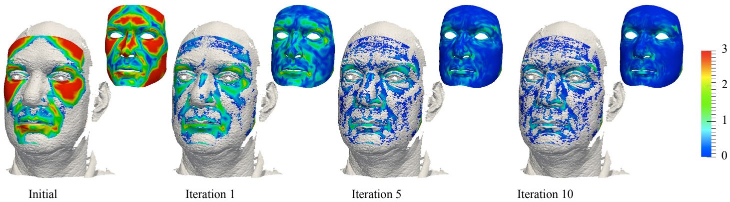

Figure 2: The process of face model reconstruction. The colour mapping shows the distances between the template face model and the range scan.

to non-rigidly register to $\mathscr{M}^{t+1}_{\text{scan}}$. This tracking procedure can be described in Equation 7.

$$\begin{array}{ccc} \mathscr{M}^{t}_{\text{scan}} & & \mathscr{M}^{t+1}_{\text{scan}} \\ \downarrow & & \downarrow \\ \mathscr{M}^{t}_{\text{template}} & \longrightarrow & \mathscr{M}^{t+1}_{\text{template}} \end{array} \tag{7}$$

4 Results and Discussion

We tested our method of face model and texture reconstruction on the Face Recognition Grand Challenge (FRGC ver2.0) data set [14]. Each of the range scans contains about 100k points and 200k triangles. The time cost for each reconstruction is less than 2 mins, measured on a 2.4 GHz Intel Core2 CPU machine with 3 GB RAM.

Figure 1 shows the curve of the root-mean-squared (RMS) error during the SICP registration of the template to the range scan. The curve definitely indicates the convergence of SICP, which is also shown by the inset figures.

Figure 2 shows the reconstruction process of a range scan. The distances from the template to the range scan are encoded into colours. As we can show from the figure, the reconstruction error rapidly decreases across the face during the first several iterations.

To demonstrate the results of texture reconstruction, we rendered the range scans and reconstructed template face model with a checkerboard texture and the original texture respectively as shown in Figure 3. We can see that the facial features are faithfully matched between the template and the range scan. The reconstructed face model along with the reconstructed texture (the rightmost in Figure 3) is more realistic than the original range scan as the holes are filled and the noise level is reduced.

We performed the facial expression transfer experiments of cloning five expressions from

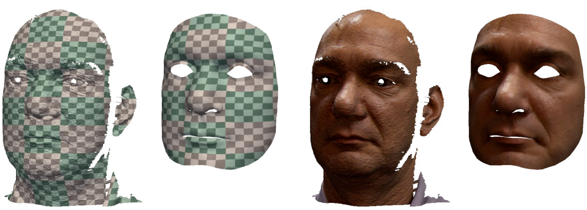

Figure 3: Texture reconstruction.

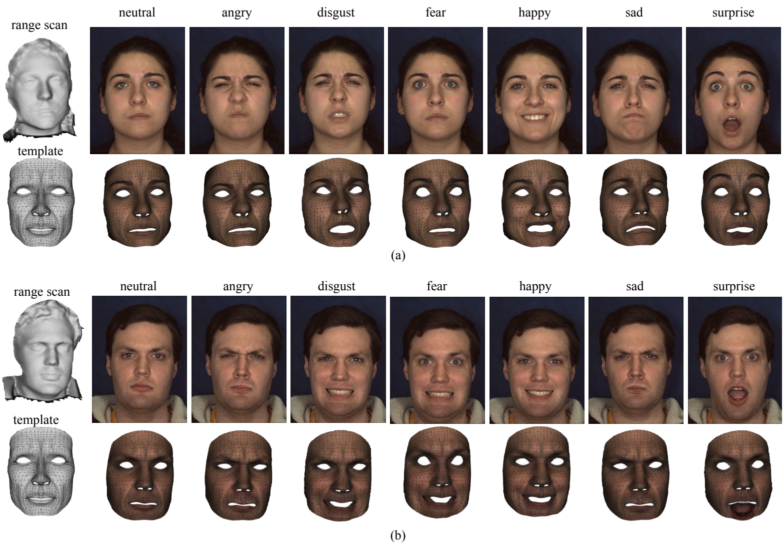

Figure 4: The results of facial expression tracking. The two sequences of range scans with facial expressions are from the facial expression database [23]. The sequences are recorded at the rate of 25 fps. Each expression lasts about 4 seconds. The first columns in (a) and (b) show the 3D range scan and the template face model. The reset columns are the facial expressions extracted from the sequences and the corresponding tracked expressions in the template face model.

the template face model onto three reconstructed facial models. The results are presented in Figure 6.

We tested our face tracking method on two data sets (a male and a female) from the 4D facial expression database [23], which collected the spatio-temporal range scan sequences of six facial expressions (angry, disgust, fear, happy, sad, surprise) for each person. The sequences of range scans are captured at a speed of 25 frames per second. Each facial expression lasts about 4 seconds, thus there are about 100 frames of range scans for each expression. The facial expression tracking results are shown in Figure 4. The first columns in Figure 4 (a) and (b) are the range scans and the template face model and the rest columns show the various facial expressions, which are presented in the range scan sequences, and their corresponding tracked expressions in the template face models. The results show that our method is able to reconstruct new face models from range scans with their textures and it can also track the facial expressions expect for that with very large deformation.

Limitations There are some limitations existing in our method. First, currently our method only employs the closest point constraints, which restricts it for tracking large and fast motion, especially in the chin region (see the surprise expressions in Figure 4). The motion of the chin often exhibits fast and abrupt and hence our deformable can fail to track it correctly. Second, our method is based on the assumption that the acquisition rate is very high so that the change of facial motion between two consecutive frames is not very large. Third, we haven't integrated any texture information into our deformable model. Actually, the textures contain very rich information about the facial motion, which can be detected using the opti-

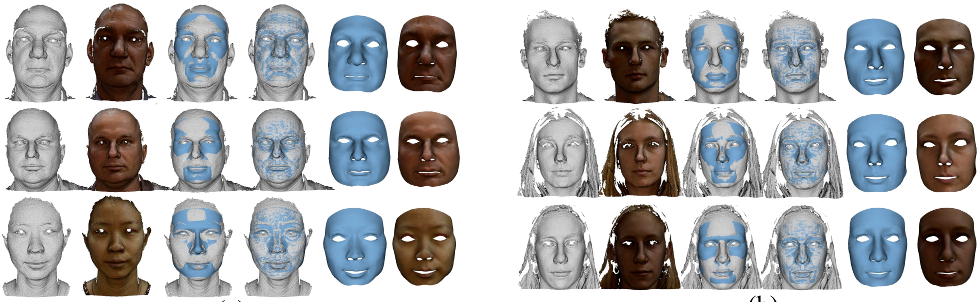
(a) (b)

Figure 5: The results of automatic 3D face model and texture reconstruction. The six range scans, shown in shaded and texture-mapped renderings in the first and second columns, are from the Face Recognition Grand Challenge (FRGC ver2.0) data set [14]. The third (fourth) column in (a) and (b) shows the overlap between the range scans (gray) and the rigid (non-rigid) registered template model (blue). The final reconstructed face models are shown in the last two columns in shaded and texture-mapped renderings. All these reconstructed models have the same mesh structures.

cal flow technique [7]. Adding such constraints into our method will improve the accuracy of the facial expression tracking.

5 Conclusions

We have presented an automatic algorithm for 3D face model and texture reconstruction from range scans of human faces. The proposed deformable model is also able to track facial expressions presented in the range scans if the facial motion is not very fast and large. One of the main benefits of our method is fully automatic. Our method requires no manual intervention and we do not require a small set of corresponding feature landmarks. Key to the success of our algorithm is the robust rigid registration based on Scaling Iterative Closest Points (SICP) algorithm and the the template fitting based on the proposed deformable model.

As for future work, we plan to employ the optical flow method to integrate the texture information into the deformable to improve the accuracy and of facial expression tracking and extend it to account for fast motion.

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Figure 6: The results of facial expression transferring. Five facial expressions (anger, laughing, pleased, rage, sad) of the template face model, shown in the first row, are transferred onto three reconstructed face models from range scans by the deformation transfer technique.

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