Research on Segmentation of Pear Shape from Unorganized Point Clouds

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***Abstract*—With the advent of 3D scanner, accurate segmentation of 3D fruit shape from unorganized point clouds has been turned out to be the most challenging task in scientists and engineers in reverse engineering. This paper herein proposes efficient and robust approach to extract pear shape from background. At first, an interactive, non-local denoising algorithm is employed to efficient denoise the pear scans; Second, geometric properties, including normal, variation and curvature, are estimated by covariance analysis; Third, a Recursive Region Increment (RRI) is proposed to add the geometric similarity points to a base set, to generate an ultimate set only including the points of pear shape; Forth, point clouds is linearized for rapidly rending in the post processing. Finally, segmentation algorithm applied on ten range scans of a pear demonstrates that our algorithm reduces the number of pear point clouds by 88.3%, proves the validity and practicability of this method in pear segmentation.**

***Index Terms*—Denoising, Covariance Analysis, Segmentation, Linearization, Point Cloud**

I. Introduction

A. Related Work

In recent years, with the development of 3D scanning technology [1] [2], rich details of the object shape can be acquired with dense sampling points (point cloud). Thus, 3D scanning of real objects has been popularly used for information acquisition in various applications. From then on, most research has focused on the reconstruction of 3D object from point clouds in 3D city modeling [3], human face reconstruction [4], architecture reconstruction [5], and tree reconstruction [6], so it's probable to use point clouds in fruit reconstruction.

On the other hand, the mesh representation and image processing is still used for digitalization of real fruits [7] , even though there is a growing demand for more detailed and real models in agriculture. So in recent years, G. W. Kim [8] has begun to set about the actual apple model through finite element method (FEM) simulation, but it takes a long time to render highly detailed meshes with more artifacts. To overcome this drawback, new processing methods must be presented to preprocess, reconstruct and render these highly complex geometric bodies. Thus in 2009, 3D scanner has been first adopted to acquire 3D digital primitives—rending primitives of irregular shaped food by Uyar R [9]. In contrast to the mesh representation, due to not requiring connectivity information for describing topological relations between vertices, point images can provide relatively fast visualization of huge 3D models and make it more realistic to obtain accurate results from simulation. So it's necessary to reconstruct pear shape from point clouds.

From above analysis, we discover that construction of pear shape from point cloud is more important, but the research on it is not intense. The main reasons are that, in those applications, the points can be obtained without any background; while the pears are often grown on trees with leaves, trunks and branches, so the pear point clouds are unorganized, noised and mixed, which makes it hardly used for pear shape reconstruction in agriculture. As a result, denoising and accurate pear shape segmentation becomes an important topic in pear shape

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reconstruction, and they must be done before classical process.

The current classic denoising algorithms are divided into the following four main categories: partial differential equation (PDE) [10], spectrum technology [11], statistical techniques [12] and bilateral filtering algorithm [13]. These algorithms are possible to achieve highly conformal effect but have low efficiency, large computation and can't fit for different parts of pear shape. So, it's necessary to present an efficient denoising algorithm for the different parts of pear. The current segmentation methods mainly focused on building features [3], characteristic edges [17], valley-ridge [18] or curve skeleton [19]. All these state-of-the-arts can only segment a specific geometric shape, but can't be used for segmentation of the random pear shape in our task, so the previous methods will not be feasible.

B. Contributions and Outline

In this paper, an interactive testing algorithm is extended for efficient denoising of different parts of pear; Covariance analysis is employed for estimation of pear geometric feature; Recursive Region Increment (RRI) process is proposed for extracting random pear points from massive point cloud; Linearization is used for efficient storage, rendering and out-of-core representation.

This paper is organized as follows. Section 2 describes the proposed algorithm; Section 3 presents simulation results of the presented algorithm on the pear shape; Section 4 concludes this paper and discusses future works which will make this work more perfect.

II. Proposed Algorithm

Point clouds from laser scanners are a set of spatial points in a three dimensional Cartesian coordinate system as in (1)

$$R = \{x_i, y_i, z_i\} \ (i = 1,2 \dots K) \qquad (1)$$

It's really unorganized 3D points set and there's no topological relationship among them. The extraction is a process of segmenting the geometric-similarity points from original point clouds and the extracted subset is geometrical significance points set, each set is a piece of complete pear scan.

In this work, a four-step algorithm is presented to segment pear shape from unorganized point clouds. At first, the denoising process is employed to preprocess unorganized point clouds; Second, the classical methods covariance analysis are employed to estimate the normals, variance, curvature and tangent vector of each point; Third, starting from a seed point, an segmentation algorithm is presented to extract ultimate purely pear points set from leaves and background by searching surrounding points recursively until encountering the border of leaves and fruit, in each iterative step, the estimated features are used to evaluate geometric similarity of two points; Fourth, extracted points are organized into a linear memory structure for more quickly access. The pipeline of this step is shown in Fig. 1.

A. Denoising Process

Denoising is a key task in point clouds processing, and many classic algorithms has been presented by now. Early method is summarized as the following four categories: The first category is partial differential equation (PDE) [10] that can extend curvature flow to the denoising process later. The second category is spectrum technology proposed by Pauly et al. [11], which create a spectral decomposition for point cloud, and deal with the noise by handling spectrum coefficient. The third category is based on statistical data analysis framework presented by Pauly et al. [12]. The last category is to extend the famous image bilateral filtering algorithm to mesh model for non-local neighborhood denoising [13] by calculating a local radial basis function (RBF) approximation. These algorithms have low efficiency and large amount of calculation, thought it is possible to achieve highly conformal effect.

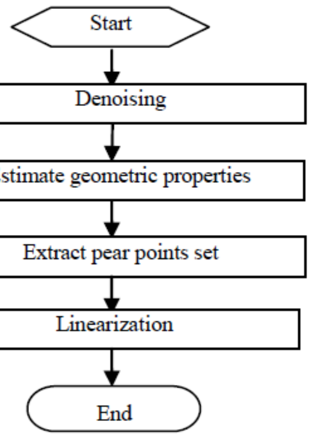


Figure 1. Pipeline of extraction algorithm for pear.

In this paper, based on interactive testing proposed by Weyrich et al [14], outliers on pear point clouds are divided into 2 types by heuristic, user-specified method. Type 1 is the point clouds of the surfaces around pear head and stem, which appear rich local details and smooth surface. For these surfaces, global similarity is first measured by weighted average of similar points within neighborhood [15], and then the smallest enclosing ball approach is adopted to denoise local rich details [14]. Type 2 is the point clouds of the pear side surfaces, which appear smooth surface and boundary characteristics. For these surfaces, outliers are classified by taking weighted average of similar points within neighborhood as measurement of nearest neighbor interaction [15], then mean-shift iterations is employed for denoising by drifting each sample point to the local maximum of density function based on selection of different surface fitting and kernel function. By applying non-local denoising method, the process of local approximation is omitted, estimation speed is more rapid, and finally the denoising process is implemented speedily without filtering, as shown in Fig. 2.

Based on the statistical weights and nonlocal similar measurements of mean-shift, the follow-up estimation of all geometry properties will be more precise.

B. Estimation of Geometric Properties

Geometric properties estimation is a key step and important foundation for extracting pear shape. By now, each point has only two properties: position and initial normals. On the other hand, edges and surfaces of pear scans can be considered as curves and curved surface respectively, while leaves consist of a lot of singular and uneven points, which results in great variance on properties of leaves' points. So, more geometric features, including precise normals, variance and curvature, should be estimated by the covariance analysis due to its merit in finding geometric features without losing much information [16].

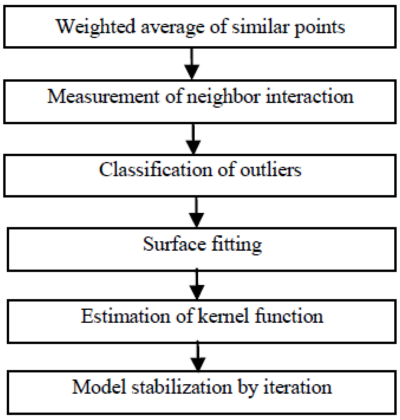


Figure 2. Denoising of pear side face point cloud.

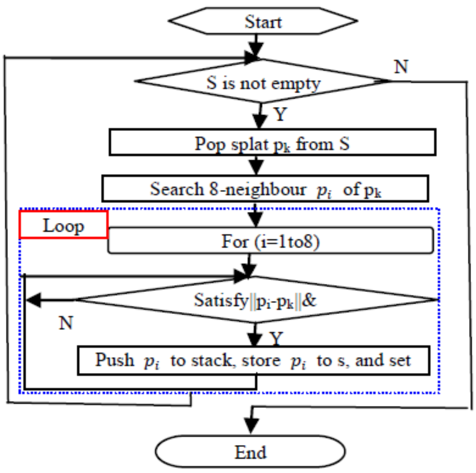


Figure 3. Pipeline of extracting pear point set from all point cloud.

A unit normals, in this paper, can be considered as point on a unit sphere, and point normals n_i (i=0,...,m−1) can be expressed by its angles $n_i=(\theta_i, \varphi_i)$, $\theta \in [0, \pi]$, $\varphi \in(-\pi, \pi]$).

First, the mean normal n is computed by weighted average on spheres based on least squares minimization that reflects spherical distances. The second step is calculation of the covariance matrix. Covariance is usually measured in two dimensions, whereas we have a set of 3-dimensional points p_i, so, 9 covariance values need to be calculated and put in a 3*3 covariance matrix M in (2) [16].

$$\mathrm{M} = \sum_{i=1}^{m}(\mathrm{p_i} - \mathrm{p}) \times (\mathrm{p_i} - \mathrm{p}) \qquad (2)$$

where, p is the center of points p_i.

The third step is calculation of the eigenvalue λ_i and corresponding eigenvector $X_i (i = 1,2,3)$ of matrix M in (3).

$$\mathrm{M} \cdot \mathrm{X_i} = \lambda_i \cdot \mathrm{X_i} \quad \lambda_1 \le \lambda_2 \le \lambda_3 \qquad (3)$$

In keeping the standardization, all eigenvectors are scaled to unit vectors in (4).

$$\mathrm{X_i} = \mathrm{X_i}/\|\mathrm{X_i}\| \qquad (4)$$

The eigen analysis gives us the variances of the Gaussian distribution. Estimated normals n at p is the unitized eigenvector of X_1, associated with the smallest eigenvalue λ_1, and surface variance V_i of the points set is given in (5)

$$\mathrm{V_i} = \lambda_1 / \ (\lambda_1 + \lambda_2 + \lambda_3) \qquad (5)$$

where $\lambda_1$indicates the sum of square distance from all points p_i to the local plane, $\lambda_1 + \lambda_2 + \lambda_3$ is the sum of square distance from all points p_i to the barycenter p. So the surface variance reflects the deviation degree of the points to the tangent plane of the points. In the flat region, the points with small V_i are close to same plane, while in the rough region, the points with large V_i are disperse, thus V_i is a good approximation of the curvature at p. So far, each point has three estimated properties, they are position p, normals n_i and variance (curvature) V_i, which will be used to extract pear in the following step.

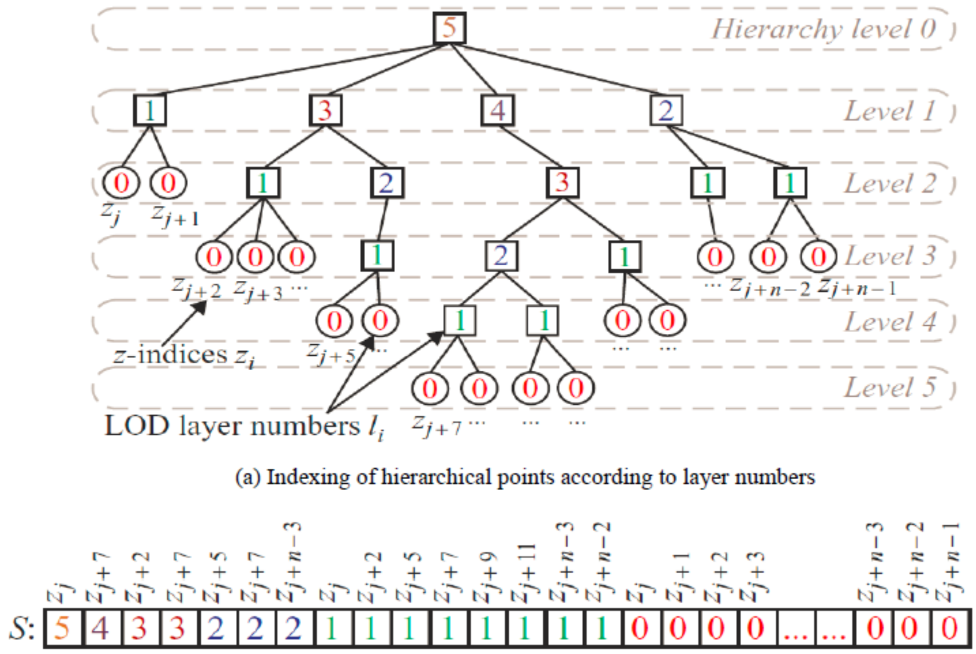
C. Segmentation of Pear Point Set

Recently, research on the extraction of characteristic has become more and more popular, region growing algorithm was usually applied to extracting building features [3]; Philippe Marin et al [17] proposed a method for the extraction of characteristic edges detected with a prior parabolic fitting; Xu-fang Pang [18] et al proposed a robust algorithm for valley-ridge extraction from point set; Jun-jie Cao [19] et al presented an algorithm for curve skeleton extraction via Laplacian-based contraction particularly from point clouds; All these extraction methods have extracted a specific geometric shape. While in our task, the fruit shape is random, so the previous methods will not be feasible.

Our segmentation method is a Recursive Region Increment (RRI) process, which takes variation V_i and dot product of normals n_i as the segmentation parameter, stack S as temporary memory and the spatial point set C as the ultimate points. The extraction algorithm starts from a seed point p_k, which is selected from pear scans $\{p_i\}$ initialized by $flag_i = 0$. Then p_k is added to C to form a new set and pushed to the stack S, set $flag_k = 1$. When the stack is not empty, repeat the follow three-step:

(1) Pop a point p_k from stack S;

(2) Seek the 8-connected neighbor point p_i (i=1, 2…8) around p_k in xyz directions by calculating the Euclidean



(a) Indexing of hierarchical points according to layer numbers

(b) Linearizing order of points into an array

Figure 4. Linearization of hierarchical structure.

TABLE I. PARAMETERS OF PEAR SCANS

items / scans	X extent (min,max)/mm	Y extent (min,max)/mm	Z extent (min,max)/mm	size (x*y*z)/mm	Num of points
Bottom1	(-32.46,62.78)	(-110.23,74.11)	(-84.2,75.13)	95.24*184.34*159.33	175583
Bottom2	(-31.93,63.23)	(-109.26,73.4)	(-85.02,73.16)	95.16*182.66*158.18	171982
Top1	(-33.34,62.14)	(-111.4,71.51)	(-83.67,74.19)	95.48*182.91*157.86	184350
Top2	(-34.27,62.18)	(-110.2,72.63)	(-82.31,75.15)	96.45*182.91*157.46	184319
Side1	(-33.81,63.56)	(-109.6,73.14)	(-83.58,73.41)	97.37*182.74*156.99	190024
Side2	(-35.5,63.62)	(-111.21,72.34)	(-84.14,74.57)	99.12*183.55*158.71	196543
Side3	(-35.28,62.74)	(-110.2,74.14)	(-85.32,75.7)	98.02*184.34*161.2	188572
Side4	(-32.34,63.25)	(-109.98,71.88)	(-82.35, 74.65)	94.59*181.86*157	190631
Side5	(-34.23,62.46)	(-111.2,73.26)	(-83.1, 73.89)	96.69*184.46*156.99	191778
Side6	(-33.54,63.28)	(-109.17,72.21)	(-82.4,74.13)	96.82*181.38*156.53	191253

distance between p_k and the 8-connected points, with $flag_i = 0$.

(3) For each p_i, the dot product of normals $|n_i \cdot n_k|$, ($\|n_j\| = 1$) and surface variance difference $|V_i - V_k|$ are used as geometric similarity $\|p_i - p_k\|$ of all leaves and the pear. When the dot product satisfies $|n_i \cdot n_k| > 0.9$, points p_i are on the same surface with p_k. $|V_i - V_k|$ is another similar criteria of surface: lower difference value means p_i on the surface of pear; while higher difference value means p_i on leaves, so when $|V_i - V_k| > 0.025$, the point p_i can be treated as the edge of fruit and leaves. When geometric similarity $\|p_i - p_k\|$ are satisfied and $flag_i = 0$, push p_i to stack S, set $flag_i = 1$ and store p_i to C, else, return to step (3) for next p_i.

This three-step iteration will stop until stack S is empty, as shown in Fig. 3.

D. Linearization of Hierarchical Structure

Any spatial point representation, such as octrees or k-d trees [21] can be converted into a linear memory array and stored on disk.

In this paper, spatial structure will first be organized into linear structure for efficient storage and rendering, then an out-of-core representation would be obtained by mapping this linear memory file to disk, which allows our program to access array points directly by virtual memory (VM) manager that automatically decides which parts of the file should be loaded into main memory by demanding paging. Thus, all LOD points are lexicographically reordered respective to a layer number and a spatial ordering index, as illustrated in Fig. 4 [20].

III. SIMULATION RESULTS

The point clouds of pear and leaves are scanned from 10 different angles by 3D Camega PCP-400, 2 range scans are bottom, 2 scans are top and 6 scans are side faces. These faces were managed by an array owned 10 elements in (6)

$$\mathrm{pear}(10) = \{\mathrm{b}_1, \mathrm{b}_2, \mathrm{t}_1, \mathrm{t}_2, \mathrm{s}_1, \mathrm{s}_2, \mathrm{s}_3, \mathrm{s}_4, \mathrm{s}_5, \mathrm{s}_6\} \quad (6)$$

The original pear scans are shown in Fig. 5, those parts circled by red color is “pure” pear faces.

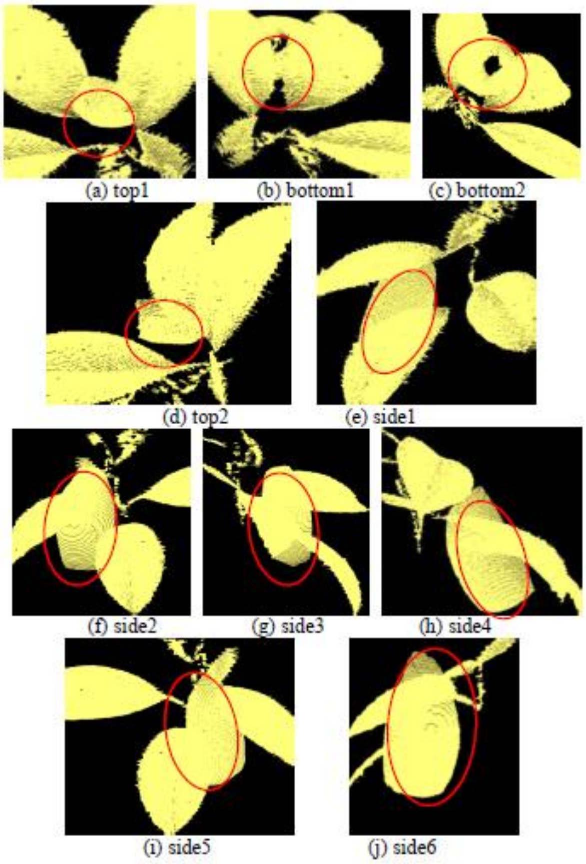


Figure 5. The original point clouds of pear.

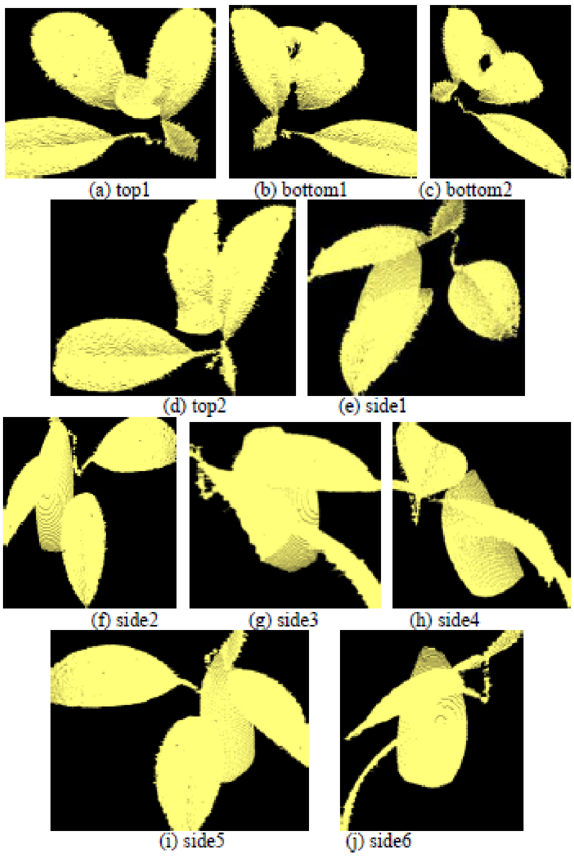


Figure 6. The denoised point clouds of pear.

The spatial resolution of point clouds is 0.03mm, and parameters of scans are shown in table1.

```
solid  pear(1)
 facet normal  -0.509082 -0.858324 0.064153
   outer loop
  vertex -28.810467 -5.502658 15.463493
  vertex -28.850819 -5.496768 15.222094
  vertex -28.517298 -5.709276 15.025510
   endloop
 endfacet
 facet normal  -0.499004 -0.862360 0.085615
   outer loop
  vertex -28.517298 -5.709276 15.025510
  vertex -28.850819 -5.496768 15.222094
  vertex -28.566435 -5.704361 14.788620
   endloop
 endfacet
 facet normal  -0.517902 -0.852686 0.068583
   outer loop
  vertex -28.850819 -5.496768 15.222094
  vertex -28.892342 -5.490918 14.981265
  vertex -28.566435 -5.704361 14.788620
   endloop
 endfacet
 facet normal  -0.515060 -0.853891 0.074726
   outer loop
  vertex -28.566435 -5.704361 14.788620
  vertex -28.892342 -5.490918 14.981265
  vertex -28.936321 -5.485356 14.741685
   endloop
 endfacet
 facet normal  -0.454053 -0.871978 0.183002
```

(a) Geometric features of bottom1

```
solid  pear(5)
 facet normal  -0.461369 -0.871547 -0.165967
   outer loop
  vertex -25.278475 -5.517074 -4.458734
  vertex -25.240240 -5.494243 -4.684917
  vertex -24.832659 -5.720109 -4.631847
   endloop
 endfacet
 facet normal  -0.446546 -0.862092 -0.239569
   outer loop
  vertex -24.832659 -5.720109 -4.631847
  vertex -25.240240 -5.494243 -4.684917
  vertex -24.755873 -5.698848 -4.851480
   endloop
 endfacet
 facet normal  -0.440534 -0.873202 -0.208441
   outer loop
  vertex -25.240240 -5.494243 -4.684917
  vertex -25.179163 -5.472042 -4.907007
  vertex -24.755873 -5.698848 -4.851480
   endloop
 endfacet
 facet normal  -0.432100 -0.867105 -0.247828
   outer loop
  vertex -24.755873 -5.698848 -4.851480
  vertex -25.179163 -5.472042 -4.907007
  vertex -25.098524 -5.449770 -5.125527
   endloop
 endfacet
 facet normal  -0.476030 -0.833404 -0.280774
```

(b) Geometric features of side1

Figure 7. Estimated geometric features of pear

A. Denoising

At first, pear point cloud is denoised by the flowchart in Fig. 2 based on the programming in VC, point clouds in Fig. 5 (a) - Fig. 5(b) are dealt with methods proposed by Ref. [15], point clouds in Fig. 5(e)- Fig. 5(j) are dealt with mean-shift iterative methods proposed by Ref. [15], the denoised result is shown in Fig. 6.

After denoising, the point number of pear(10) is changed into the following list: {168427, 164826, 177194, 177163, 182868, 189387, 181416, 183475, 184622, 184097}.

B. Estimation Result of Geometric Properties

Then, every point is normalized by $\|n_i\| = 1$, normal and curvature of every point is estimated by covariance

TABLE II. CONTRAST ON POINTS NUMBER OF PEAR SCANS BEFORE AND AFTER SEGMENTATION

scans	Bottom1	Bottom2	Top1	Top2	Side1	Side2	Side3	Side4	Side5	Side6
un-extracted	175583	171982	184350	184319	190024	196543	188572	190631	191778	191253
extracted	11186	7585	19953	19922	25627	32146	24175	26234	27381	26856
decrement rate /%	93.6	95.6	89.2	89.2	86.5	83.6	87.2	86.2	85.7	86

analysis. These estimated features of bottom1 and side1 of pear are shown in Fig. 7 respectively.

Fig. 7 gives part of the estimation results of geometric properties only in the form of text file. Among them, the content between facet and end-facet is the attributes of a point; The three values behind the facet-normal are the estimated normal vector of the current point; The content between outer-loop and end-loop is the center of neighbor points and surface information, in which, the three values at the back of vertex are the center of neighbor points and the three values behind f are the point surface change rate along three dimensions.

C. Extraction Result of Pear

Next, based on the extraction parameters in sec *II.C*, the pear surfaces are final segmented from leaves, the ultimate segmented pear range scans are shown in Fig. 8.

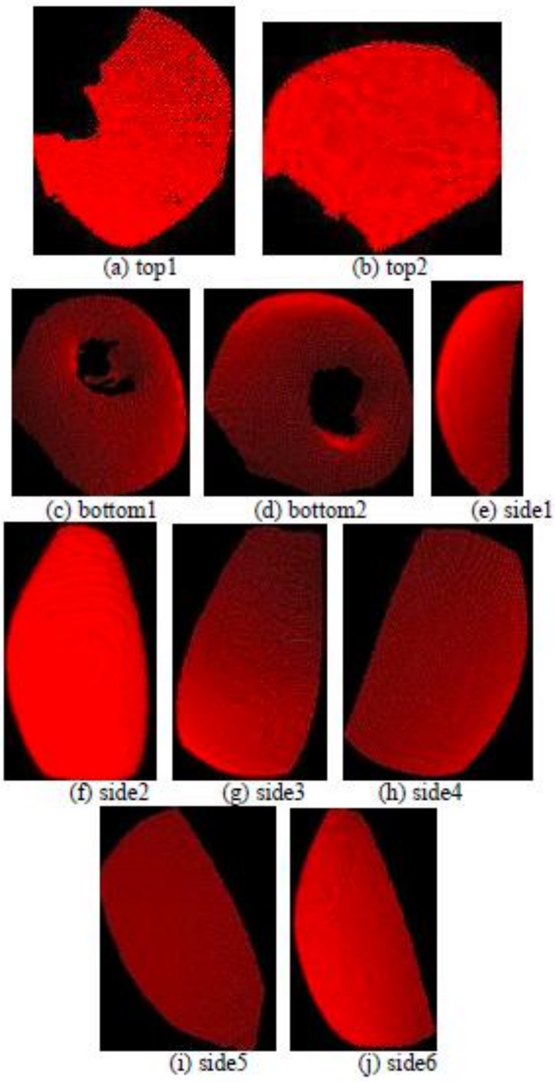


Figure 8. The extracted pear scans

D. Comparison

After extraction, the number of points is markedly reduced; the contrast on number between un-segmented and segmented of all pear scans is presented in table 2.

Analysis of data from table 2 shows that, point number of segmented pear scans is decreased by 88.3% on average than those of un- segmented. This is a down of larger proportion, due to the larger proportion of leaf and branch in point clouds, so the number of points decreases obviously after segmentation.

IV. CONCLUSION AND FUTURE WORK

In this paper, an efficient strategy is proposed to segmenting pear from unorganized background. An interactive, non-local and mean-shift based denoising algorithm is employed for efficiently removing the outliers; covariance analysis is presented for precise estimation of geometric features; a Recursive Region Increment (RRI) process is proposed to segment pear shape from background speedily, in sharp contrast to the traditional cluster methods, those points outside the bounding needn't to be processed, which minimizes the number of processed points and makes the segmentation process rapidly. Additionally, spatial structure of points was linearized for the efficient access. The algorithm has reduced the calculation complexity, speed up the extraction process while remaining details of pear shape, reduce the number of points by 88.3%, and can be extended to segmentation of other fruits shape with smooth surface. Even though, this work is only suitable for segmenting continuous smooth surface, and can't be used for coarse surface.

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A simplified and accurate registration for splat-based fruit scans. ICIC Express Letters, Part B: Application. 2012, 3(4):733-741.

Optimal pairwise registration of fruit scans based on splat-oriented. International Journal of Advancements in Computing Technology. 2012, 3(4): 148-159.

A novel algorithm for segmenting fruit from unorganized point clouds. VRCAI2011: ACM SIGGRAPH Conf.

Currently, she is interested in fruit shape reconstruction in agriculture, point cloud segmentation and graphics technology.

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