# Organizing Lidar Data Based on Octree Structure

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**Abstract:** Laser scanned lidar data record 3D surface information in detail. Exploring valuable spatial information from lidar data is a prerequisite task for its applications, such as DEM generation and 3D building model reconstruction. However, the inherent spatial information is implicit in the abundant, densely and randomly distributed point cloud. This paper proposes a novel method to organize point cloud data, so that further analysis or feature extraction can proceed based on a well organized data model. The principle of the proposed algorithm is to segment point cloud into 3D planes. A split and merge segmentation based on the octree structure is developed for the implementation. Some practical airborne and ground lidar data are tested for demonstration and discussion. We expect this data organization could provide a stepping stone for extracting spatial information from lidar data.

**Keywords:** laser scan, Lidar, octree structure, 3D information extraction

## 1. Introduction

Laser scanning has become a viable technique for the collection of a large amount of accurate 3D point data densely distributed on the scanned object surface. The inherent 3D nature of the sub-randomly distributed point cloud provides abundant spatial information. To explore valuable spatial information from laser scanned data becomes an active research topic [1,2].

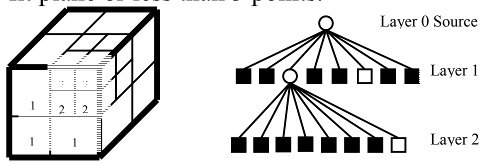
Lidar data record 3D surface information in detail. Exploring valuable spatial information from lidar data is generally the purpose of its application, such as DEM generation and 3D building model reconstruction. However, the information is implicit in the abundant, densely and randomly distributed point cloud, so that traditional image processing techniques are no longer suitable [1]. Although point cloud may be transformed into a gird data set through an interpolation procedure, some spatial information may be lost after interpolation [3]. This paper proposes a new method to organize Lidar data. The theory applied in this method is hierarchically splitting the data space based on the octree structure until the points contained in each node are coplanar, or say distributed in a 3D plane or less than 3 points. A merge process is performed after splitting to form larger planes.

## 2. Organization Method

The principle of the method is to segment point cloud into 3D planes. A split and merge segmentation based on the octree structure (Fig. 1.a) is developed.

### 1) Split process

The split process starts from the whole data set as a root node. The data set space will be divided into 8 sub-spaces, if the data set could not pass the distance or density threshold. The split generates 8 sub-nodes (Fig. 1.b) representing the split spaces. Each sub-node will be split continuously until the scan points contained in the split space of the sub-node are distributed close to a 3D best-fit plane or less than 3 points.




(a) (b)

**Fig. 1. Octree structure (a) divided sub-spaces (b) the tree representation**

### 2) Calculating best-fit planar of point cloud

The best-fit plane in each sub-node is determined using least-squares estimation, i.e., minimizing the squares sum of the distances from points to the fitting plane. In the 3D Euclid space, a 3D plane can be formulated as follows:

$$Ax + By + Cz + D = 0 \qquad (1)$$

The distance ($d_i$) from the $i^{\text{th}}$ point $P_i(x_i, y_i, z_i)$ to the plane can be expressed as:

$$d_i = \frac{|Ax_i + By_i + Cz_i + D|}{\sqrt{A^2 + B^2 + C^2}} \qquad (2)$$

Then, the best-fit condition of minimizing the squares sum of the distances will be:

$$\sum_{i=1}^{N} d_i^{\,2} \Rightarrow \min \qquad (3)$$

Eq. (2) is non-linear, so that it needs initial approximation values of the unknown parameters ($A$, $B$, $C$, $D$) for the calculation of least-squares estimation. To solve this problem, we use a two-stage calculation to determine the unknown parameters.

At first stage, a 3D plane is formulated as a slope-intercept form, which has 3 types as Eq. (4):

$$\begin{aligned} x &= ay + bz + c \\ y &= ax + bz + c \\ z &= ax + by + c \end{aligned} \qquad (4)$$

To avoid the situation of obtaining infinite numbers for $a$ and $b$ parameters, which slope-intercept form is suitable can be predetermined according to the distribution ranges of the point cloud. Fig. 2 shows the idea. The outer frames in Fig. 2 represent the sub-node spaces, and the inner frames represent the distribution ranges of the point cloud. The decision can be done by checking the minimum distribution range. For example, if $x$ dimension has the minimum distribution range, then the first type is the choice.

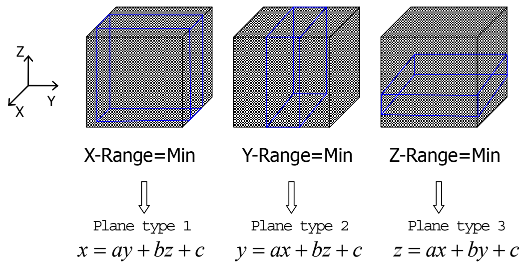



**Fig. 2. The idea of selecting a suitable slope-intercept form.**

Because the slope-intercept form is linear, the parameters can be calculated without the need of iteration. The least-squares linear regression can be applied to determine the plane parameters. For example, if the slope-intercept form, $x = ay + bz + c$ , is used, the matrix form of the observation equations can be listed as follows:

$$\begin{matrix} V & = & A & \cdot & X & - & L \end{matrix}$$

$$\begin{bmatrix} v_1 \\ \vdots \\ v_i \end{bmatrix} = \begin{bmatrix} y_1 & z_1 & 1 \\ \vdots & \vdots & \vdots \\ y_i & z_i & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix} - \begin{bmatrix} x_1 \\ \vdots \\ x_i \end{bmatrix} \tag{5}$$

The parameters are then solved as:

$$\hat{X} = (A^T A)^{-1} A^T L \tag{6}$$

The calculation in this stage actually is to minimize the squares sum of the *x* ranges from points to the fitting plane rather the perpendicular distances. After the parameters are determined, the *x* range residuals can be calculated. Split will proceed continuously if there is a residual larger than the preset threshold, otherwise rigorous calculation of the second stage will be triggered.

Eq. 2 is applied for the rigorous calculation. Given the solution in the first stage as the initial approximation, the rigorous adjustment is performed iteratively. Following the use of the slope-intercept form, Eq. 2 can be reformed as:

$$d_i = F_i(a,b,c) = \frac{\left| -x_i + ay_i + bz_i + c \right|}{\sqrt{(-1)^2 + a^2 + b^2}} \tag{7}$$

The observation equations can be obtained by linearizing Eq. 7:

$$0 + v_i = \left[ \frac{\partial F_i}{\partial a} \right]_0 \Delta a + \left[ \frac{\partial F_i}{\partial b} \right]_0 \Delta b + \left[ \frac{\partial F_i}{\partial c} \right]_0 \Delta c + F_0 \tag{8}$$

In Eq. 8, the parameters $\Delta a, \Delta b, \Delta c$ are increments of unknown parameters. The increments will be added into the previous approximations until the calculated increments get to very small. The best-fit plane is determined if the computation converges.

The distance residuals can be calculated after the parameters are solved. Again, split will proceed continuously if there is a residual larger than the preset threshold, otherwise a plane is formed.

### 3) Density of the point cloud on a fitting plane

The point cloud in a sub-space may not distribute evenly on the fitting plane. If the fitting plane is assumed to represent a scanned ground or object surface, the point cloud should distribute evenly on the plane. In order to find planes corresponding to the distribution of point cloud, distribution density is checked for further splitting. For example, unbalanced distribution of points in Fig. 3 will show a low distribution density. Split can proceed further, until the distribution density of point cloud on each fitting plane is higher than a preset threshold.

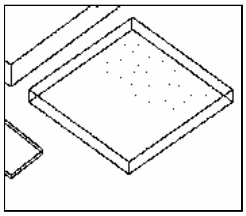


**Fig. 3. An example of unbalanced distribution of points**

The intersection points of a fitting plane and the sub-space frame define the boundary of the plane, so that the area of the plane can be calculated. The number of intersection points ranges between 3 and 6, and they should form a convex polygon. Finding the order of the intersection points to form a convex polygon is essential to calculate the area of the plane.

### 4) Merge process

A merge process is needed after splitting to connect neighboring planes which are similar. The octree structure allows us to find neighboring planes easily [4]. When a neighboring plane is found, the merge process will first check whether their normal vectors are similar. Fig. 4.a shows the idea of checking normal vectors. However, one may find planes in different layers having similar normal vectors (Fig. 4.b). To solve this situation, additional check of the node relation is needed. After two neighboring planes are found similar, the rigorous calculation will be triggered again to recalculate the parameters of the merged plane and to ensure the merge availability.

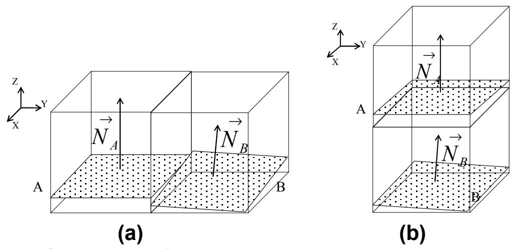



**Fig. 4. Similarity of two neighboring nodes A and B (a) available for merge (b) not available for merge**

## 3. Examples and Analysis

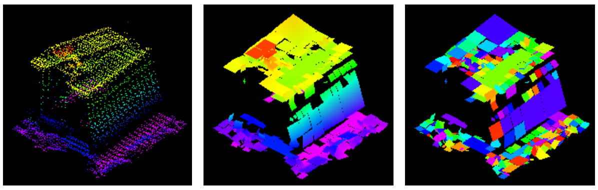
The proposed method can be applied to both airborne and ground lidar data. However, the thresholds used in the program should be adjusted to fit different data sets. Our test data include an airborne lidar data set collected in Hsinchu, Taiwan with Leica ALS40 and a ground lidar data set obtained in Tainan Confucian temple with Optech ILRIS-3D laser scanner. Table 1 lists the basic data attributes and the thresholds applied in the tests.

**Table 1 Information of examples**

| | ALS40 | ILRIS-3D |
|---|---|---|
| Scan Date | April 14 ,2002 | January 24, 2003 |
| Scan Area | Hsinchu | Tainan Confucian temple |
| Point density | About 1.7pt/㎡ | About 1136pt/㎡ |
| Point cloud size | 4700 | 247427 |
| Distance threshold | 1m | 0.05m |
| Density threshold | 0.5p/㎡ | 250p/㎡ |
| Angle threshold | 3° | 3° |

### 1) Airborne lidar example

Fig. 5.a shows a set of point cloud of airborne lidar covering a large building. Most of the points distribute densely over the top part of the building and the ground surface, and some points scatter on a side wall of the building. Fig. 5.b shows the best-fit planes after the split process. Table 2 lists the computation time, the parameters of the octree structure, and the statistic data of extracted planes. In this case, 90.7% of the total points were used to form planes, the rest are scattered points which cannot be used to form planes. Fig. 5.c shows the results after merge process. Attributes, such as gradient, area size, point density, roughness, and average intensity etc., of the merged planes can be calculated for further analysis or classification.



(a) (b) (c)

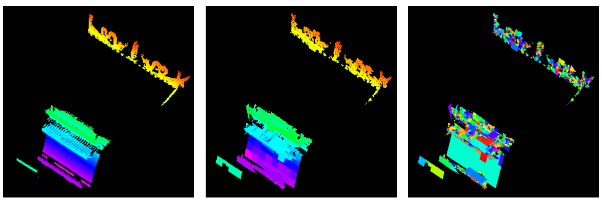
**Fig . 5. Airborne lidar example (a) point cloud (b) results after split (c) results after merge**

**Table 2. Airborne laserscan information**

| | |
|---|---|
| Computation time for split process | 0.25 sec. |
| Computation time for merge process | 0.16 sec |
| Number of the total octree layers | 6 |
| Number of the total leave nodes | 616 |
| Extracted planes and % of the total points used | 297, 90.7 |
| Number of nodes have less than 3 points | 319 |

### 2) Ground lidar example

Fig. 6.a shows the original point cloud of the ground lidar example. Extracted planes shown in Fig. 6.b containing 99.4% of the total points. Fig. 6.c shows the results after the merge process.



(a) (b) (c)

**Fig . 6. Ground lidar example (a) point cloud (b) results after split (c) results after merge**

**Table 3. Ground laserscan information**

| | |
|---|---|
| Computation time for split process | 10.79 sec. |
| Computation time for merge process | 52.22 sec. |
| Number of the total octree layers | 12 |
| Number of the total leave nodes | 4342 |
| Extracted planes and % of the total points used | 3321, 99.4 |
| Number of nodes have less than 3 points | 1021 |

## 4. Conclusions

Lidar data is indeed a kind of 3D image. Traditional image processing techniques do not fit the needs of handling lidar data. Therefore, a new split-and-merge method is proposed to organize randomly distributed lidar data in the 3D space. The point cloud of a lidar data set can be clustered into point groups which form 3D planes and are organized in an octree structure. This process is equivalent to a 3D segmentation of the lidar data to extract plane surfaces. Plane-based classification according to the attributes of the extracted planes then becomes possible [5]. This method can be applied to both airborne and ground lidar data. The thresholds designed in the algorithm can be adjusted to fit different data sets. This data organization can be a stepping stone for extracting spatial information from lidar data.

We also expect that this process would benefit many applications of lidar data. For example:

- Data filtering and compression – points were not used to form planes can be filtered out and densely distributed on a plane can be reduced.
- Feature extraction and classification – 3 dimensional geometric properties can be maintained and explored based on the true 3D segmentation.
- Data merge and adjustment – the extracted planes can be used as control surfaces to connect data sets collected from different scans.
- Texture mapping – digital images or textures of the scanned surface can map onto the extracted planes to form a photo-realistic view.

Continuous improvement and modification of this data organization method will be made in our further study to fit various applications of both airborne and ground lidar data.

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