Region based User-generated Human Body Scan Registration

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Abstract

We present a region-based registration method to robustly register low-quality human body scans that are acquired with cost-effective devices accessible to general users, like Microsoft Kinect, Structure Sensors et al.

Traditional Iterative Closest Point (ICP) is prone to fall into local minimum when it performs on low-quality scan data.

To address this problem, we learn *prior knowledge* of body shape from publicly available dataset and combine it with ICP algorithm. Sparse annotated markers are used to change pose of template, making it perform in the same way as target scans do. In the registration stage, two groups of statistical shape models are trained: (a) holistic shape model for the basic figure of human and (b) a set of local shape models for describing the details of each body part.

During registration, we fit the holistic model roughly to the target mesh and leave the body shape details for a later step. To capture more body details, we combine local shape models with the non-rigid ICP method to deform the template part-by-part.

Objective

The goal of this paper is to robustly register the low-quality scanning date with a high-quality template.

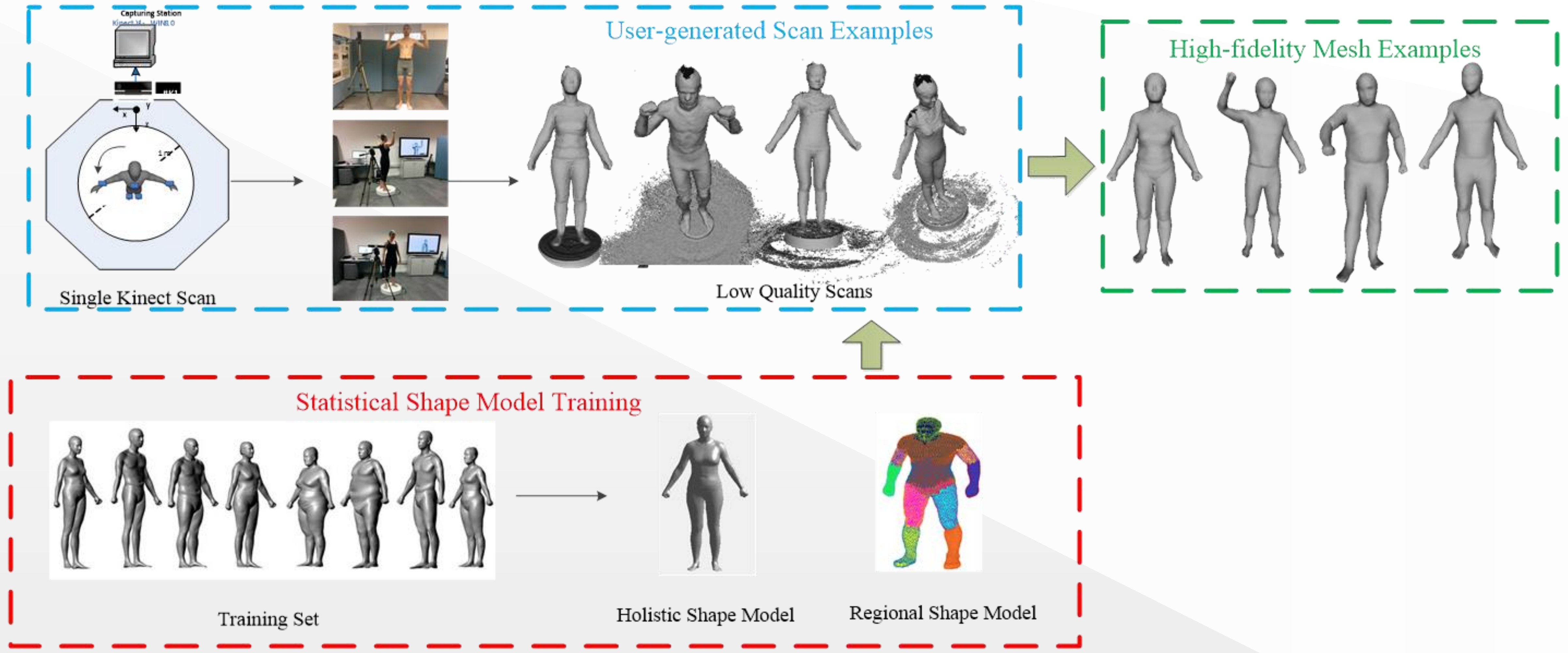
The low-quality data poses challenges to robust registration:

(a) Noises

(b) Holes (Missing data)

(c) Distorted parts

Methods



1. Pose Template:

Given bounded biharmonic weights, linear blending scheme is applied.

$$P' = \sum_{j=1}^{m} w_j(P) T_j P$$

,where w_j is the weight associated with bone j and T_j is the transformation of bone j.

2. Training of Morphable Shape Model:

Principal Component Analysis (PCA) is used to train the holistic and regional shape model:

$$v = Bc + m,$$

where v are the coordinates of all N vertices; B is the eigenvectors of PCA; m is the mean shape and c contains the non-rigid parameters for shape deformation.

3 Registration

3.1 Holistic level registration

With target point clouds u retrieved by NN search, the cost function to be minimized is:

$$E(c) = ||v - u||^2 = ||(Bc + m) - u||^2$$

3.2 Regional level registration

Here, we combine the pre-trained regional shape model for 12 parts with traditional Nonrigid ICP (NICP) to capture the nonrigid nature of body surface and provide an accurate fitted mesh.

Main Body Parts

$$E(X) = E_d(X) + E_s(X)$$

,where $E_d(X)$ is distance term to minimize the Euclidean distance between the source and target; $E_s(X)$ is smooth term; X is the transformation matrix.

Hand Parts

$$E(c^*) = \alpha E_d(c^*) + \beta E_b(c^*)$$

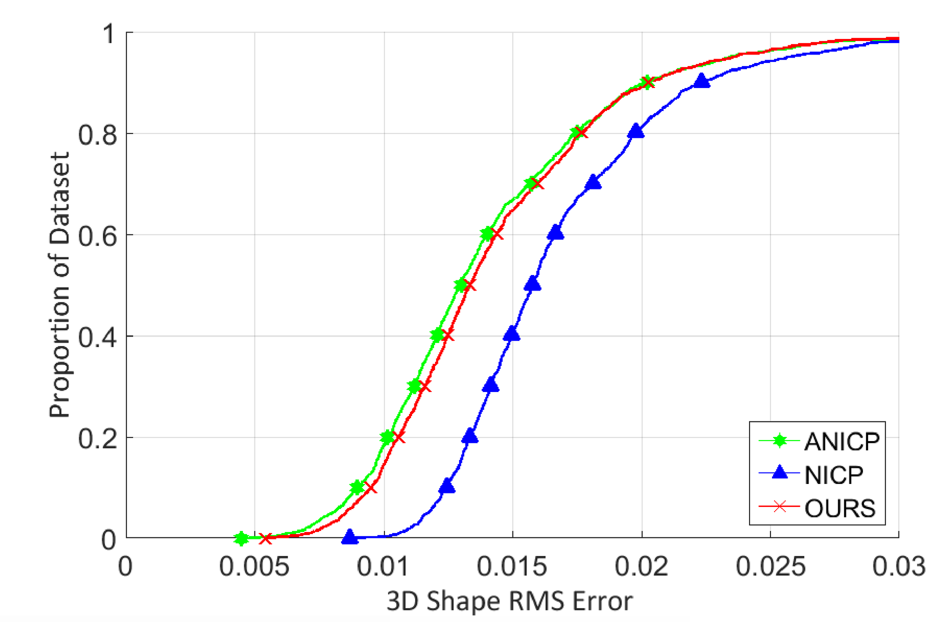
,where $E_d(c^*)$ is the distance term; $E_b(c^*)$ is the boundary tern to ensure the hand parts are connected to the main body part smoothly.

Results

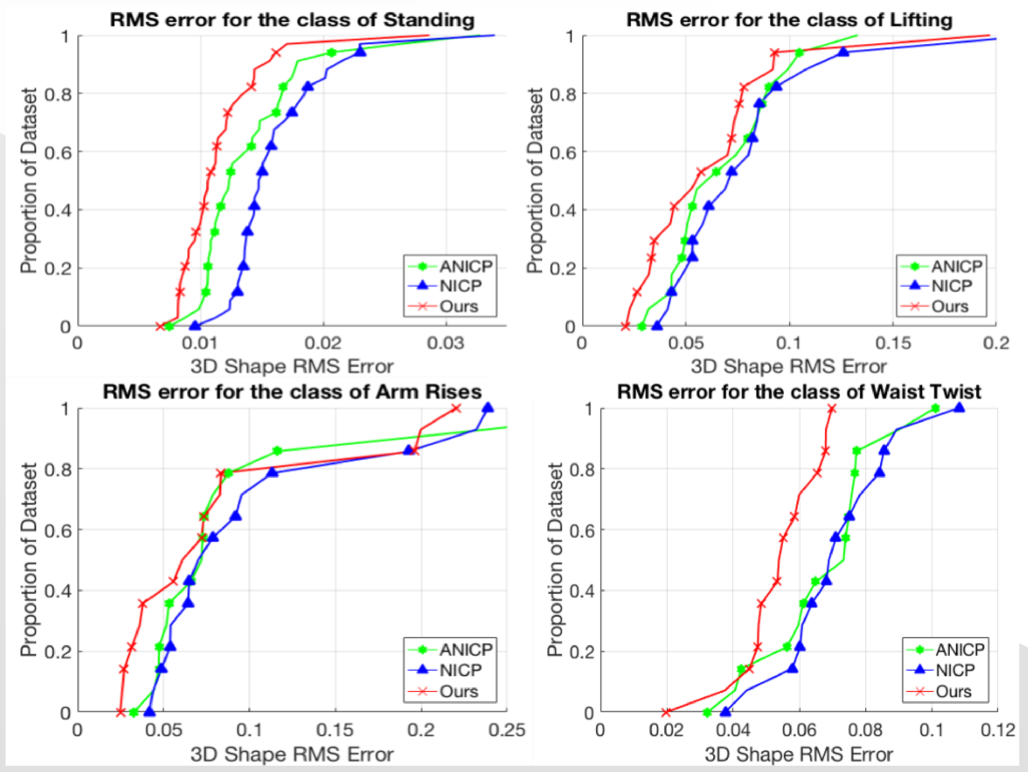
Quantitative Evaluation

Accuracy: RMS error = $\sqrt{\frac{\sum_{i=1}^{n}(p_i - \bar{p_i})^2}{n}}$

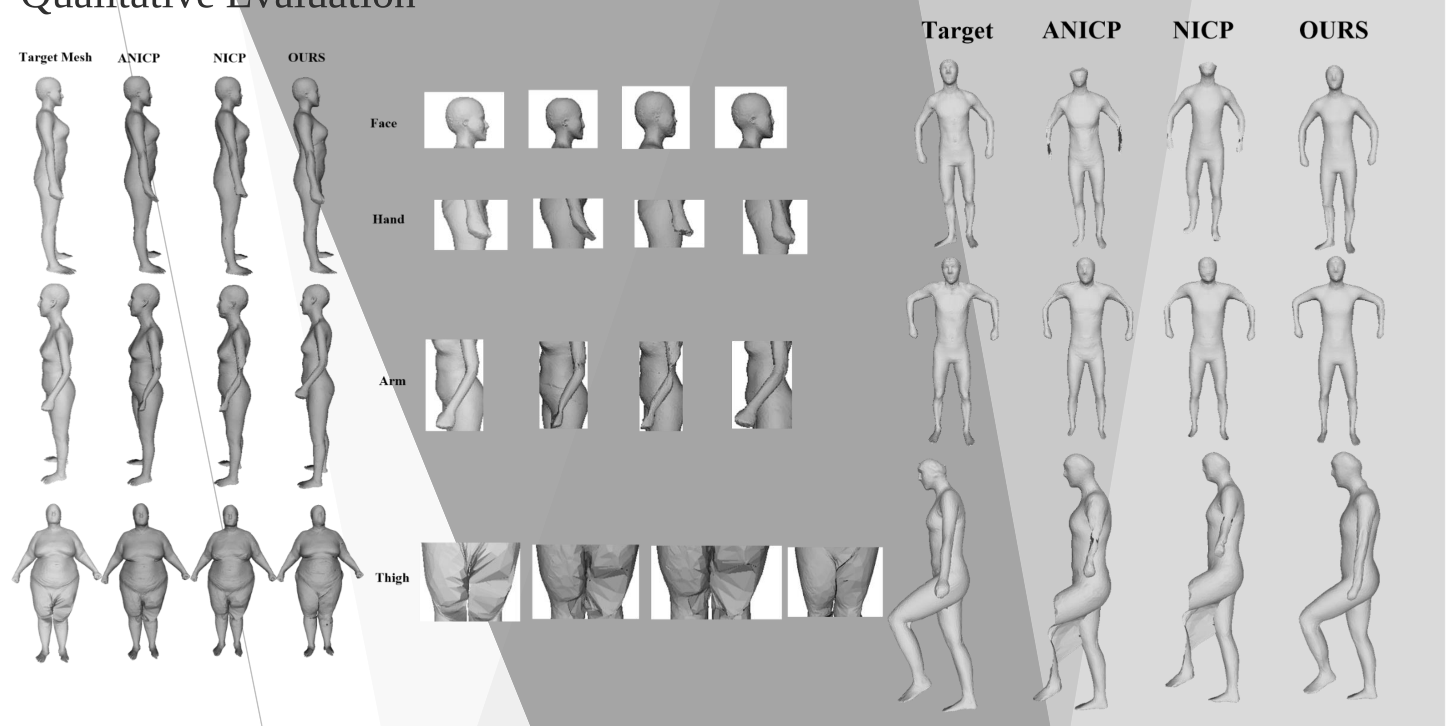
High-quality meshes

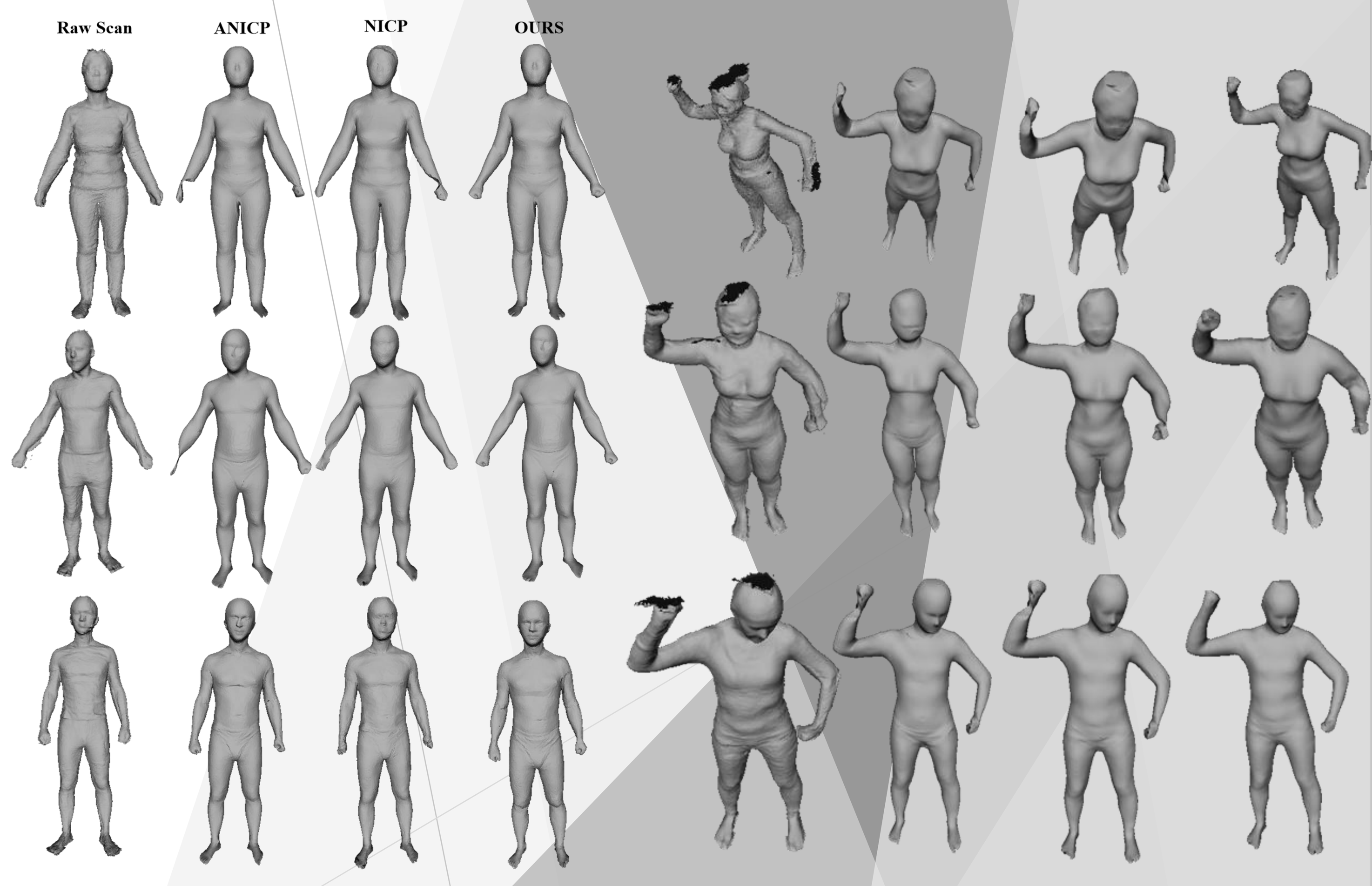


Medium-quality meshes



Qualitative Evaluation





Conclusion

This paper presents a region based human body mesh registration approach which combines the non-rigid ICP with the statistical shape model to fit the body template to user-generated point clouds. Compared with the popular NICP and ANICP, out method takes special care of particular body parts by defining different energy functions. The experiments demonstrate the outperformance of our approach.

References

[1] Amberg, B., Romdhani, S. and Vetter, T., 2007, June. Optimal step nonrigid ICP algorithms for surface registration. In *Computer Vision and Pattern Recognition, 2007. CVPR'07. IEEE Conference on* (pp. 1-8). IEEE.

[2] Cheng, S., Marras, I., Zafeiriou, S. and Pantic, M., 2017. Statistical non-rigid ICP algorithm and its application to 3D face alignment. *Image and Vision Computing*, *58*, pp.3-12.