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A Model Deformation Approach for 3D Reconstruction

Yung-Yang Chiang[1], Min-Liang Wang[1,2], Huei-Yung Lin[1], Pei-Yung Lee[2] and Chin-Chen Chang[3*]

[1]*Department of Electrical Engineering and Advanced Institute of Manufacturing with High-tech Innovations*
National Chung Cheng University, Chiayi 621, Taiwan
[2]*Asian Institute of TeleSurgery*
IRCAD-Taiwan, Changhua County 505, Taiwan
[3]*Department of Computer Science and Information Engineering*
National United University, Miaoli 360, Taiwan
**ccchang@nuu.edu.tw*

Abstract

In this paper, we present a model deformation approach based on a visual hull technique for improving 3D reconstruction. The proposed approach combines the exquisite 3D model derived by active acquisition methods and the constraints from the rough 3D model derived by passive methods. We take the advantages of active and passive methods to obtain a 3D model with the better quality. The clustering method is adopted to segment 3D models into several sub-models and we then match the sub-models individually via an iterative closest point algorithm. Three testing 3D models are used for evaluating the proposed approach. The results demonstrate the feasibility of the proposed approach.

Keywords: *3D reconstruction, model deformation, visual hull, clustering*

1. Introduction

Reconstructing a 3D model of an object is crucial in computer vision. Numerous applications of 3D reconstruction range from industrial inspection to computer graphics and multimedia. Many 3D reconstruction algorithms [21] have been proposed. These approaches are based on some visual cues, such as stereo, motion, shading, silhouette, and so on. For an object, however, not all of the methods can reconstruct a whole 3D model without acquisition, registration and data fusion of multiple range images [22]. For example, stereo vision or shape from shading can only provide the 2.5D range data from a single viewpoint. Multiple images captured from different viewing directions are imperative for 3D reconstruction.

The shape from silhouette method reconstructs a 3D model using the object silhouettes acquired from the surrounding cameras [15]. The whole 3D model is recovered by the intersection of all silhouette cones back-projected from the camera centers. This method can be easily implemented and is also suitable for the reconstruction of moving objects. However, the computed visual hull is generally not a desired geometric approximation of the observed shape. It might be even worse if the number of cameras is reduced or the object contains apparent concave surface shape. Thus, several approaches have been proposed to improve shape from silhouette with more constraints [5, 7, 14, 19].

Similar objects are generally equipped with similar characteristics, even they are formed in different deformation. In this paper, we refer to the concept of human face deformation [4, 12, 18] to adjust 3D models from similar objects. The objective is to

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[*] Corresponding Author

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derive the 3D models with a high degree of similarity. For a non-ideal 3D model, the quality of the 3D model can be improved as much as possible. We present a model deformation approach to enhance the quality of 3D reconstruction. The main purpose of our approach is to solve the general problem of poor quality for the passive method. Our approach is based on the exquisite model from active methods with the constraints based on a rough model from passive methods. The 3D reconstruction by the passive method is based on visual hull, which is easy to use but quite sensitive to camera parameters. To solve the above problems, we propose the method to combine the advantages of active and passive methods.

A flowchart of the proposed approach is shown in Figure 1. For model reconstruction, we use a prior model of an object to be the active 3D reconstruction. In addition, we apply a visual hull technique to reconstruct a target model of an object for the passive 3D reconstruction. For model normalization, we perform a normalization process to reduce the difference between the prior and target models and adjust the global characteristics of the prior and target models. For model segmentation, we segment the target and prior model into several sub-models. For model deformation, the sub-models of the target and prior model are matched. We apply the iterative closest point (ICP) algorithm [3] for processing of the rotation and translation, and the scaling is adjusted in accordance of the model size. For model recovery, the 3D model then becomes the one with more details to achieve as much similar to the reconstructed 3D model under poor image quality.

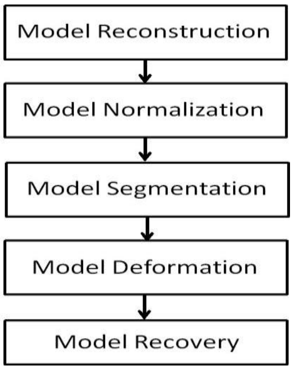


Figure 1. A Flowchart of the Proposed Approach

The rest of this paper is organized as follows. In Section 2, we briefly discuss related works. Section 3 is our approach. Section 4 presents results. Finally, Section 5 is conclusions.

2. Related Works

Li, *et al.*, [16] presented a system combining depth from stereo and visual hull reconstruction. They used the silhouettes from multiple views to construct a visual hull to limit the disparity range during stereo estimation. In addition, they used the constraints imposed by the silhouettes to reduce computation cost. Esteban, *et al.*, [10] proposed an algorithm based on a deformable model for 3D reconstruction from a calibrated sequence of color images. Their approach can reconstruct both the 3D geometry and the texture by defining a texture driven force and a silhouette driven force. Cheung, *et al.*, [7] introduced an algorithm for estimating the shape of a dynamic object by combining the silhouette images of the object. They proposed a one dimensional element called a bounding edge to represent the visual hull. Moreover, they used the geometric constraints to align visual hulls. Franco, *et al.*, [8] utilized the relationship between contact points and viewing edges to approximate the visual shapes under smoothness assumption of the visible surface.

Their approach can identify silhouette shapes different from the visual hull and give a way to estimate such shapes in real-time.

Zeng, *et al.,* [23] proposed a maximum a posterior model for large-scale 3D reconstruction. First, this model can easily incorporate image clustering prior knowledge. Second, they introduced an annealing clustering algorithm for organize large number of images into clusters. Their approach can solve the large-scale 3D reconstruction problem. Kolev, *et al.,* [13] presented an energy model for multiview 3D reconstruction by combining silhouette and stereo information. They also introduced a method to globally optimize the energy model based on the visibility constraint. Their approach can cast multiview 3D reconstruction as a continuous convex optimization problem.

Beall, *et al.,* [2] proposed an algorithm for 3D reconstruction of an underwater object based on stereo images. They used a dense stereo matching technique to find the corresponding points in stereo images. Also, they used a triangulation technique to estimate the depth of images. Geiger, *et al.,* [9] proposed an algorithm to build 3D maps from stereo sequences. They developed a sparse feature matcher combined with a visual odometry algorithm for stereo matching. Their method can achieve certain accuracy and is suitable for online 3D reconstruction. Izadi, *et al.,* [11] presented a 3D reconstruction system called KinectFusion. In this system, a user can hold and move a Kinect camera to generate 3D reconstructions. They used the depth data from Kinect to track the 3D pose of the sensor and reconstruct 3D models.

3. The Proposed Approach

The five phases of the proposed approach are described below.

3.1. Model Reconstruction

For the model reconstruction, we follow Linsenmaier's method [17] to prepare a prior model for an object which is obtained from an active approach. This prior model is considered to be the active 3D reconstruction. In addition, we apply the visual hull technique to reconstruct the target model of an object [6, 15] for the passive 3D reconstruction [1, 10, 20]. We obtain the object images, extract the contours of the images, and calculate the camera parameters via the camera calibration procedure. Hence, we can obtain a rough target model.

3.2. Model Normalization

After the prior and target models of an object are obtained, we perform a normalization process to reduce the difference between them. A particular issue needs to be overcome is the non-equal system coordinates. First, let the object be bounded by a box. Therefore, the length, width and height for the two models are relatively unified in the center of world coordinates. Then, we rotate the axis of the object by the calculated volume of the cuboid manner to achieve the minimum volume.

According to the aspect ratio of the object, we redefine the axes, such that the longest axis to be x-axis, the second axis to be y-axis, and the last axis to be z-axis. Since the position and orientation for those cuboids are unified, we can resize the target model corresponding to the prior model of the object. Both of the prior and target models would be in the same size. Although the cuboids of both models are similar in certain areas, the direction of the object is still unique. Thus, we adjust the orientation of the target model to generate the four possibilities. Figure 2 shows the initial orientations of the prior (left) and target (right) models. The ICP algorithm is applied to calculate the distance error between the prior and the four possibilities of the target model separately. We adopt the smallest error according to the error magnitude as the initial condition. We perform this process iteratively for several times. In the experiments, the ICP error converges to 0.035.

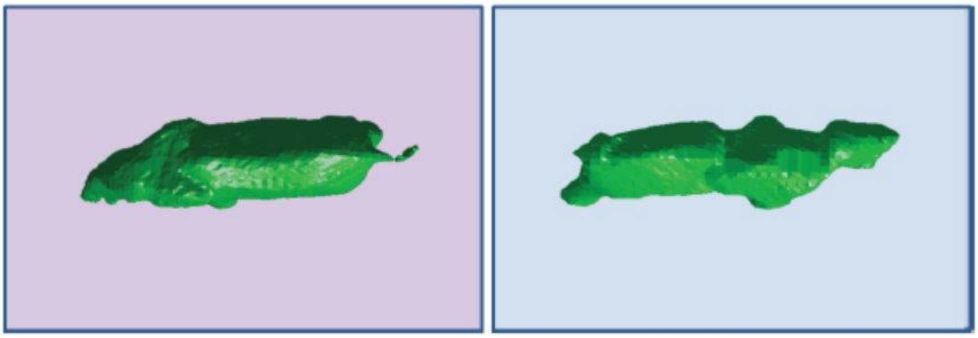


Figure 2. The Initial Orientations of the Prior (Left) and Target (Right) Models

3.3. Model Segmentation

After the model normalization, we segment the target model to several sub-models. We use the hierarchical clustering method and treat the target model as mesh points for data cluster processing. It can distinguish the most different cluster data and classify the most similar 3D points to the same group. The number of clusters is set as 2, due to the most appropriate number of clusters is usually unknown. In addition, the overall model may retain some characteristics and is much easier for further segmentation. After clustering, the result of the target model is shown in Figure 3. Both sub-models usually have an overlapping region in the intersection area. To segment the prior model simultaneously, we use the condition on the clustering results of the target model to decide which axis to segment and use the overlap ratio for both sub-models to calculate the transformation.

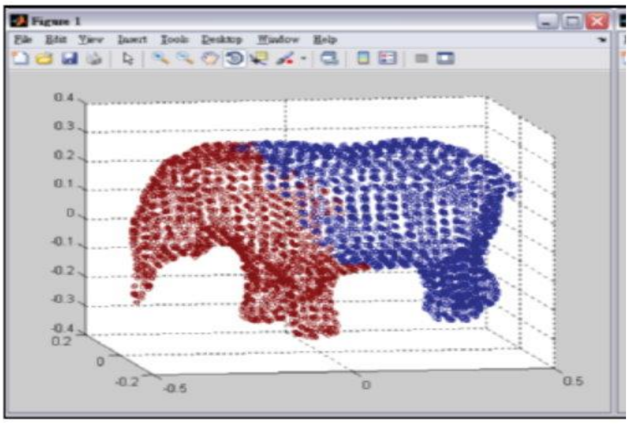


Figure 3. The Clustering Results for a Model

After calculating the overlapping region for each axis, we choose the lowest value as the cutting direction. To narrow the cutting range, we set a constraint on the cutting range inside the intersection between sub-models. Then, we choose the smallest cross-sectional area to be the location for the appropriate points to segment both sub-models. This process is to ensure the integrity of sub-models after segmentation.

Finally, the cutting area is restricted outside the axis, and we choose the smallest sub-model as the limitation for the scope of the model in order to ensure the continuity of the segmentation.

3.4. Model Deformation

After the model segmentation is completed, we match and adjust the corresponding sub-models of the prior and target models separately. Compared to the whole model, these sub-models may be different in position, orientation, and size, *etc*. Generally, these sub-models are close in size after the model normalization. Therefore, we can directly use the ICP algorithm to process the differences on position and orientation for those sub-models. After processing, these sub-models will match in the way of position and orientation gradually. We can then resize the dimension of the sub-models. When calculating the size of those sub-models, it is important to avoid the misjudgment for the size in some cases, for instance, due to noise, redundant and missing areas, and so on.

To avoid the inappropriate scaling for solving the above cases, the noise removal process is introduced by applying the cutting method of the head and tail with the lower noise ratio to the overall noise. The method can remove 10% amounts of grid points at head and tail. In addition, the rest points are used to represent the length of the target model. We calculate the scaling rate from the target and the prior sub-models. However, the scaling rate may contain errors in certain circumstances. For example, if there is redundancy or shortage area inside the model. This case is usually caused by inaccurate camera calibration parameters, and results in bad target model via the visual hull algorithm during cutting the cube. From the observation, most of the above situations occur in the scale ratio of about 10%. Nevertheless, the cutting error does not usually affect to all axes, and the scale ratio of each axis is still in a high correlation. Therefore, we use a scaling ratio from the other axis and restrict the scale range less than 10% for the above cases.

The process of the model deformation is performed for a total of six times, and results in a total of 127 sub-models. As expected, this model is segmented into front-part and rear-part, and then segmented into the body and feet. The feet is further segmented into the left and right foot. Following the process to sequentially conduct the local matching in position, orientation and size respectively. Finally, the ICP error is 0.019, with an error reduction of 45.7%.

3.5. Model Recovery

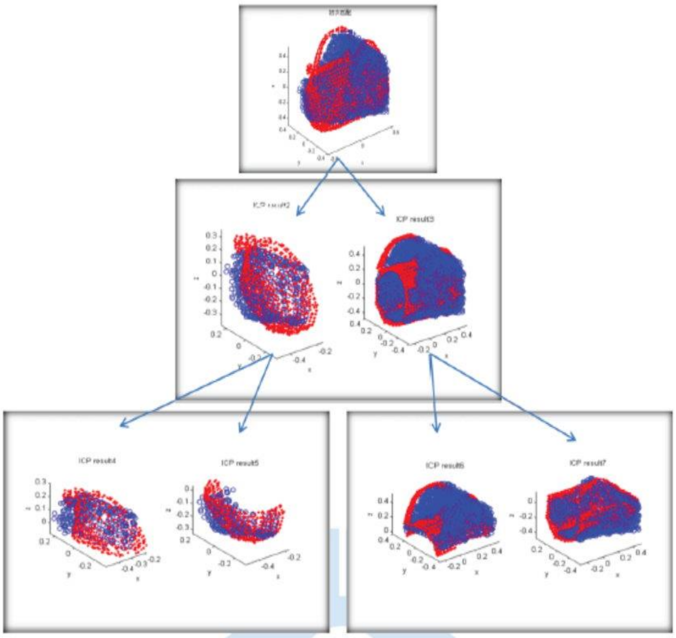
After the model deformation, both of the sub-models would be generated, and the detail of the target model will gradually appear. We can appropriately recover the appearance of an object according to the initial conditions.

4. Results

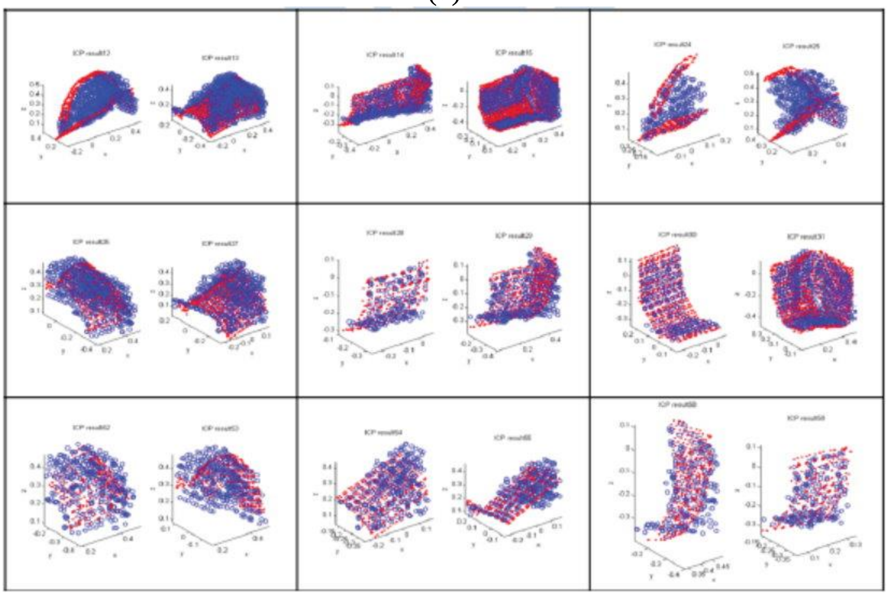
The platform is a PC with an Intel Core i7-2600 CPU and 4.0 GB of memory and the Windows XP. To test the proposed approach in the experiments, a cup, a mouse and a doll are used as the testing objects. An Olympus-4040 camera is used to capture the images with 640 × 480 image resolution.

The process of the model deformation for the cup is shown in Figure 4. In Figure 4(a), the clustering method is adopted to segment the target model into several sub-models; in Figure 4(b), the hierarchical matching method is performed individually via the ICP algorithm. Figure 5 shows (a) the prior model of the cup, (b) the target model of the cup, and (c) the recovery model of the cup. Figure 6 shows the process of the model deformation for the mouse. In Figure 6(a), the clustering method is adopted to segment the target model into several sub-models; in Figure 6(b), the hierarchical matching method is performed individually via the ICP algorithm. Figure 7 shows (a) the prior model of the mouse, (b) the target model of the mouse, and (c) the recovery model of the mouse. The process of the model deformation for the doll is shown in Figure 8. In Figure 8(a), the clustering method is adopted to segment the target model into several sub-models; in Figure 8(b), the hierarchical matching method is performed individually via the ICP algorithm. Figure 9 shows (a) the prior model of the doll, (b) the target model of the doll, and (c) the recovery model of the doll.

From the experimental results, the original cup model is less precise due to less sample images available. After processing, the mug and handle show much more detail. The surface of the original mouse model is non-smooth and flat. Hence, we can recover the smooth and circular surface after processing. The original doll model contains less detail for identification. After processing, the final model is improved with much better quality.

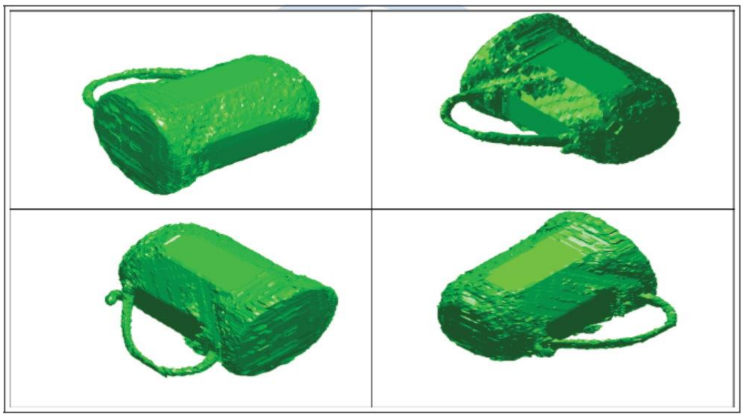


(a)

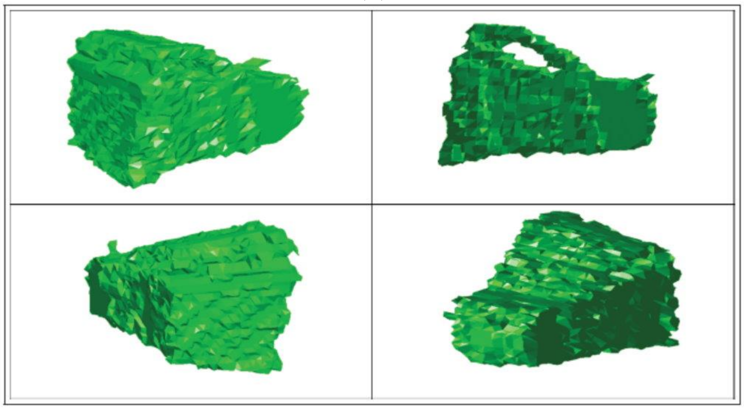


(b)

Figure 4. The Model Deformation (Cup) (a) The Clustering Method is Adopted to Segment the Target Model INTO Several Sub-models. (b) The Hierarchical Matching Method is Performed Individually Via the ICP Algorithm



(a)



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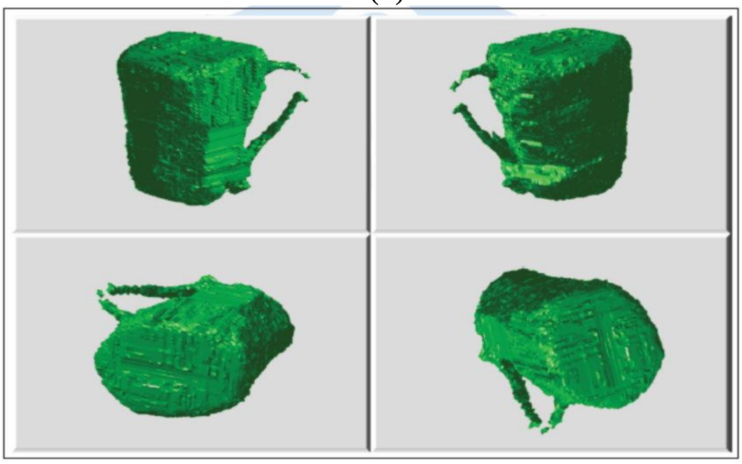
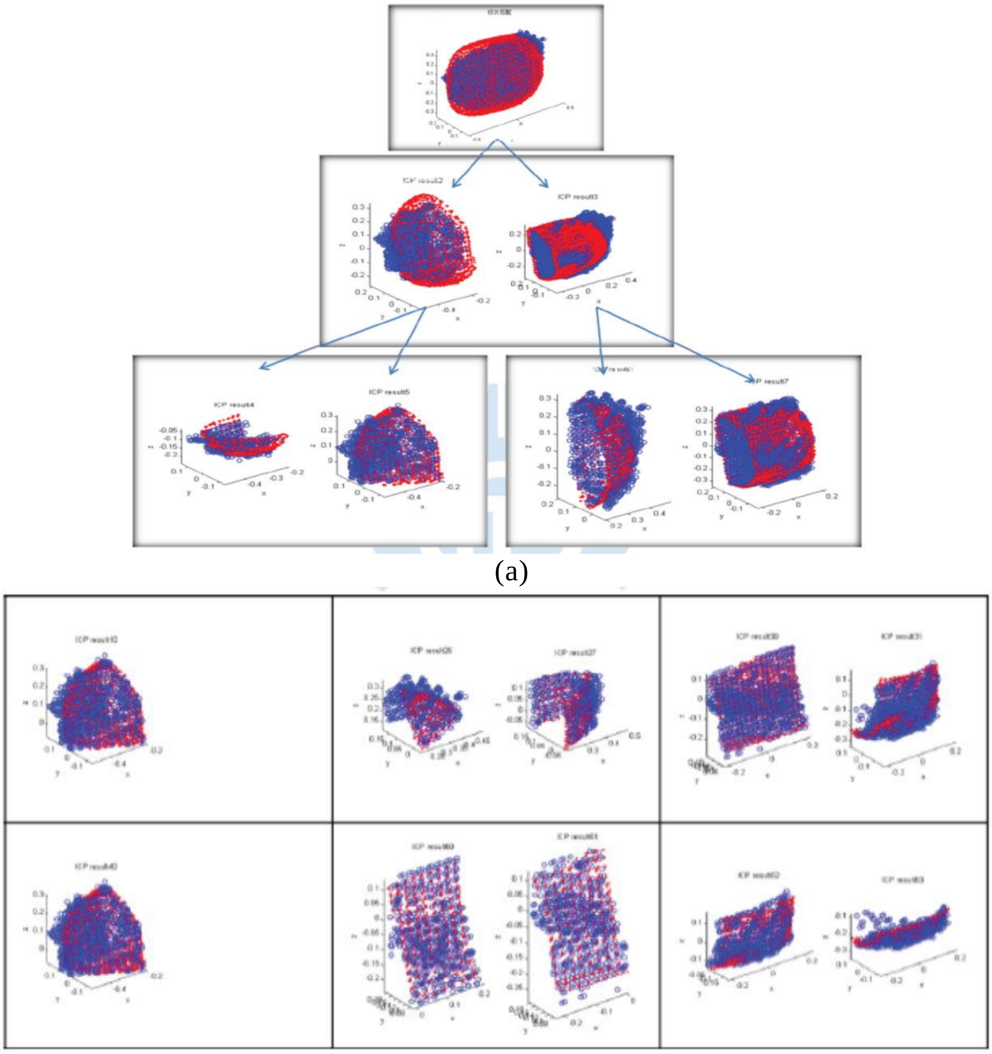


(c)

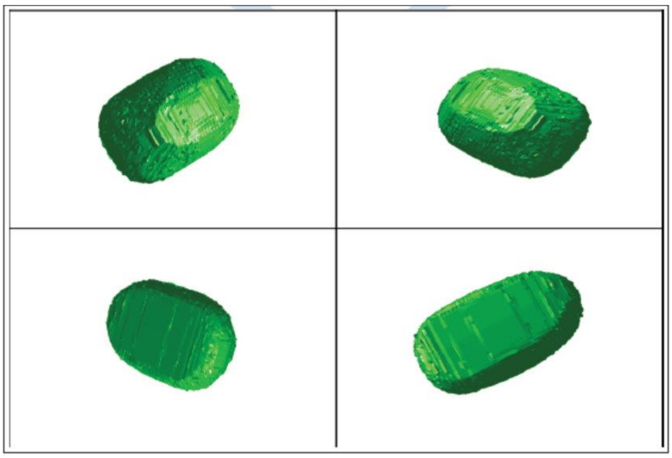
Figure 5. (a) The Prior Model of the Cup, (b) the Target Model of the Cup, and (c) the Recovery Model of the Cup



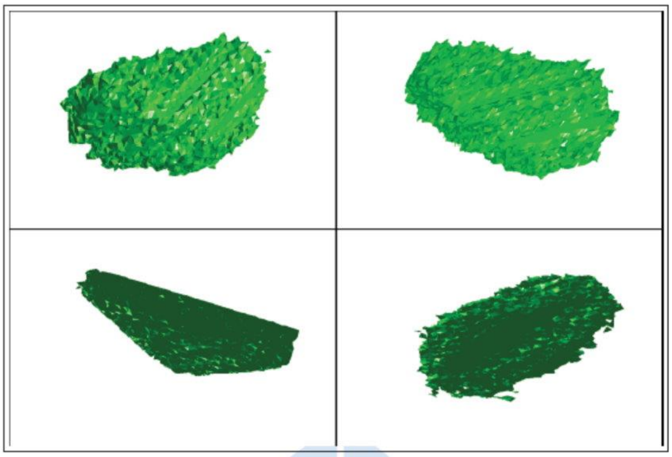
(a)

(b)

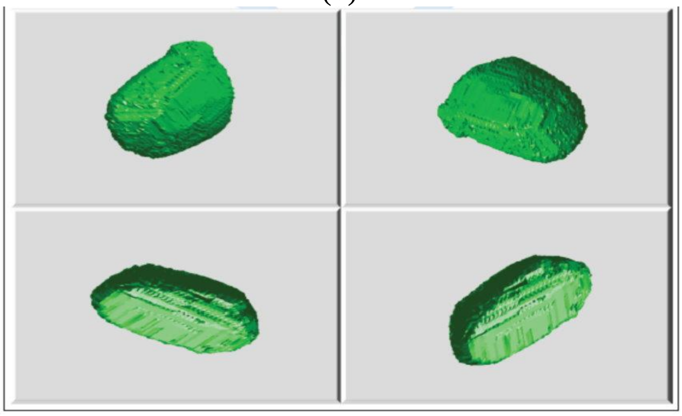
Figure 6. The Model Deformation (Mouse) (a) The Clustering Method is Adopted to Segment the Target Model into Several Sub-models. (b) The Hierarchical Matching Method is Performed Individually Via the ICP Algorithm



(a)

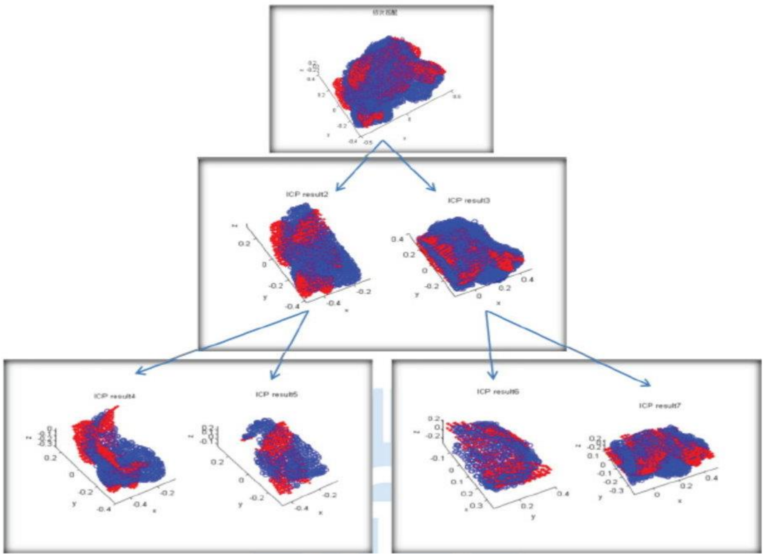


(b)

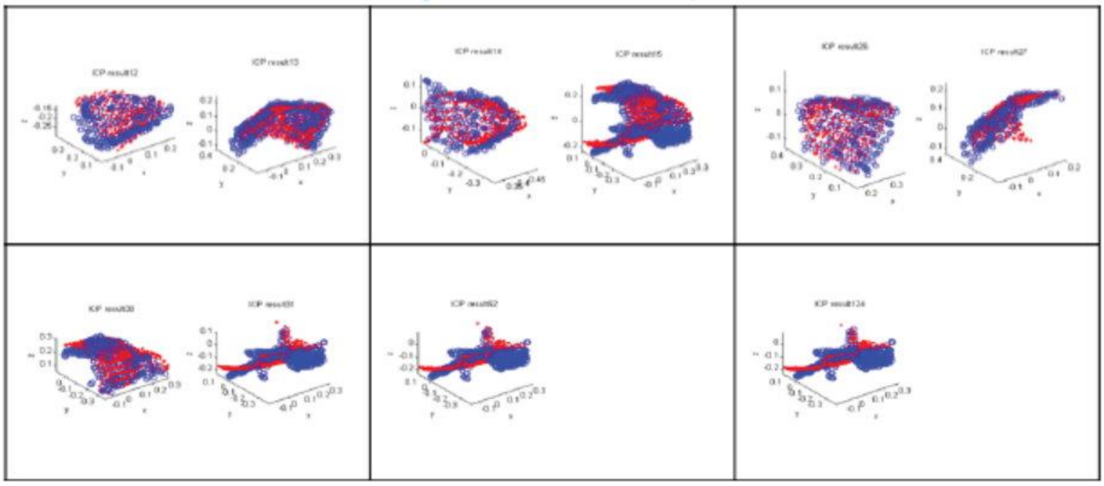


(c)

Figure 7. (a) The Prior Model of the Mouse, (b) the Target Model of the Mouse, and (c) the Recovery Model of the Mouse

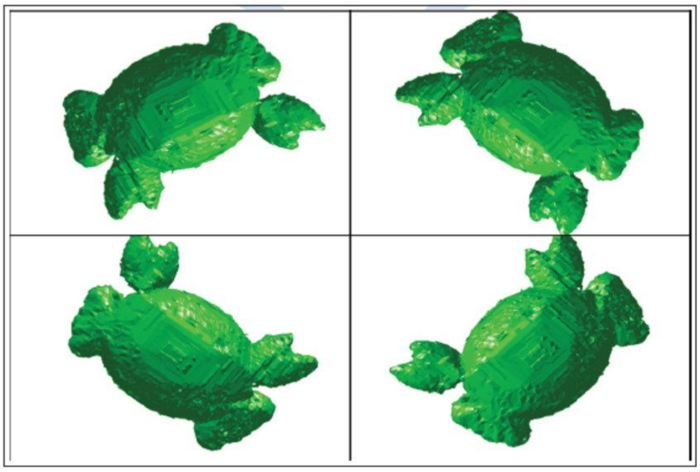


(a)

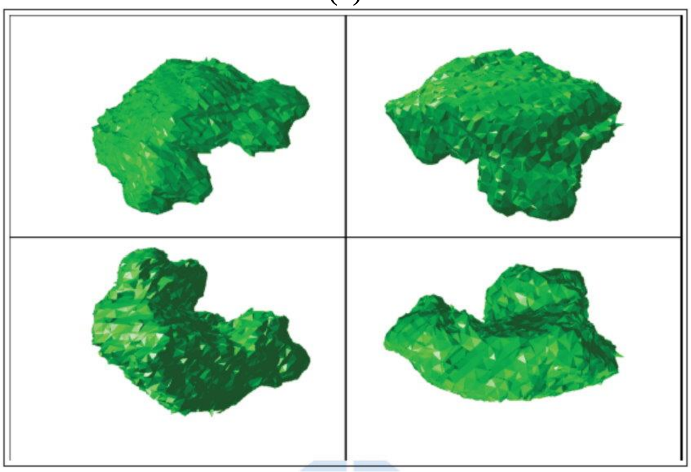


(b)

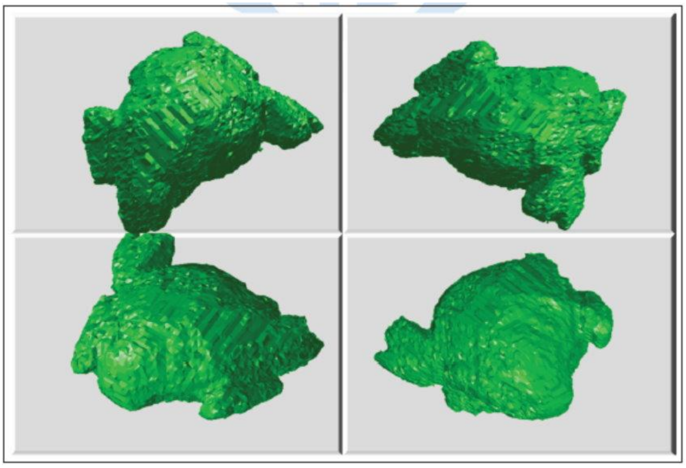
Figure 8. The Model Deformation (Doll) (a) The Clustering Method is Adopted to Segment the Target Model into Several Sub-Models. (b) The Hierarchical Matching Method is Performed Individually Via the ICP Algorithm



(a)



(b)



(c)

Figure 9. (a) The Prior Model of the Doll, (b) the Target Model of the Doll, and (c) the Recovery Model of the Doll

5. Conclusions

We have proposed a hierarchical clustering deformation approach based on visual hull for improving the 3D model reconstruction. We combine the exquisite 3D model derived by active acquisition methods and the constraints from the rough 3D model derived by passive methods. We can recover the appearance of the target model appropriately. In the future research, we will try to enhance the accuracy of our algorithm in error tolerance and improve the 3D model quality. Its applications related to the medical fields will be considered in the future.

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