Parts Identification and Motion Estimation on CT Scanned Assembly Meshes

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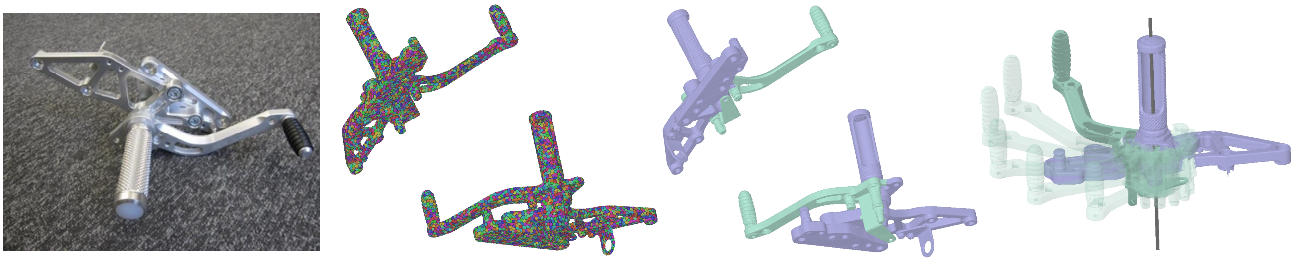

(a) (b) (c) (d)

Figure 1: (a) An example of mechanical assembly (a bike pedal), (b) clustering for pair of CT scanned assembly meshes acquired at different joint angles, (c) identified parts, and (d) estimated motion.

1 Introduction

Along with the recent improvements of the industrial X-ray CT scanning systems, it is now possible to non-destructively acquire the entire meshes of mechanical assemblies. This technology has the potential to realize an advanced inspection of assemblies, such as examining assembling errors or dynamic behaviors in motion using the meshes reflecting really-assembled situations. However, to realize such advance inspections, it is required to identify each part and to estimate their motions in the meshes.

Many methods have been proposed for estimating part boundaries and decomposing the models into parts by analyzing the concavity, e.g. [Katz and Tal 2003]. However these methods cannot uniquely find the correct boundaries between parts from the multiple concavities in the mechanical assemblies. Non-rigid registration methods, e.g. [Chang and Zwicker 2009], can identify the rigid parts in the registration process, however, they cannot explicitly find the motion parameters such as rotational axes. Moreover since these methods rely on the local properties such as principle curvatures or spin images for initial correspondence computations, they may fail to robustly indentify the parts for noisy meshes.

2 Our Approach

In this work, we develop a new method for uniquely identifying each part and correctly estimating the motion of the mechanical assemblies on their CT scanned meshes acquired at different configurations. Our method is robust for scanning noise and does not depend on spatial positions and orientations of the assemblies in the CT scanning process. An overview is as follows.

Step 1: Clustering In the first step of our method, mesh triangles are clustered based on Euclidean distances. It improves the accuracy, stability, and efficiency of the shape matching in the next step.

Step 2: Parts identification Next, clusters are classified into parts. Each pair of parts in the meshes can be considered as the largest pair which can be closely matched under a certain rigid transformation. To identify such pairs of parts, we propose a combinatorial method of random sampling, congruency test based on ICP matching, and pairwise region growing. In our proposed method, a cluster in each mesh is randomly sampled, neighboring topologically-connected clusters within a certain distance are extracted, and then their congruency is tested based on ICP matching. If they are congruent, they are simultaneously enlarged using pairwise region growing where an ICP matching and a search of matched cluster-pairs are iterated. As a result of this process, the largest set of clusters which can be closely matched under the user specified tolerance are extracted. By repeating the above process, the maximally enlarged set of clusters are extracted and identified as a pair of parts. For identifying multiple parts, a series of above processes are repeated until the number of non-identified clusters are small enough.

Step 3: Motion estimation Next, motion parameters such as rotational axes are estimated by evaluating the relative positions and orientations of the identified parts. First a mesh is transformed to the other so that a pair of corresponding parts are matched (a blue pair in the example in Figure 1). Then motion parameters are estimated so that the pair of connecting parts to the matched ones (green pair in the example) can be closely matched under the motion (a rotation in the example).

3 Results and Future Work

An experimental result is shown in Figure 1. We scanned the bike pedal in Figure 1(a) at different joint angles and created the pair of meshes both including about 1.4 million triangles. The CT resolution is 0.3mm. Clusters are shown in Figure 1(b), identified parts are in Figure 1(c), and estimated motion is in Figure 1(d). We visually confirmed that the appropriate parts boundaries are identified and the correct motion parameters are estimated. We also verified that our method enabled the identification and the estimation even on the same meshes including the artificial noise generated by displacing each vertex along its normal direction by a Gaussian distributed random distance with the standard deviation 200% proportional to the averaged mesh edge length.

In future work, we optimize the parts boundaries and the motion parameters by local shape matching based on mesh triangles. We also extend this work for realizing kinematic simulation by classifying the types of assemblies.

References

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