

A STATISTICAL SHAPE MODEL FOR DEFORMABLE SURFACE REGISTRATION

Wei Quan, Bogdan J. Matuszewski and Lik-Kwan Shark
*Applied Digital Signal and Image Processing (ADSIP) Research Centre
University of Central Lancashire, Preston PR1 2HE, United Kingdom
{wquan, bmatuszewski1, lshark}@uclan.ac.uk*

Keywords: Deformable Registration, Surface Matching, Shape Modelling and Face Articulation.

Abstract: This short paper presents a deformable surface registration scheme which is based on the statistical shape modelling technique. The method consists of two major processing stages, model building and model fitting. A statistical shape model is first built using a set of training data. Then the model is deformed and matched to the new data by a modified iterative closest point (ICP) registration process. The proposed method is tested on real 3-D facial data from BU-3DFE database. It is shown that proposed method can achieve a reasonable result on surface registration, and can be used for patient position monitoring in radiation therapy and potentially can be used for monitoring of the radiation therapy progress for head and neck patients by analysis of facial articulation.

1 INTRODUCTION

The registration of 3-D surfaces can be considered as a subset of the general image registration problem as surveyed by Maintz and Viergever (Maintz and Viergever, 1998), and has been for many years of great interest to computer vision community (Audette et al., 2000). Its applications include biomedical modelling (Vrtovec et al., 2004), automated segmentation of medical images (Lamecker et al., 2003), integrating multiple range scans into a 3-D model (Hahnel et al., 2003), visual navigation (Zhang, 1994) and recognition of objects from database (Lu et al., 2006), etc. In general, surface registration can be partitioned into three major components: choice of transformation model, similarity measure, and optimization method.

The first component concerns the assumptions made about the relation between the surfaces which need to be registered. Transformation models can be roughly classified into two categories, rigid and deformable. A general rigid transformation can be expressed as a superposition of rotation and translation. Deformable transformation could be similarity, affine, perspective, B-spline, radial basis function, etc (Audette et al., 2000). The second component determines what type of characteristic needs to be extracted from 3-D surfaces. Generally,

the spectrum of surface characteristics includes landmarks, curves, regions, and dense point sets. Landmarks are well-localised, sparse loci of important geometric significance (Thirion, 1994). Landmarks are frequently determined using computed surface curvatures or are selected manually. Curve features typically consist of differential structures which are usually extracted from ridges or boundaries between two different regions in the surfaces (Maintz et al., 1996). Region features are defined by the areas processing some homogeneous characteristics, such as consistent curvature signs (Toriwaki and Yokoi, 1988). Dense point sets are the feature which constitutes all or significant subset of all available surface points (Besl and McKay, 1992). The third component is about finding parameters of the transformation which could maximise the similarity measure. This usually includes the search for the correspondence of surface characteristics which are used for measuring the similarity of surfaces. Some frequently used methods are the random sample consensus (RANSAC) (Chen et al., 1999), expectation maximization (EM) (Granger et al., 2001), various ICP algorithms (Hahnel et al., 2003), etc.

In this paper, a novel method for deformable surface registration is proposed based on the authors' previous work (Quan et al., 2009), which uses the statistical shape modelling technique to

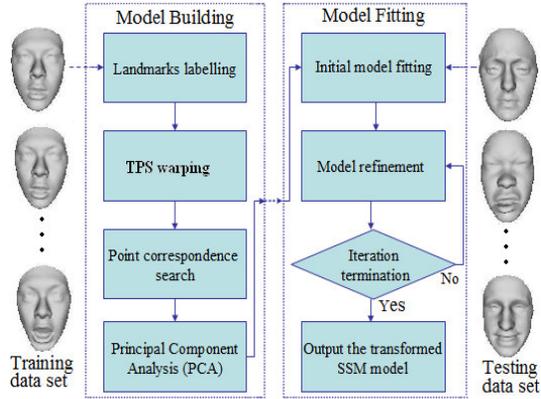


Figure 1: A general framework of proposed surface registration method.

achieve the deformable registration. The whole registration contains two main processing stages: model building and model fitting, as illustrated in Figure 1. In the model building stage, all data in the training set are aligned together. Subsequently the correspondences of point between each training data are established, and a statistical shape model (SSM) is constructed by applying the principal component analysis (PCA) technique. In the model fitting stage, the built SSM is roughly aligned with the new data followed by the iterative model refinement using a modified ICP algorithm. The proposed method is applied to facial surfaces in BU-3DFE database (Yin et al., 2006) that are captured from real persons. This can be considered as an assessment tool for facial articulation. Authors believe that it can be used for monitoring the progress of radiation therapy for head and neck patients on a daily bases.

The remainder of this paper is organised as follows. Section 2 describes details of construction of the SSM. Section 3 explains the procedure of model fitting process. Finally, concluding remarks are given in Section 4.

2 MODEL BUILDING

The SSM is developed based on the point distribution model (PDM) which was first proposed by Cootes et al. (Cootes et al., 1995), and it is one of the most widely used techniques for data registration. Building a statistical shape model is the first processing stage of the proposed surface registration method, which involves two phrases of calculation, estimating dense point correspondence

and PCA. In the following subsections, the model building is generally introduced.

2.1 Estimating Point Correspondence

The knowledge of the dense point correspondence between data in the training set is essential, since the incorrect correspondence can either introduce too much variation or illegal instance of the model. In this work, the estimation of correspondence is achieved in three steps: (i) landmarks determination, (ii) thin-plate spline (TPS) warping, and (iii) closet point matching. The first step is to identify the corresponding landmarks on the selected reference data and other training data. The second step is to warp the reference data to different training data using TPS transformation that is calculated based on the selected landmarks as control points. The last step is to estimate the point correspondence between warped reference data and different training data based on the closest distance metric. Figure 2 shows the framework of computing the dense point correspondences for all training data.

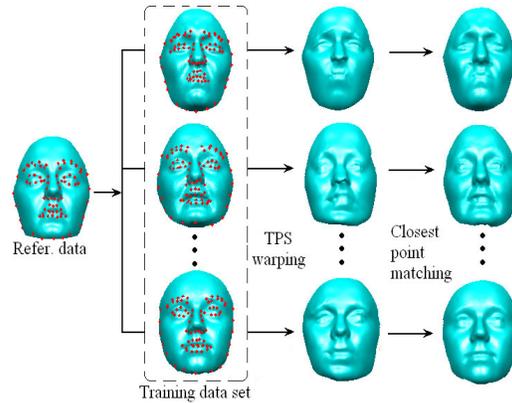


Figure 2: Framework of point correspondence estimation for the training data set.

2.2 Principal Component Analysis

Having the estimated point correspondences for all training data, a statistical shape model can be built using standard PCA, and approximately represented using a linear model of the form

$$\hat{\mathbf{Q}} = \mathbf{W}\mathbf{b} + \bar{\mathbf{Q}} \quad (1)$$

where $\bar{\mathbf{Q}}$ is the mean vector of all training data, $\mathbf{W} = [\mathbf{u}_1, \dots, \mathbf{u}_K]$ is a so called ‘‘Shape Matrix’’ of

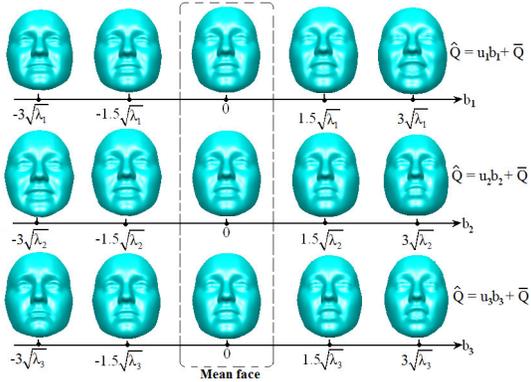


Figure 3: From top to bottom: superposition of the mean vector and weighted first three principal components. In each case the principal component weights vary between $\pm 3\sqrt{\lambda_i}$.

K eigenvectors which correspond to the K largest eigenvalues, and $\mathbf{b} = [b_1, \dots, b_K]$ is the shape space vectors (SSV) which controls the contribution of each eigenvector that are calculated by PCA, in the approximated surface $\hat{\mathbf{Q}}$. The details of PCA deduction can be found in (Quan et al., 2009). Figure 3 shows the effect of varying the first three largest principal component of the SSM which is built using 450 training data from BU-3DFE database.

3 MODEL FITTING

Model fitting is an iterative surface matching process which includes the estimation of both pose and shape parameters of the built SSM. Whilst the pose parameters contain a translation vector, a rotation matrix and a scaling factor, the shape parameters are defined by the SSV. As described in the following subsections, the algorithm starts by aligning a new data with the mean vector of SSM using similarity transformation. Subsequently the model continues to be refined by iteratively estimating the SSV and pose parameters.

3.1 Initial Alignment

The purpose of initial alignment is to generally match the SSM to the new data without deforming itself. The ICP scheme (Besl and McKay, 1992) and similarity transformation are used together to achieve the alignment, which iteratively refine the

alignment by alternatively estimating point correspondence and finding the best similarity transformation that minimises a cost function between the corresponding points. In this work the cost function is defined using Euclidean distance

$$E = \sum_{i=1}^N \left\| \mathbf{q}_i' - (s\mathbf{R}\mathbf{q}_i + \mathbf{t}) \right\|^2 \quad (2)$$

where \mathbf{q}_i' and $\mathbf{q}_i (i=1, \dots, N)$ are respectively the corresponding points from the model and the new data. \mathbf{R} is a rotation matrix, \mathbf{t} is a translation vector and s is a scaling factor. They can be calculated directly following the algorithm in (Umeyama, 1991). Figure 4 shows some intermediate results obtained during the initial alignment.

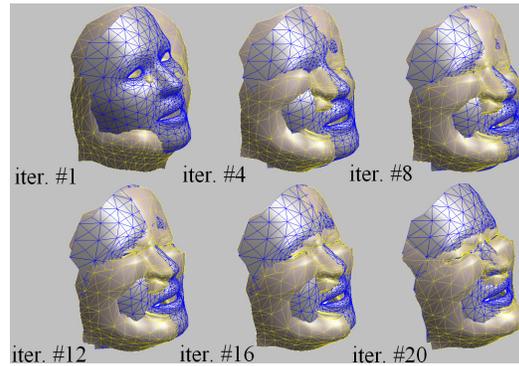


Figure 4: Some intermediate results obtained during the initial alignment.

3.2 Model Refinement

The objective of the model refinement is to deform the model so that it is better matched to the new data after the initial alignment. This requires for a further optimisation of the pose parameters as well as the shape parameters, which can be seen as a superposition of the ICP method and the least squares projection onto the shape space. The least squares projection onto the shape space provides the SSV, $\hat{\mathbf{b}}$, which controls the deformations of the model. The SSV, $\hat{\mathbf{b}}$, for an new data is calculated from

$$\hat{\mathbf{b}} = \mathbf{W}^T (\mathbf{Q}_c + \bar{\mathbf{Q}}) \quad (3)$$

where $\mathbf{Q}_c \in R^{3N}$ is a vector which contains corresponding points representing the new data. The mean vector of all training data $\bar{\mathbf{Q}}$ and shape matrix \mathbf{W} are computed through the PCA as shown in Equation 1.

From Equation 3, it can be seen that the size (dimension) of SSV is fixed during iterations of model refinement. Using the fixed size of SSV can usually provide a reasonable final result of refinement if a good initial alignment is achieved. Otherwise, it may mislead the minimization of the cost function for the model refinement towards a local minimum, i.e., approximating to an inappropriate shape. This is because when a large size of SSV is used, the model will have high degree of freedom for generating shapes, but with an incorrect initial alignment this freedom can make the model approximate to an incorrect arbitrary shape, which leads to a failure result of the refinement eventually. On the other hand, although a model with the small size of SSV has low degree of freedom, which constrains the deformation capability of the model and prevents it from generating an arbitrary shape, it also limits the model to evolve to the right shape. Figure 5 shows some failure examples of refinement in which the sizes of SSV used are fixed.

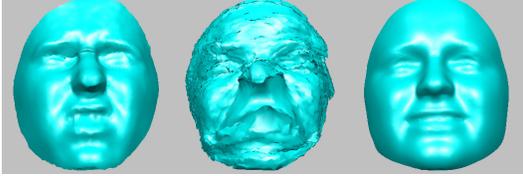


Figure 5: From left to right: new data, corresponding SSM using fixed large size of SSV, and corresponding SSM using fixed small size of SSV.

In order to solve the problem caused by the fixed size of SSV, the authors proposed a model refinement process using a SSV with the adaptive size in this work, and the Equation 3 needs to be rewritten as

$$\hat{\mathbf{b}}_k = \mathbf{W}_k^T (\mathbf{Q}_c + \bar{\mathbf{Q}}) \quad (4)$$

where $\hat{\mathbf{b}}_k$ is the SSV with the adaptive size, and \mathbf{W}_k is the corresponding shape matrix estimated separately for each k . k indicates level of the refinement. In the beginning of the refinement SSV has a small size. Although the registration error can be very big at this stage, the algorithm is able to provide rough approximation of the data. When the

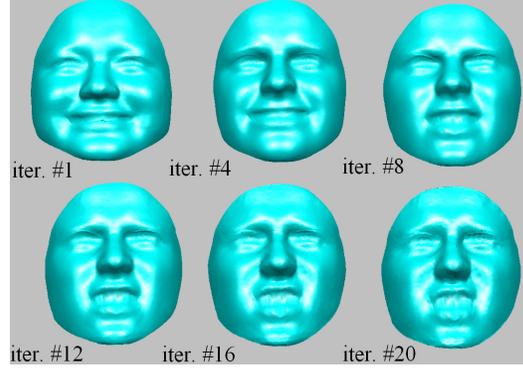


Figure 6: Example of intermediate results obtained during iteration of the model refinement. The new data which needs to be matched is shown in Figure 5.

registration error is decreased, the size of SSV will be gradually increased, which provides more shape flexibility and allows the model to match the data. Parts of intermediate results of the model refinement are shown in Figure 6. In the figure, it can be seen that using the SSV with the adaptive size the model refinement is able to provide a smooth transition during the iterations and eventually deform the model to the right shape even in the case that the result of initial alignment is not very good.

4 CONCLUSIONS

This paper describes a novel deformable surface registration method which uses statistical shape modelling technique and the modified ICP scheme. In order to avoid the local minima of the cost function of the model refinement process, a SSV with the adaptive size is proposed which enables the SSM eventually converge to the right shape even if the initial alignment does not provide a reasonable result. The proposed method is successfully applied to the real facial data from BU-3DFE database, and it can model well with different facial shape across genders, races or expressions. This suggests that the proposed method can be potentially used for some associated medical applications, such as the quantification of 3D face articulation for early predication and assessment of facial dysfunctions or the progress monitoring of radiation therapy for head and neck patients.

ACKNOWLEDGEMENTS

The work presented in this paper has been supported from the MEGURATH and the TERAFAFS projects (EPSRC Project No.EP/D077540/1, EP/H024913/1)

REFERENCES

- Audette M F. P., A., Ferrie Peters T. M., 2000. *An algorithm overview of surface registration techniques for medical imaging*, *Medical Image Analysis*, Vol. 4, 201-217. Elsevier science.
- Besl P. J., McKay N. D., 1992. *A method for registration of 3-D shapes*, *IEEE Trans. PAMI*, vol. 14(2), 239-256.
- Chen C. S., Huang Y. P., Cheng J. B., 1999. *Ransac-based darces: a new approach to fast automatic registration of partially overlapping range images*, *IEEE Trans. PAMI*, vol. 21(11), 1229-1234.
- Cootes T. F., Taylor C. J., Cooper D. H., Graham J., 1995. *Active shape models – their training and application*, *Computer Vision and Image Understanding*, vol. 61(1), 38-59.
- Granger S., Pennec X., Roche A., 2001. *Rigid point surface registration using an EM variant of ICP for computer guided oral implantology*, *Medical Image Computing and Computer-Assisted Intervention*, 752-761.
- Hahnel D., Thrun S., Burgard W., 2003. *An extension of the ICP algorithm for modelling nonrigid objects with mobile robots*, *Proceeding of the International Joint Conference on Artificial Intelligence*, 1-6.
- Lamecker H., Lange T., Seebass M., 2004. *Segmentation of the liver using a 3D statistical shape model*, *ZIB-Report 04-09*.
- Lu X., Jain A., Colbry D., 2006. *Matching 2.5D face scans to 3D models*, *IEEE Trans. PAMI*, vol. 21(12), 1357-1362.
- Maintz J. B. A., Van den Elsen P. A., Viergever M. A., 1996. *Evaluation of ridge seeking operators for multimodality medical image matching*, *IEEE Trans. PAMI*, vol. 18(4), 353-365.
- Maintz J. B. A., Viergever M. A., 1998. *A survey of medical image registration*, *Med. Image Anal.*, vol. 2(1), 1-36.
- Quan W., Matuszewski B. J., Shark L. K., Ait-Boudaoud D., 2009. *Facial expression biometric using statistical shape models*, *EURASIP Journal on Advances in Signal Processing*, vol. 2009.
- Thirion J. P., 1994. *External points: definition and application to 3D image registration*, *Proceeding of Computer Vision and Pattern Recognition*, 587-592.
- Toriwaki F. I., Yokoi S., 1988. *Voroni and related neighbours on digitised two-dimensional space with application to texture analysis*, *Computational Morphology*.
- Umeyama S., 1991. *Least-square estimation of transformation parameters between tow point patterns*, *IEEE Trans. on VCG*, vol. 13(4), 376-380.
- Vrtovec T., Tomazevic D., Likar B., Travnik I., Pernus F., 2004. *Automated construction of 3D statistical shape models*, *Image Anal Stereo*, vol. 23(1), 111-120.
- Yin L., Wei X., Sun Y., Wang J., Rosato M., 2006. *A 3D facial expression database for facial behaviour research*, *International Conference on Automatic Face and Gesture Recognition*, 211-216.
- Zhang Z., 1994. *Iterative point matching for registration of free-form curves and surfaces*, *International Journal of Computer Vision*, Vol. 13(2), 119-152.