

# 3D Dense Correspondence for 3D Dense Morphable Face Shape Model

Tae in Seol, Sun-Tae Chung, and Seongwon Cho

**Abstract**—Realistic 3D face model is desired in various applications such as face recognition, games, avatars, animations, and etc. Construction of 3D face model is composed of 1) building a face shape model and 2) rendering the face shape model. Thus, building a realistic 3D face shape model is an essential step for realistic 3D face model. Recently, 3D morphable model is successfully introduced to deal with the various human face shapes. 3D dense correspondence problem should be precedently resolved for constructing a realistic 3D dense morphable face shape model. Several approaches to 3D dense correspondence problem in 3D face modeling have been proposed previously, and among them optical flow based algorithms and TPS (Thin Plate Spline) based algorithms are representative. Optical flow based algorithms require texture information of faces, which is sensitive to variation of illumination. In TPS based algorithms proposed so far, TPS process is performed on the 2D projection representation in cylindrical coordinates of the 3D face data, not directly on the 3D face data and thus errors due to distortion in data during 2D TPS process may be inevitable.

In this paper, we propose a new 3D dense correspondence algorithm for 3D dense morphable face shape modeling. The proposed algorithm does not need texture information and applies TPS directly on 3D face data. Through construction procedures, it is observed that the proposed algorithm constructs realistic 3D face morphable model reliably and fast.

**Keywords**—3D Dense Correspondence, 3D Morphable Face Shape Model, 3D Face Modeling.

## I. INTRODUCTION

REALISTIC 3D face model is desired in various applications such as face recognition, games, avatars, animations, and etc. During the last decades, considerable researches efforts have been engaged in obtaining more realistic and easier 3D face modeling [1-12].

Construction of 3D face model consists of face shape modeling and texturing. 3D face shape is usually represented by mesh, polygonal surface. Mesh is composed of vertices. After face mesh is built, 3D face model is obtained by rendering the face mesh using vertex colors or a face model texture map. Thus, building a 3D face shape model is precedent for constructing 3D face model.

Many 3D realistic face shape modeling methods have been introduced. Among them, 3D face shape modeling using 3D

scan data obtained by 3D scanner [13], 3D face shape modeling based on a generic face shape model [2,3,4,6,7,8], 3D morphable face shape model [5,9,10,11,12] are representative.

3D scanner samples 3D real face and provides 3D coordinates of the sampling points on 3D face surface, and thus one can construct face shape model. However, 3D scanner is prohibitively expensive for using in the real situations. 3D face shape modeling based on a 3D face generic model obtains a 3D face shape model by transforming a 3D face generic model so as to be fitted into the 3D vertices of some facial landmarks of the sample face. This modeling method is relatively simple and fast in processing, but cannot obtain an accurate 3D face model since the adopted 3D generic model has a sparse number of vertices and triangles. 3D morphable face shape modeling represents a 3D face shape as a linear combination of 3D mean face shape and 3D face shape modes. Since it can represent various face shape easily and effectively, it currently draws lots of research attention. Among various approaches proposed for constructing 3D face shape models, the most realistic approach is surely based on real 3D dense scan data. In this case, 3D correspondence problem among different 3D face scan data must be resolved.

Several algorithms for 3D dense correspondence problem in 3D face modeling have been proposed previously, and many of them are based on optical flow based algorithms or TPS (Thin Plate Spline). Optical flow based algorithms require texture information of faces, which is sensitive to variation of illumination, and is sometimes unavailable. In TPS based algorithms proposed so far, TPS process is performed on the 2D projection representation in cylindrical coordinates of the 3D face data, not directly on the 3D face data and thus error due to distortion in data during 2D TPS process may be inevitable.

In this paper, we propose a new 3D dense correspondence algorithm for 3D dense morphable face shape modeling. The proposed algorithm first selects a reference 3D face scan data, and aligns all other 3D face scan data into the reference 3D face scan data. After alignment, the proposed algorithm searches points in the aligned face scan data which is closest to each vertex of the reference face data and satisfies the threshold condition. If such points are found, then the points are determined as the corresponding points. When aligning a sample face data (one of the remaining 3D face scan data) to the reference face scan data, the proposed algorithm aligns globally using Procrustes analysis and aligns locally by applying 3D TPS, not 2D TPS. The proposed algorithm does not need texture information and do TPS process directly on 3D face data.

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Through construction procedures, it is observed that the proposed algorithm constructs realistic 3D dense morphable face shape model reliably and fast.

The rest of the paper is organized as follows. Section 2 explains some technical background for this paper, and Section 3 proposes a 3D dense correspondence algorithm for building 3D dense morphable face shape model. Section 4 explains how to construct a 3D dense morphable shape model based on the proposed 3D dense correspondence, and the conclusion is presented in Section 5.

## II. BACKGROUND

### A. Shape and Procrustes Analysis

According to D. G. Kendal [14], 'shape is all the geometrical information that remains when location, scale and rotational effects are filtered out from an object'. Shape is usually represented as a set of landmarks on an object. A landmark is defined to be a point of correspondence on each object that matches between and within populations.

Procrustes analysis [14] is a rigid shape analysis that uses isomorphic scaling, translation, and rotation to find the best fit between two or more landmarked shapes.

### B. ICP(Iterative Closest Point)

ICP is an algorithm employed to match two point clouds [15,16]. This matching is used to reconstruct 3D surfaces from different scans, to localize robots, to match bone models with measures in real-time, and etc. The algorithm is very simple and is commonly used in real-time. It iteratively estimates the transformation (translation, rotation) between two raw scans.

Most ICP algorithms are applied between two mesh models, and thus usually start after mesh models from point clouds are obtained and proceed as follows.

- 1) First estimate a relative transform between two meshes.
- 2) Aligns two meshes by using the transform
- 3) Locates the corresponding vertices between two meshes
- 4) Find a transform which can minimize the sum of distances between the corresponding points
- 5) Repeat from 2) through 4) until the sum of distances between the corresponding points satisfies the given threshold

The final corresponding points are correspondent points and the final transform is the transform which achieves the minimal correspondence.

Since ICP algorithm is introduced by Besl and McKay [15], many variants of ICP algorithm [16] had been proposed.

### C. TPS(Thin Plate Spline)

TPS (Thin Plate Spline) is a class of non-rigid nonlinear spline mapping function and is an effective tool to connect sparse points in space smoothly [18, 10, 17].

In this paper, we apply 3D TPS for aligning a sample face scan data into the reference face scan data locally.

### D. 3D Dense Morphable Face Shape Model

The 3D dense morphable face shape model adopted in this paper is constructed from 3D scan data. The 3D face shape scan data consisting of  $n$  vertices can be represented as a shape vector

$S = (x_1, y_1, z_1, x_2, y_2, z_2, \dots, x_n, y_n, z_n)^T$  where  $x_i, y_i, z_i$  are  $x, y, z$  coordinates of vertex  $i$ . Now, if one finds the mean 3D shape vector  $\bar{S}$  and shape principal modes  $S_i$  ( $i = 1, \dots, m - 1$ ) by applying PCA analysis for  $m$  3D face shape scan data, a face shape vector  $S$  can be represented as

$$S = \bar{S} + \sum_{i=1}^{m-1} \alpha_i S_i \quad (1)$$

The most important process in constructing 3D dense morphable face shape model is to arrange all 3D face scan data so that they consist of only corresponding points by using 3D dense correspondence, which is discussed in the next section.

## III. 3D DENSE CORRESPONDENCE FOR 3D FACE SHAPE MODEL

More precise 3D face data is desirable for constructing realistic 3D face shape model and thus we used 3D face scan data in this paper.

In order to construct a 3D dense morphable face shape model like (1) from 3D face scan data, one first needs to resolve 3D dense correspondence among 3D face scan data. Several approaches to 3D dense correspondence have been suggested [5,10,19,20]. Optical flow-based dense correspondence [5] is affected by illumination conditions, and TPS-based dense correspondence [10] had been suggested to alleviate defects of optical-flow based one, but are not sufficiently satisfactory. Optimization-based dense correspondence such as SPHARM [19] and MDL[20] are known to show the excellent performance, but SPHARM and MDL can be applied to genus 0 closed surface which 3D scan face scan data do not belong to.

In this paper, we propose a simple and computationally fast solution to 3D dense correspondence. The procedure for 3D dense correspondence proposed in this paper is summarized as follows.

- 1) Selections of a reference 3D face shape scan data and control points.
- 2) Global alignment into a reference face shape scan data
- 3) Local alignment into a reference face shape scan data
- 4) Search of corresponding nearest points
- 5) Determination of the corresponding points

In the below, we explain the above procedures in detail.

1) Selection of a reference 3D face scan Data and Control points

In order to resolve 3D correspondence among all 3D scan data, one first select a reference 3D face scan data and then align all other 3D scan face scan data into the selected reference scan data. Among 3D face scan data, we select a 3D face scan

data which has least vertices so that alignment of other scan data into it can be done effectively.

For effective alignment, we use cascade alignment of global alignment first and local alignment next. For global alignment, we apply a Procrustes analysis, and for local alignment we apply 3D TPS. Procrustes analysis and TPS requires control points. In this paper, we choose 23 vertices around eyes, nose, mouth, and ears which are shown in Fig. 1.

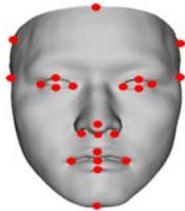


Fig. 1 Control points

2) Global Alignment into a reference face shape scan data using Procrustes Analysis

3D face scan data can have different scale and orientation about the given 3D coordinates. Fig. 2 shows this case where 2 overlaid 3D face scan data is displayed in 2D images with different colors. In Fig. 2(a), transparency is not applied and the below image is blocked by the above image and not shown while the below image is transparently shown in Fig. 2 (b).

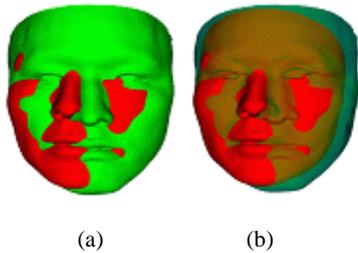


Fig. 2 Two 3D face scan data with different size and orientation

One can see in Fig. 2(a) that two 3D face scan data have different orientation and scale by noting that noses of two faces scan data head toward different directions.

To resolve the 3D correspondence among all 3D face scan data effectively, one needs to render all 3D face scan data have similar global shapes with similar scale and orientation and the same origin. Thus, after a reference 3D face is selected, all other 3D face scan data need to be aligned globally into the reference so that all 3D scan data have similar global shapes. Global alignment needs scaling, rotation and translation of 3D scan data. In this paper, we applied 3D Procrustes analysis to achieve global alignment. Fig. 3 shows the result of global alignment after Procrustes analysis is applied.

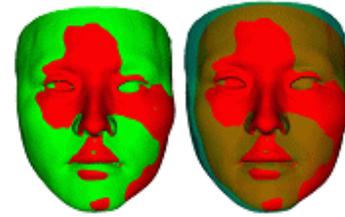


Fig. 3 Comparisons of two scan data after Procrustes analysis

One can see that two 3D face scan data have now similar scale and orientation after Procrustes analysis is applied.

3) Local Alignment into a reference face shape scan data using 3D TPS

Even though a sample 3D face scan data is similar to the reference 3D face scan data in global shape, it may still have differences in local shape like around eyes, mouth and nose (See Fig. 3).

In this case, if one tries to determine a corresponding point by locating a nearest point to a point in the reference 3D scan data, one may have erroneous corresponding points since two 3D face scan data may have significantly different local shape. Thus, before starting to locate a nearest point, one may also need to align the sample 3D face scan data locally as close as possible to the reference 3D face data.

In this paper, we applied 3D TPS for aligning a sample face scan data into the reference face scan data locally as follows.

Suppose the set of  $n$  (control) points of a sample face and that of the reference face are  $Q = \{Q_1, Q_2, \dots, Q_n\}$  and  $P = \{P_1, P_2, \dots, P_n\}$ . Now, one can map each vertex of the sample 3D face scan data into a vertex in the reference 3D face scan data by defining a vector function  $\mathbf{f}$  called Thin Plate Spline function with  $\mathbf{f}(P_i) = Q_i$  for all  $i = 1, 2, \dots, n$  as follows:

$$\mathbf{f}(O) = \sum_{i=1}^n \omega_i U(\|O - P_i\|) + \mathbf{a}_0 + \mathbf{a}_1 x + \mathbf{a}_2 y + \mathbf{a}_3 z \quad (2)$$

where  $\omega_i, \mathbf{a}_0, \mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3$  are weighting vectors,  $O$  and  $P_i$  are 3-dimensional points denoted as  $O = (x, y, z)^T, P_i = (x_i, y_i, z_i)^T$ , and  $U(r) = |r|^3$ . Weighting vectors  $\omega_i$  should satisfy the following constraints.

$$\sum_{i=1}^n \omega_i = 0, \sum_{i=1}^n \omega_i x_i = 0, \sum_{i=1}^n \omega_i y_i = 0, \sum_{i=1}^n \omega_i z_i = 0 \quad (3)$$

With the constraints (2) and  $\mathbf{f}(P_i) = Q_i$  for  $i = 1, 2, \dots, n$ , it can be shown that  $\omega_i, \mathbf{a}_0, \mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3$  satisfy the following linear relation

$$\begin{bmatrix} K & P \\ P^T & 0 \end{bmatrix} \begin{bmatrix} \omega^\alpha \\ \mathbf{a}^\alpha \end{bmatrix} = \begin{bmatrix} Q^\alpha \\ 0 \end{bmatrix} \quad (\alpha = x, y, z) \quad (4)$$

where  $K$  is a  $n \times n$  matrix with  $K_{ij} = U(\|(x_i, y_i, z_i) - (x_j, y_j, z_j)\|)$ ,  $P$  is a  $n \times 4$  matrix whose  $i$ -th row is represented as  $(1, x_i, y_i, z_i)$ . Also,  $\omega^\alpha$  is such that  $\omega^\alpha = (\omega_1^\alpha, \omega_2^\alpha, \dots, \omega_n^\alpha)^T$  where  $\omega_i^\alpha$  represents  $\alpha$  ( $\alpha = x$  or  $y$  or  $z$ ) coordinate of  $\omega_i$ .

Then, weighting vectors  $\omega_i$ ,  $\mathbf{a}_0, \mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3$  is obtained by solving equation (4).

Fig. 4 shows the result of local alignment using the 3D TPS function (2).



Fig. 4 Two faces scan data after TPS

If one compares Fig. 4 with Fig. 3, one can see two 3D face scan data in Fig. 4 are aligned more closely even in local shape.

#### 4) Search of Corresponding nearest points

Now, one searches the corresponding nearest points on the aligned sample face scan data for each vertex on the reference face scan data using ICP. If the distance between the two points is within the threshold, then one determines the closest point as the corresponding point, and if not, discard the closest point.

#### 5) Localization of the corresponding points in the original 3D face scan data

Since the corresponding points found in 4) are transformed by TPS, the corresponding points in the globally aligned scan data are localized using the inverse TPS.

### IV. 3D FACE MORPHABLE MODEL

We can now construct a 3D morphable face shape model (1) by applying PCA to the several 3D scan face data consisting of corresponding points.

In this paper, for the construction of 3D dense morphable face shape model, we use 40 persons' 3D face scan data captured by Cyberware Model 3030 Color Scanhead[13]. 40 people consist of man and woman of ages from 20's through 50's. The laser scans provide head structure data in a cylindrical representation, with radii of surface points sampled at 512 equally-spaced angles, and at 512 equally spaced vertical steps. All faces are scanned without cosmetics, accessories. All 3D face scan data have different number of vertices from 81,134 points through 598,121 points. Fig. 5 shows some examples of 3D scan face data after preprocessing (removing ears and hairs) for the construction of 3D face shape model in this paper. Hair and ears are cut from the face scan data.



Fig. 5 Some face scan data

After we apply 3D dense correspondence procedures in Section III, we obtain aligned 40 face shape vector, each of which has approximately 40,000 points.

For these 40 aligned shape vectors  $F_1, F_1, \dots, F_m$  ( $m = 40$ ), we first seek a mean face shape,  $\bar{S} = (F_1 + F_2 + \dots + F_m) / m$ . Now, for scan data matrix  $A = (A_1, A_2, \dots, A_m)$  where  $A_i = F_i$  ( $i = 1, \dots, m$ ), let's seek principal modes  $S_1, S_2, \dots, S_{m-1}$  ( $m = 40$ ) from the covariance matrix  $C$  by applying PCA analysis to covariance matrix  $C = \frac{1}{m} AA^T$ . Then, we can represent a 3D sample face scan vector  $S$  as follows.

$$S = \bar{S} + \sum_{i=1}^{m-1} \alpha_i S_i$$

Fig. 6 shows the result of the 3D dense correspondence procedures developed in this paper. One can see very close similarity between the original face scan data and face scan data consisting of the corresponding points only, which shows the proposed correspondence algorithm works well.



Fig. 6 Comparison between original face scan data (above) and face scan data consisting of the corresponding points only (below)

## V. CONCLUSION

Realistic 3D face modeling requires construction of realistic 3D face shape model. For construction of a realistic 3D face shape model, 3D dense correspondence problem should be resolved.

In this paper, we proposed an easy and fast way to solve 3D face dense correspondence for 3D dense face shape modeling. The proposed algorithm does not need texture information which the optical flow based 3D dense correspondence algorithm needs but is sensitive to. Also, the proposed algorithm utilizes 3D TPS so that it reduces error due to distortion coming from using 2D TPS on the projection representation in cylindrical coordinates of the 3D face scan data. Through construction procedures, we found the proposed algorithm constructs a realistic 3D face morphable model reliably and fast.

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## REFERENCES

- [1] W. Zhao and R. Chellappa, *Face Processing: Advanced Modeling and Methods*, Elsevier, 2005.
- [2] Y. Lee, D. Terzopoulos, K. Waters, "Realistic Modeling for Facial Animation", *Proc. SIGGRAPH*, Los Angeles, pp.55-61, August, 1995.
- [3] F. I. Parke and K. Waters, "Appendix 1: Three-dimensional muscle model facial animation", *Computer Facial Animation*, A.K. Peters, Sept. 1996.
- [4] F. Pighin, J. Hecker, D. Lischinski, R. Szeliski, and D. H. Salesin, "Synthesizing realistic facial expressions from photographs", In *Computer Graphics, Annual Conference Series, SIGGRAPH*, pp75-84, July, 1998.
- [5] V. Blanz, T. Vetter, "A Morphable Model for the Synthesis of 3D Faces", *Proc. of the SIGGRAPH'99*, August 1999, Los Angeles, USA, pp.187-194, 1999.
- [6] J. Ahlberg, "CANDIDE-3 -- an updated parameterized face", Report No. LiTH-ISY -R-2326, Dept. of Electrical Engineering, Linköping University, Sweden, 2001.
- [7] R. L. Hsu, A. K. Jain, "Face Modeling for Recognition", *Proc. Int'l Conf. Image Processing (ICIP)*, Vol.2, pp.693-696, 2001.
- [8] A. Ansari and M. Abdel-Mottaleb, "3-D Face Modeling Using Two Views and a Generic Face Model with Application to 3-D Face Recognition", *IEEE Conf. on Advanced Video and Signal Based Surveillance*, pp.203-222, 2003.
- [9] Y. Hu, D. Jiang, S. Yan, L. Zhang, H. zhang, "Automatic 3D reconstruction for face recognition", *Proc. 6th IEEE Int'l Conf. on Automatic Face and Gesture Recognition*, pp.843-848, 2004.
- [10] H. Guo, J. Jiang and L. Zhang, "Building a 3D morphable face model by using thin plate splines for face reconstruction", *LNCS Vol. 3338*, pp.258-267, 2004.
- [11] Z. Zhang, Z. Liu, D. Adler, M. F. Cohen, E. Hanson, and Y. Shan, "Robust and Rapid Generation of Animated Faces from Video Images: A Model-Based Modeling Approach", *International Journal of Computer Vision*, Vol.58, No.2, pp.93-119, June 2004.
- [12] T. Russ, C. Boehnen, T. Peters, "3D Face Recognition Using 3D Alignment for PCA", *IEEE Conf. on Computer Vision and Pattern Recognition*, Vol.2, pp.1391-1398, 2006.
- [13] Cyberware, <http://www.cyberware.com/>
- [14] M. B. Stegmann, Mikkel B., Gomez, David Delgado: *A Brief Introduction to Statistical Shape Analysis* Technical University of Denmark, Lyngby, 2002.
- [15] Besl, P. and McKay, N. "A Method for Registration of 3-D Shapes", *Trans. PAMI*, Vol. 14, No. 2, 1992.
- [16] S. Rusinkewicz and M. Levoy, "Efficient Variants of the ICP Algorithm", *Third International Conference on 3D Digital Imaging and Modeling*, pp.145-152, June, 2001.
- [17] B. Brown and S. Rusinkewicz. "Non-Rigid Range-Scan Alignment Using Thin-Plate Splines", *Symposium on 3D Data Processing. Visualization and Transmission*, Vol.6, No.9, pp.759-765, September 2004.
- [18] F. L. Bookstein., "Principal warps: Thin-plate splines and the decomposition of deformations", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol.11, No.6, 567-585, June 1989.
- [19] C. Brechbuhler, G. Gerig, G., O. Kubler, O.: "Parameterization of Closed Surfaces for 3-D Shape Description", *Comp. Vision and Image Understanding*, Vol.61, Issue.2, pp.154-170. 1995.
- [20] R. Davies, C. Twining, T. Cootes, J. Waterton, and C. Taylor. "A minimum description length approach to statistical shape modeling", *IEEE Transactions on Medical Imaging*, Vol.5, Issue.5, pp.525-537, May 2002.