Proc. of the 9th Intl. Conf. of Asian Society for Precision Engg. and Nanotechnology (ASPEN 2022)
15–18 November 2022, Singapore. Edited by Nai Mui Ling Sharon and A. Senthil Kumar
doi://10.3850/978-981-18-6021-8_OR-05-0288

High accuracy alignment of X-ray CT volume with CAD data using feature vectors

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KEYWORDS: CT volume, CAD surface, alignment, feature vectors, feature points

We present an algorithm to accurately align CAD data to X-ray CT scan data (CT volume). CT volume is a 3D image, so it does not have explicitly defined surface points. The core idea of our algorithm is to extract feature points from CT volume and CAD data, and align them by optimization using feature vectors assigned to the feature points. The feature vectors represent the shape around the feature points. The optimization minimizes the geometric differences between the CT volume and CAD data expressed by their feature vectors. Experiment for CT volumes of assembly product show that the two data can be aligned with a higher accuracy with the proposed algorithm than other methods based on iterative closest point.

1. Introduction

1.1 Background

Inspection is an important process in manufacturing assemblies. While destructive inspections may alter their shapes and fits, X-ray CT scanning gives a volumetric image (CT volume) of an object which enables observation of the internal structure of the product in a non-destructive manner. For detecting defects on an assembly's CT volume, it is effective to compare it with CAD data of each part. However, the coordinate systems of a CT volume and CAD data are generally different, which means that the positions and postures of a part are not the same in the CT volume and CAD data. In addition, there is a possibility that the shape of parts may be modified from the CAD data's one due to a damage during a use or an intended deformation in manufacturing or a use (see Fig.1). This shape discrepancy also makes alignment difficult. An alignment is currently performed manually, but for improving the efficiency of inspection, an automatic alignment method for the CAD data to the CT volume is necessary.

Fig. 1 X-ray CT scan data (left) and CAD data (right) with different shapes

1.2 X-ray CT scan

X-ray CT scan is a non-destructive inspection technology. The flow of scanning is in Fig. 2. CT volume is a three-dimensional image of an object that is a stack of slice images of the object. Each voxel (volumetric pixel) has a value (CT value) reflecting the density of the material. CT volume is used for various applications for instance observation as it is, measurement and inspection using the object's surface extracted from it.

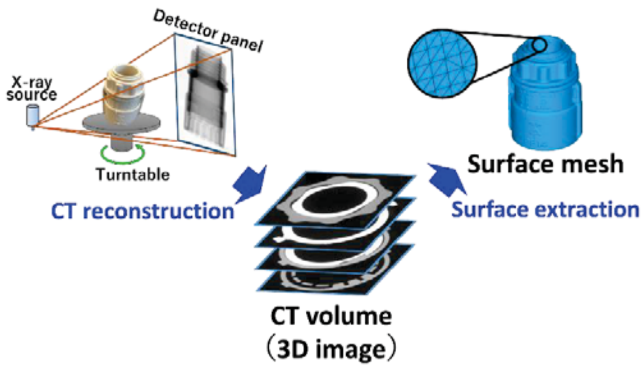


Fig. 2 Flow of data processing of X-ray CT scan

The simplest way to determine the surface is to extract the points with a CT value which is the intermediate value of the air and the object. However, when products have narrow gaps, the CT value out of air part does not decrease enough to extract a surface (see Fig. 2). In that case, the surface is defined as the points with a large norm of the gradient of the CT value [1].

Fig. 3 Blurred boundary (left: scanned object, center: CT volume and enlarged image, right: the change in CT value)

2. Related works

2.1 Iterative closest point

Iterative closest point (ICP) is a typical algorithm for alignment of point clouds [5]. ICP iteratively moves a point cloud to minimize the sum of distances between the closest points from the two point clouds. The results are greatly influenced by the initial position. We describe the flow of ICP as follows:

1. Generate pairs of the closest points and calculate the sum of the distances between them.
2. Calculate a transformation matrix for one point cloud to minimize the sum of the distances.
3. Move the vertices of the point cloud using the calculated transformation matrix
4. Iterate step1-3 until converges.

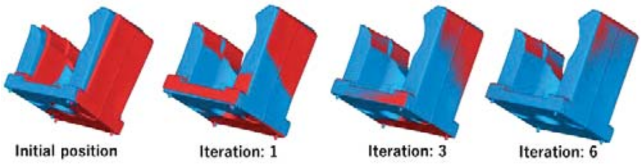


Fig. 4 Flow of ICP

3. Proposed algorithm

We propose an alignment algorithm for a CT volume and CAD data. Its input is a CT volume and a surface mesh, and the output data is CAD data aligned to the CT volume. Our proposing method can be divided into three parts: extraction of feature points, rough alignment and high-accuracy alignment. For extraction of feature points, we choose vertices or voxels with geometric features. In the rough alignment, we align the extracted feature points of the two data. Then, we perform an optimization of feature point coordinates using not only feature points but also feature vectors assigned to them for a more accurate alignment. We describe the details of each step below.

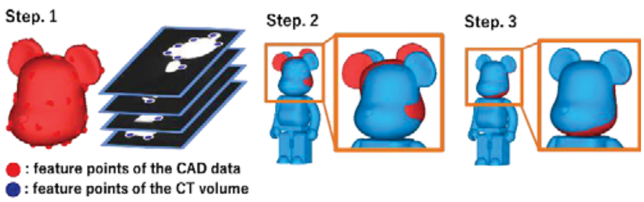


Fig. 5 Flow of the proposed method

3.1 Extraction of feature points

We extract feature points from the CAD data and CT volume using Intrinsic Shape Signature (ISS) [2]. It is a 3D shape descriptor based on principal component analysis (PCA). While some shape descriptors compute a view-dependent local features, ISS accomplishes the invariance by defining an intrinsic coordinate system at a point independency. ISS is calculated as follows by the eigen analysis of the point scatter matrix. First, we collect the vertices $\{\boldsymbol{p_j}\}_{j=1}^{N}$ in the vicinity of the point of interest $\boldsymbol{p_i}$. Second, we calculate scatter matrix $\mathrm{cov}(\boldsymbol{p_i})$ defined as follows using the collected vertices:

$$\mathrm{cov}(\boldsymbol{p_i}) = \sum(\boldsymbol{p_j} - \boldsymbol{p_i})(\boldsymbol{p_j} - \boldsymbol{p_i})^{\mathrm{T}}/N$$

Third, we compute its eigen values $\{\lambda_i^1, \lambda_i^2, \lambda_i^3\}$ $(\lambda_i^1 \geq \lambda_i^2 \geq \lambda_i^3)$. The vertices whose ratios of eigenvalues λ_i^2/λ_i^1 and λ_i^3/λ_i^2 are smaller than a threshold are considered as feature points. For a CAD data, all vertices are used to extract feature points. For a CT volume, we consider each voxel with a large norm of gradient vector as a point $\boldsymbol{p_i}$ or $\boldsymbol{p_j}$. Finally, the extracted feature points are decimated by the non-maximum suppression (NMS) [3] to make a uniform distribution.

3.2 Rough alignment

We use random sample consensus (RANSAC) [4] for rough alignment. It is effective for alignment of data sets with outliers, so RANSAC enables alignment even when objects have different shapes, and alignment of a part and the entire assembly. For alignment, it repeats a random vertex extraction, a computation of a transformation matrix for the extracted vertices, and an alignment. In the alignment, it counts the number of vertices (called inliers) enough to be close that the deviations are smaller than a threshold. If there are enough inliers, RANSAC align two data sets using the transformation matrix.

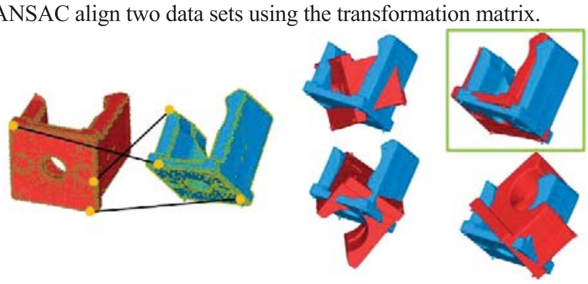


Fig. 6 Schematic figure of RANSAC (left: Example of vertex extraction, right: Example of iterative transformation. In this case, transformation surrounded by green square has the most inliers)

Our algorithm which is an adoption of RANSAC is shown as follows. First, for each three randomly selected feature points from the CAD data and CT volume, the algorithm calculates a transformation matrix to fit the three points from the CAD data to the three points from the CT volume. Then, it counts the number of inliers. In order to avoid making pairs from different regions, we only count the pairs with the normalized normal/gradient vectors whose inner product is greater than δ (in our experiments δ was set to 0.865). This computation is iterated with different three pairs many times, and the transformation matrix with the most inliers is selected.

3.3 High accuracy alignment

For a high accuracy alignment, we propose a variation of ICP using not only vertices but also feature vectors. In this section, we describe the definition of the feature vectors and an alignment with them.

3.3.1 Calculation of feature vectors

At each feature point, we perform PCA for the decimated vertices in a distance less than εd (ε is a constant and d is the average length of the edges of the CAD mesh). The eigenvectors $\{\boldsymbol{e}_i^1, \boldsymbol{e}_i^2, \boldsymbol{e}_i^3\}$ (corresponding to the eigenvalues $\{\lambda_i^1, \lambda_i^2, \lambda_i^3\}$) represent the shape around the feature point. We integrate the eigenvectors to make a left-handed coordinate system and rotate the eigenvectors so that the normal on that feature point and the eigenvector $\boldsymbol{e}_i^3$ point the same directions.

3.3.2 Alignment

For alignment, we minimize the weighted sum of the distances of the feature points, and the differences in the directions of the feature vectors. The use of differences of these feature vectors is the keys of highly accurate alignment. If the distance of the paired feature points or the difference in the directions of normal vectors is larger than a threshold, that pair is not used for optimization. The optimization function for a rotation matrix $\boldsymbol{R}$ and a translation vector $\boldsymbol{t}$ is shown as follows using the feature points $\boldsymbol{p}_i$ and $\boldsymbol{v}_i$ of the CAD mesh and the CT volume, normalized feature vectors $\boldsymbol{E}_i^{CAD}$ and $\boldsymbol{E}_i^{CT}$ of the CAD mesh and the CT volume, weights w_i^p and w_i^E and constants α and β (In our experiments α was set to 3.0, β was set to 40.0).

$$\min \sum_i \left\{\alpha w_i^p \|\boldsymbol{v}_i - (\boldsymbol{R}\boldsymbol{p}_i + \boldsymbol{t})\|^2 + \beta w_i^E \left\|\boldsymbol{E}_i^{CT} - \boldsymbol{R}\boldsymbol{E}_i^{CAD}\right\|^2\right\}$$

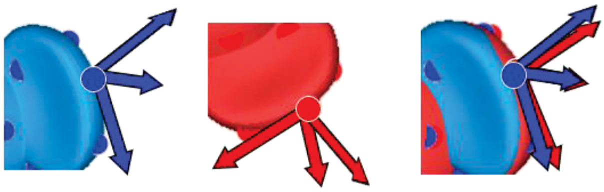


Fig. 7 Alignment using feature vectors

4. Results

We used assembly manufactured by a 3D printer for the experiment. Assembly was scanned by METROTOM1500 by Carl Zeiss, to generate CT volumes. The parameters of X-ray CT scanning and the CAD data are shown in Table 1 and 2.

Table 1 Parameters of X-ray CT scan

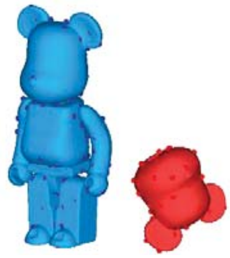
	Bear
Material	PLA
Voltage [V]	180
Current [μA]	900
Filter [mm]	Cu: 0.25
Resolution of CT volume	239 × 444 × 376
Voxel size [μm]	172.6
Number of feature points	179

Table 2 Parameters of CAD data

	Bear head
Number of vertices	9,538
Number of faces	19,072
Size of oriented bounding box [mm]	25 × 30 × 20
Number of feature points	54

In this section, the surface mesh extracted from the CT volume with blue and a part of the CAD data as red. We show the surface mesh extracted from CT volume for only visualization. During the experiments, we did not use the vertices of this surface mesh and the alignments were performed on the CT volume.

We use the CT volume of an assembly of bear and CAD data of bear head. Initial position and feature points are shown in right figure.



We show the result of the rough alignment in Fig. 9. We were able to almost align the CAD data of the bear's head to the scanned data of the bear's entire body.

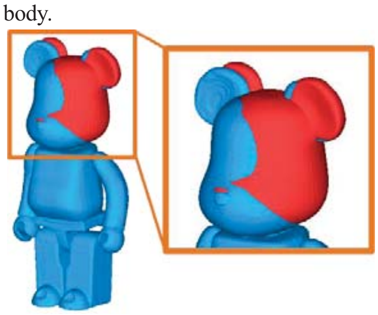


Fig. 9 Results of rough alignment

Fig. 10 shows a comparison of alignments with different indexes for high accuracy alignment: only vertices, vertices and normal vectors, and proposed algorithm. While with the comparison algorithms the left ear was not well aligned, the proposed algorithm gave a better fit.

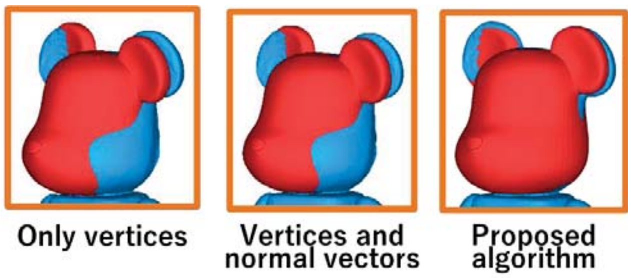


Fig. 10 Comparison of high accuracy alignment with different indexes

5. Conclusions

This paper presented an alignment algorithm for a CT volume and CAD data. using feature vectors for high accuracy alignment the experiments showed that our algorithm had successfully aligned CT volume and a surface mesh with different shape.

ACKNOWLEDGEMENT

This work was partially supported by JSPS KAKENHI Grant Number JP20H02055.

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