Title:
Segmentation and Local Reconstruction of Turbine Blade Point Cloud

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Introduction:

Engine blades are key components of aero-engine and greatly affect the engine's performance including actual thrust, fuel efficiency as well as structure reliability. Turbine blades are normally very thin and usually built as complex spatial surfaces. These features and the high finishing precision requirement increase the difficulty of blade machining. Since the blades must have precise dimensions, faithful shapes and strict surface integrity, as a measure and evaluation of the processing quality, the inspection of the processed blades plays a very important role in closed-loop quality control. Recently, laser scanning measurement methods have become a viable alternative to traditional coordinate measuring method. As a non-contact inspection method, laser scanning has fast and accurate 3D scanning capability, and can effectively improve the inspection efficiency. However, laser scanning can only provide the discrete point cloud which does not reflect the surface's finishing quality we want to find out, so how to reasonably derive surface features from the point cloud as well as clarify the processing flow of measured data is an urgent problem to be solved, based on which the hardware's full capacity can be exerted and more competent quality management measures can be setup.

Considering scattered point cloud data measured by laser scanner, we can calculate the profile error of blade section curves by means of region segmentation and local surface reconstruction to evaluate the blade's processing quality. Our present work focuses on the reverse processing flow of blade point cloud data, including the algorithms involved in part segmentation and local surface reconstruction, as well as the application of deep neural network in 3D part segmentation. Finally, some experimental results are given to verify the feasibility of the process.

Blade Part Segmentation:

In the circumstances of this paper, structural parameters and the profile error of blade section curves are the main quotas for surface quality, which need to be determined by the model comparison. While before that, the point cloud data need to be segmented by region, so geometric features belonging to different sub-structures can be differentiated, and the critical working surface of the blade, which is the main concern of the tooling process, can be sorted out. It's obvious that this region segmentation of point cloud will decide the effectiveness of surface reconstruction largely and also make the structural parameter extraction more convenient if reasonable segmentation results can be obtained

By region segmentation, point cloud data will be divided into non-overlapping regions with fewer features. That is, points on the same surface are assigned the same mark, and points on different surfaces with different marks. The points in each region have similar characteristics which can be local geometric features, for instance, the similar normal vector and the consistent curvature of the points. Human-constructed 3D features like shape descriptors and even more abstract features can also be included, which can be retrieved through deep learning. According to the results of segmentation, we can distinguish the various profile features of the blade and provide assistance for subsequent local surface fitting and shape parameter extraction.

Based on the above analysis, this paper studied the application of three segmentation methods in blade inspection respectively: (1) region growing method, (2) super-voxel clustering method; and (3) deep learning method. The first is a typical method based on local geometric features; the super-voxel method is a supervised clustering method that incorporates artificial shape descriptors; the last is a data-driven, unsupervised deep learning method. Our work on the three methods of blade point cloud segmentation will clarify the application background and characteristics of each one, which will guide us to choose different methods according to inspection scenarios and measured objects.

Application of Region Growing

Firstly, we use a clustering method based on region growing to segment the point cloud. This method takes advantage of the geometric properties of the points in two aspects: clustering criterion is based on the normal vector angle between the current point and its neighbour points, and the criterion for determining the seed is based on the curvature value of the point.

The idea is as follows: firstly, the current minimum curvature value point is selected as the clustering center, then the K-nearest neighbor (KNN) is searched according to a certain constraint (user defined radius or specified K number). Kd-tree structure is used during searching process. The neighboring points are added to the current area and removed from the current point set. Repeat the above process of selecting seeds and clustering, and continue to generate more regions until the current point set is empty, which means that segmentation is ended.

The essence of regional growth is to bring together points that belong to smooth small patches, while smooth patches are growing based on clustering constraints. To provide a trade-off between under- and over-segmentation, we can modify the curvature threshold in this algorithm.

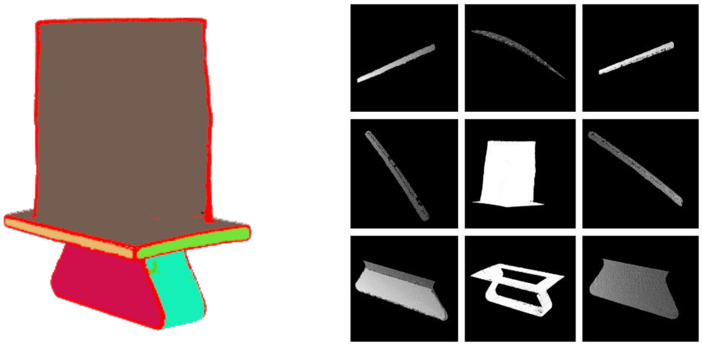

Fig. 1: Left: Part segmentation result; Right: Clusters of blade data.

Application of Super-voxel Segmentation

The super-voxel clustering method is the second method this paper applied to blade point cloud segmentation, which is a learning-free and bottom-up algorithm. Firstly, the point cloud is voxelized, and then the voxels are over-segmented to obtain a region with a slightly larger scale than voxel—super-voxel. Finally, the Constrained Planar Cuts method is used to segment the super voxels so that we obtain the segmentation result. Different from the former method, the processing object in this algorithm is super-voxel rather than single point.

The method of obtaining super-voxels is essentially an improvement of K-means clustering. Its clustering criterion is the distance defined in 39-dimensional feature space, and the metric is the user-specified search radius. Voxel search is performed using kd-tree-based adjacency maps. This method effectively reduces the number of areas that need to be processed in subsequent calculations at the cost of losing a small amount of information, which is acceptable in general engineering cases.

Fig. 2: Left: The first output is the super-voxel obtained by the local point cloud through local iterative clustering, and each super-voxel is marked with colour point cloud block.; Right: The second output is the result of Constrained Planar Cuts based on the concavity and convexity, that is, the various parts of the blade, such as blade body, platform and tenon, are marked with different colours.

Application of 3D Deep Learning

Combining 3D feature recognition with deep learning methods can not only effectively improve the accuracy of recognition and segmentation, but also achieve the goal of segmentation for specific scenes (like blade inspection) without the need for users to reset parameters, which enhances the process efficiency.

In this part, the method of 3D deep neural network is applied to implement turbine blade recognition and segmentation. We choose PointNet as deep learning framework, organize the measured point cloud data into a three-dimensional dataset, adjust some training parameters (batch size, epoch times etc.), and finally obtain the blade segmentation results through deep learning.

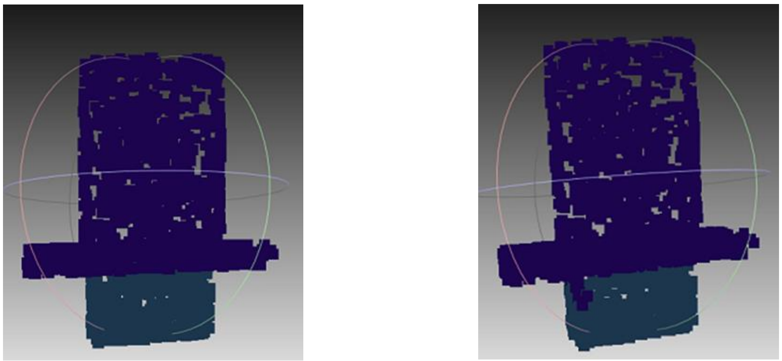

Fig. 3: Left: Ground Truth (2048 points) for Training; Right: Predict Segment Results (2048 points).

The performance on our testing blade datasets is favorable. Specifically, the accuracy of blade segmentation reaches 95.98%, with the average IoU (Intersection over Union) at 0.8989.

Comparison of the methods

In order to provide more referable information for practitioners of different plants, in this part, we summarize the characteristics of the three segmentation methods and make comparisons of them. For the first two methods, they both use the local geometric properties of point cloud. The DNN-based (deep neural network) method implements segmentation by extracting abstract features of point cloud and is sensitive to the dataset. There are several connections and differences between the two categories of methods.

Firstly, about application conditions, the two geometric methods are not large data-driven and do not require a previous labeling, while accurate labeled data is a prerequisite for training the network and learning the features. Secondly, geometric method needs to readjust certain parameters when used for different objects, such as number of neighboring search points K, threshold of clustering criterion, etc. For the DNN method, as an end-to-end structure, if the network can obtain sufficient variety of objects and large amount of data in a specific scene, there is no need to reset relevant parameters after training. In the third, as for the speed, DNN training is time-consuming, but the network implement the segmentation faster than geometric method. Finally, judging from the attributes of the point cloud, the three segmentation methods have something in common. They all implement point cloud segmentation by using the utmost of local characteristics. They all lack the ability of identifying the object's global topology and recognize the geometry in a top-down manner, which may be the real difference of these methods from human intelligence.

As for the region growing method and super-voxel clustering method, there are something similar between them. They essentially both belong to the clustering method: the former belongs to a kind of KNN method, and the latter belongs to a variant of K-means method. Since they are both of lazy learning mechanisms, a large number of calculation of distance defined in metric space is inevitable.

Region Growing	*Super-voxel Clustering*	*Constrained Planar Cuts*
10549 ms	1581 ms	938 ms

Tab. 1: Comparison of running time in the same experimental environment and input (VS2010 + PCL1.8.1, 361646 points)

Besides that, the difference also lies in speed and application scene. As the result in Table 1 shows, which summarizes the speed information of former examples as in Fig.1 and Fig.2, super-voxel clustering method is much faster than the region growing method. We believe that large number of curvature estimation slows down the region growing method.

For practical applications, although region growing method consumes more time, it can obtain more segments and details finally. So it is more suitable for scenes with single object. Super-voxel method performs better in that they have advantages in boundary recognition and can void improper segmentation between different objects. So if the application needs segmentation in complex scenes and with multiple objects, super-voxel method should be a choice worthy of more consideration.

<u>Local Surface Reconstruction:</u>

In the view of the entire data processing flow, we regard the region segmentation as the pre-processing stage of local surface reconstruction. For the purpose of calculating the error of key profile parameters, local surface reconstruction based on segmentation makes up the last piece of the puzzle.

For scattered point cloud, this paper adopts a method based on the trimmed curve, combined with the progressive and iterative approximation for least squares to implement the local surface fitting. Progressive and iterative approximation for least squares is a kind of geometric iterative method. Starting from the given initial control vertices, this method adjusts control vertices according to some criterion, and finally the curve or surface determined by the control vertices satisfies the requested geometric constraint.

The specific implementation steps of the algorithm are as follows:

- **Step1**: According to the PDM (point-distance-minimization) method, the initial B-Spline fitting surface **S** is obtained;
- **Step2**: By parameterizing the initial fitting surface of the first step, the parameter values corresponding to each data point to be fitted can be obtained. Mark these parameter values in the UV parameter field;
- **Step3**: Identify and extract the boundary of the point cloud within the parameter domain;

- **Step4**: Perform progressive iterative least squares fitting on the boundary data points, and obtain the trimmed curve **C**;
- **Step5**: Calculate the three-dimensional representation of the corresponding boundary curve on S, and trim S using the 3D curve. The outer part of the boundary is removed, and the rest is the final surface fitting result.

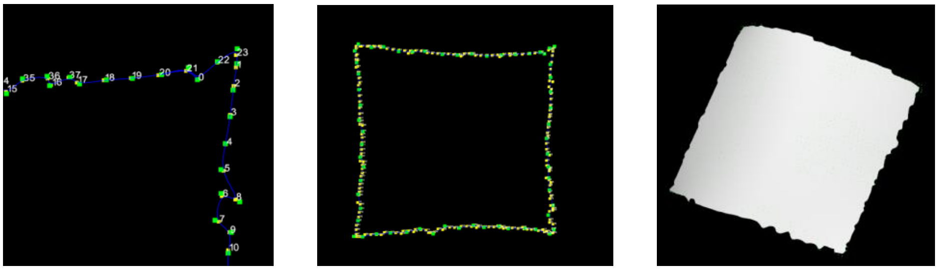

Fig. 4: Left: Partial magnification of boundary curve; Middle: Trimmed curve; Right: Surface S after trimmed.

Conclusions:

In order to obtain shape parameters from turbine blade point cloud and realize surface quality assessment, point cloud segmentation as well as surface reconstruction are required to extract geometric features. Reasonable segmentation results make it convenient to reconstruct surface and obtain the digital model. This paper implements blade point cloud segmentation in three methods. Region growing method achieves refined segmentation, while super-voxel clustering method is efficient and suitable for multi-object scenes. In addition, DNN-based method makes segmentation more automatic. Deep learning method combined with 3D point cloud information extraction is worthy further researching. Finally, we implement surface fitting with the method of trimmed B-spline, which is improved efficiently by LSPIA. The realization of these method verifies the feasibility of the process. We look forward that the rapid inspection process based on point cloud data will obtain more attention and gain rapid expansion.

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