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Biography

I'm a Ph.D. student at New York University. Before that, I was a research assistant in NYU Multimedia and Visual Computing Lab, advised by Professor Yi Fang. I am broadly interested in 3D Computer Vision, Pattern Recognition and Deep Learning.

M.S. Thesis: An Efficient 3D Global Consistent Shape Correspondence Method for Statistical Shape Modeling

1 Description

Statistical shape models have many applications in medical image processing and 3D computer vision. As shown in Figure.1, automatically finding accurate corresponded landmarks from a set of training shapes is the key issue in constructing statistical shape models. Currently, there are many methods of finding this correspondence such as manual annotation and minimizing descriptor length. In this paper, we propose a global optimization-based algorithm to automatically address this landmark registration problem for 3D cases. Specifically, this approach is able to efficiently identify global consistent shape correspondences from a collection of 3D training samples by formulating it as a low-rank recovery problem with nuclear-norm relaxation for rank minimization. We test our method on 3D mandible data and compared to the state-of-the-art Shape Context Matching method, the evaluation result of our proposed method improves. We find that false matching and missing matching are corrected by our global consistent optimizing method. The 3D model we built has better compactness quantitatively. Hence, higher quality statistical shape models can be constructed based on our method.

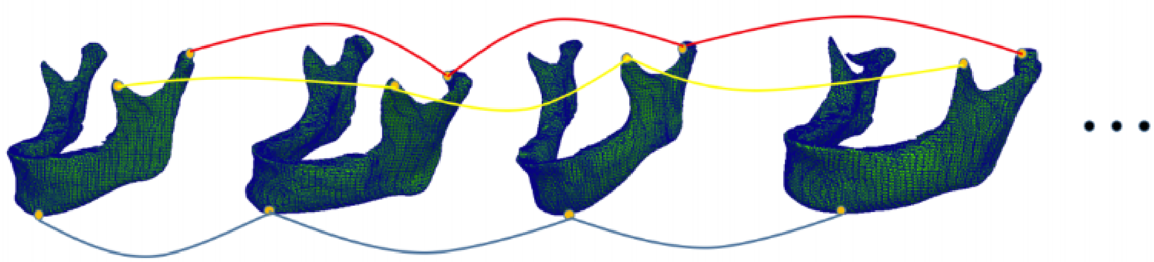

Figure 1: An illustration of point correspondences.

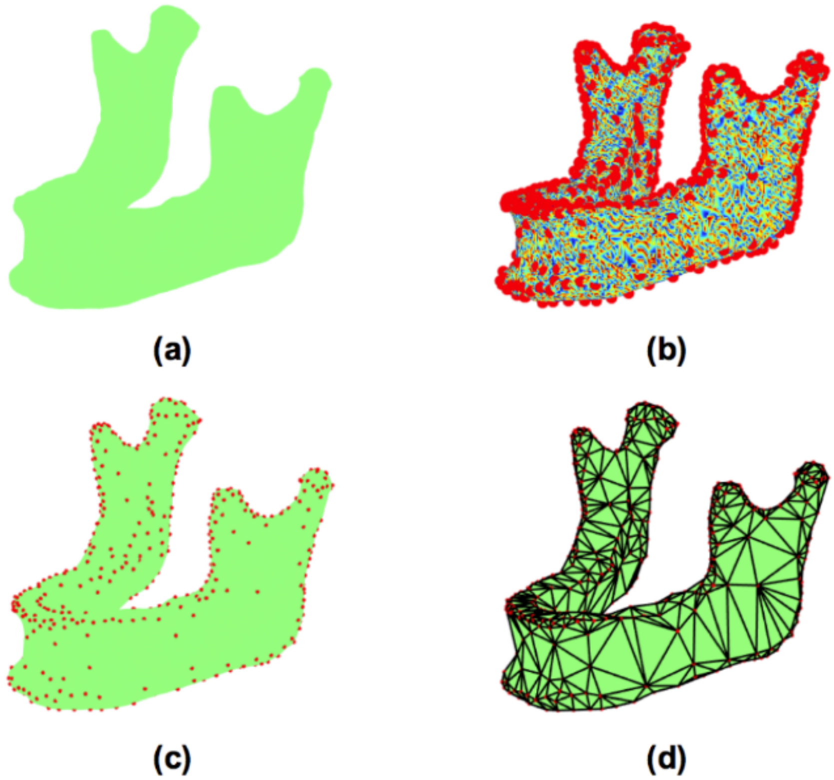

Figure 2: The process of feature sensitive remeshing.

2 Method

In this section, we will introduce our proposed method for 3D registration. Our proposed method consists of four phases:(1)Choose landmark and 3D shape descriptors to represent the surface points of each 3D sample , (2)find the pairwise correspondence based on 3D shape descriptors, (3)match a set of 3D shapes simultaneously via low-rank recovery optimization, and(4) construct 3D statistical shape model. Figure.1 shows the process of feature sensitive remeshing. (a)The original triangle mesh data with 40,736 points. (b)Design a metric that sampling is dense in the region with large curvature. (c)Sampling more points (denoted by red points) in the region with large curvature. (d)The new triangle mesh result with only 500 landmarks. After successfully completing the 3D point registration, we can use the point correspondence result to build 3D active shape model(ASM). 3D ASM is a 3D statistical model which can deform to fit the 3D training data. We will use the well-corresponded training data from multiple matching to construct 3D active shape model.

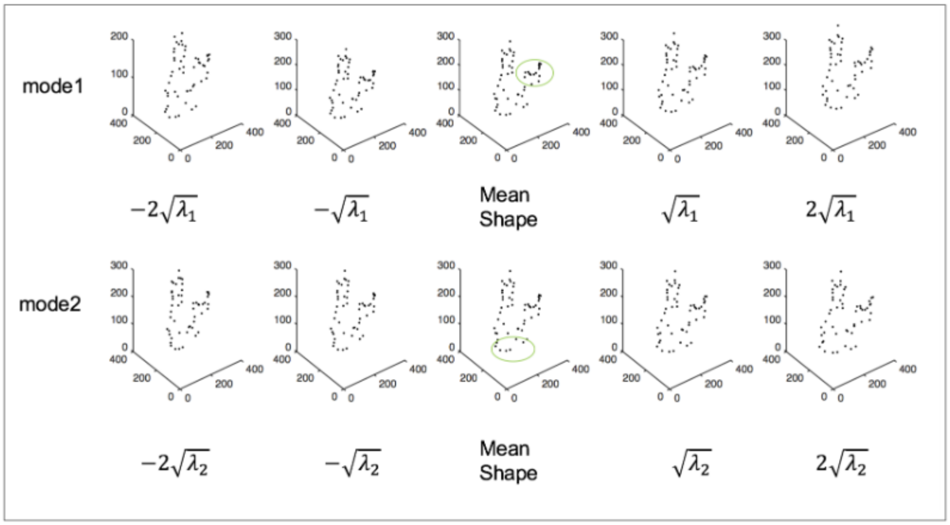

Figure 3: Plausible shapes generated after Multiple Shape Matching refining.

3 Results

In this project, we use the the 3D mandibular dat. It is a small canal inside the mandible. People with different ages and genders own different sizes and shapes of mandible. These 3D data obtained from cone beam computed tomography (CBCT) are 400x400x352 matrices at first. We need to find the surface data based on the four steps of our proposed methods. After the preprocess, we obtain the surface point data with triangulated meshes. As displayed in Figure.3, our method shows great improvement in terms of the quality of generated plausible shapes. Shapes generated by Shape Context Matching are inconsistent and many points of them does not lie on edge of hands. Shapes in Figure.3 are more similar to hands contour edges in plausible variations from the mean shape. The global multiple shape matching has greatly improved the quality of ASM.