

PLANAR FEATURE EXTRACTION FROM LIDAR DATA BASED ON TENSOT ANALYSIS

Chung-Cheng Lin¹ Rey-Jer You²

¹PhD. candidate and ²Assoc. Prof., Department of Geomatics

National Cheng Kung University

1 University Road, Tainan 701, Taiwan, R.O.C.

E-mail: ¹p6889102@mail.ncku.edu.tw, ²rjyou@mail.ncku.edu.tw

KEYWORDS: LIDAR, Tensor Voting, Feature Extraction, Cluster

ABSTRACT: Recently, LIDAR (Light Detection and Ranging) technique is in widespread use for obtaining a large number of points with three-dimensional coordinates. Detection and extraction of the objects from LIDAR data is needed for practical use. The LIDAR data, however, do not explicitly contain any geometric information, and features of objects implicitly exist in point clouds. The features, such as planes, lines and corners, can be only indirectly extracted by segmentation algorithms. In this article, we present a two-step algorithm based on the tensor voting framework for the extraction of planar features. First, we infer the normal vector at each LIDAR point by the plate tensors derived from geometric relations among the LIDAR points. In the second step, these normal vectors are classified by the density cluster method based on the directions of normal vectors. The density clusters can be divided into sub-clusters if the coordinates of points are introduced. The normal vectors at points in the same sub-clusters possess the same planar feature. The results of our experiments show that our algorithm is very effective in the automatic extraction of planar features from both airborne and terrestrial LIDAR data.

1. INTRODUCTION

Airborne LIDAR scanning becomes one of the important technologies in object modeling due to the increasing quality and quantity of the LIDAR data. Although three-dimensional data can be directly obtained by a LIDAR system, the geometric features are implicit in point clouds. One major task for LIDAR data processing is to select an appropriate method for extracting geometric features from the irregularly distributed point clouds. If objects are composed of planar segments, the planar information in point clouds will be the most important element for the reconstruction of objects. Many methods are concerned with the extraction of planar information from point clouds. Based on different data structures, they can be categorized into

the point cluster, the line cluster, the mesh cluster and the voxel cluster methods. The point cluster method directly groups unstructuralized points according to a comparison of point properties. The method has two categories: (1) In the feature space, a point and its neighboring points are clustered if they are homogeneous geometrically (Filing, 2002); (2) In the parameter space, the well-known Hough transform (Hough, 1962) is extended to the three-dimensional transform for the extraction of planes from the irregularly distributed point sets (Vosselman 1999).

Except the point cluster method, the rest algorithms gather points together in the structuralized elements. In these methods the structuralization LIDAR data can be categorized to line, mesh and voxel structures. Jiang and Bunke (1994) describe a scan line segmentation method for the extraction of planar faces on range images. Haala and Brenner (1997) extract scan lines from the regular DSM grids and divide them into straight line segments based on the geometric relation between points and their neighboring lines. The line segments are added to a region according to their geometric properties such as the perpendicular distance between their two endpoints and the plane equation of the region. The mesh structuralization is divided into the regular and irregular meshes. Most of algorithms applied for segmentation from LIDAR data work in the regular grids, and the region growing with similar pixels is applied for the segmentation of planar faces (Geibel and Stilla, 2000). For the irregular mesh method, a TIN (Triangular Irregular Network) is often used. In the planar segmentation algorithm based on TIN structure, triangle meshes are merged into planar segments by measuring a similarity between adjacent triangle meshes (Gorte, 2002). Wang and Tseng (2004) determined a plane in each sub-voxel and then merged neighboring voxel with similar property of the plane by an algorithm of planar feature extraction based on an Octree structure and a voxel cluster method.

The method presented in this article is to directly cluster original points by their planar properties. We infer the normal vector at each point based on the Tensor Voting proposed by Medioni et al. (2000) and develop a cluster method based on density clusters for grouping the similar normal vectors in the normal space. Different plane clusters are divided according to their positions in the origin space. The experiments of airborne and terrestrial LIDAR data demonstrate a possibility of the automatic extraction of planar features by the presented method. Applying the extracted planar features, we can produce the nDSM for the 3D city modeling and perform the strip adjustment for calibrating the systematic errors.

2. TENSOR COMMUNICATION

The geometric feature of a point can be described by a second-order symmetric tensor which is expressed as follows:

$$\mathbf{T} = [\bar{e}_1 \ \bar{e}_2 \ \bar{e}_3] \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{bmatrix} \begin{bmatrix} \bar{e}_1 \\ \bar{e}_2 \\ \bar{e}_3 \end{bmatrix} \quad (1)$$

where \bar{e}_1 , \bar{e}_2 and \bar{e}_3 indicate three independent and orthogonal eigenvectors; λ_1 , λ_2 and λ_3 are eigenvalues with respect to the eigenvectors \bar{e}_1 , \bar{e}_2 and \bar{e}_3 . The eigenvalues are real and $\lambda_1 \geq \lambda_2 \geq \lambda_3$ if \mathbf{T} is a positive-semidefinite tensor. Most of LIDAR systems provide only three-dimensional Cartesian coordinates of points, and implied vector information cannot be directly obtained. The tensor voting algorithm presented here can be applied for deriving the vector information. The kernel of the tensor voting is the tensor communication among points. Each point receives vector information from its neighboring points and stores the vector information by the tensor addition rule. In this article, we apply plate tensors for establishing the normal vector field.

In Fig. 1, suppose that A, B and C are the points on the same plane, and the circles at these three points represents the plate tensors at the points. A plate tensor represents the possibility of a normal vector, because the normal vector of a plane is perpendicular to the connection direction of two points. Then the tensor field can be set up and the planar feature can be extracted from the field. Suppose \bar{e}_1 and \bar{e}_2 are any two unit orthogonal bases of the plate tensor and \bar{e}_3 is unit vector pointing towards the direction of A to O. If points lie on the plane, the accumulated tensor at O may be an ellipsoid (Fig. 1(b)). The direction of the maximum principle axes of the ellipsoid is the normal vector of this plane. Assume that the influence of neighboring points on the receiving point is lower while the distance among points increases. The accumulated tensor of any point can be expressed as follows:

$$\mathbf{T} = \sum_{i=1}^m w_i \mathbf{T}_i^p \quad (2)$$

where m is the number of neighboring points, \mathbf{T}^p is the plate tensor of second order and w_i is the weight depending on Euclidean distance between two points. By eigen-analysis of the accumulated tensor at each point, the normal vector direction of a plane can be determined.

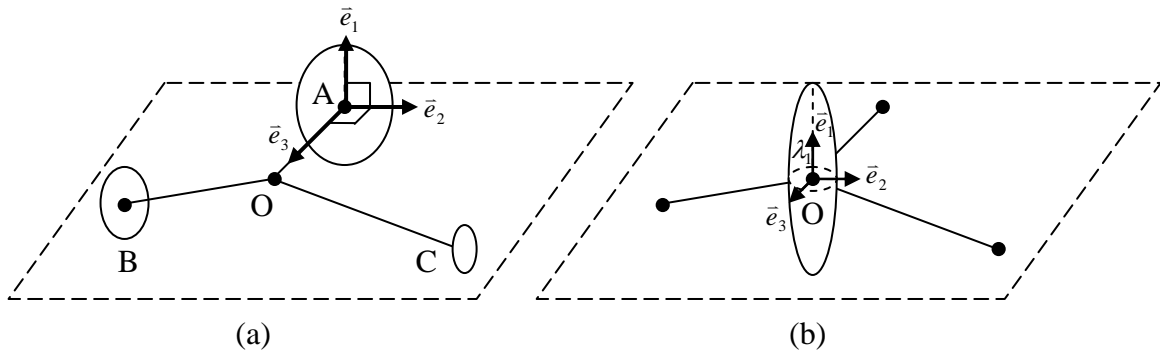


Figure 1. Tensor communication with the help of plate tensors

3. CLUSTER

The implicit normal vector at each point can be derived by eigenvalue analysis from the accumulated tensor (2). For the purpose to cluster points with similar normal vectors, an algorithm based on the density cluster is used. The density cluster is a cluster in which the normal vectors are gathered together in a normal space according to their components. The components of a normal vector are regarded as the coordinates of a point in the normal space. The density of a cluster indicates the number of the normal vectors with the similar direction. Consider the simulated LIDAR data in Fig. 2 where there are 7 planes. After transferring the normal vectors to the normal space, we can find 5 point clusters which mean that we have only 5 different normal directions in the data set. Two out of 7 planes have the same normal directions with other planes (cp. the point clouds in Fig. 2(a)).

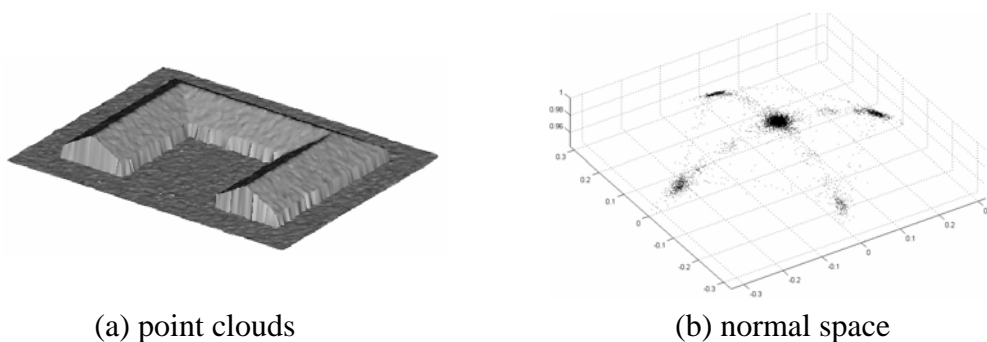


Figure 2. Simulated data set and its normal vector cluster

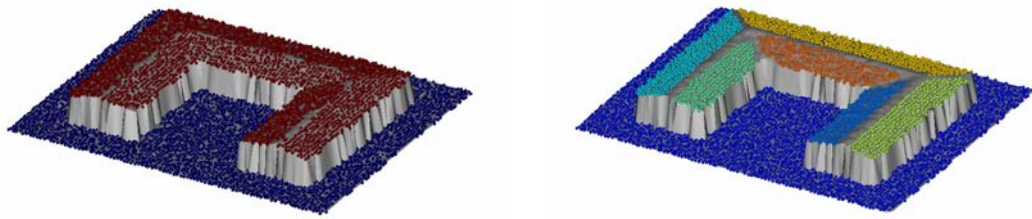
In this article, the density cluster is applied for collecting points with similar planar feature. The place where the points are most intensive is the cluster center. The first step of the current algorithm is to search a cluster where the density in a certain neighborhood is of the maximum. Before searching the cluster with the second high density, we should remove the first cluster from the normal space. Repeating the steps until the rest clusters whose densities are lower than a specified threshold, we get, finally, 5 clusters. However, we have 7 planes in our data set totally (Fig. 2(a)). Hence, the last step in our density cluster method is to transfer each grouped cluster back to the original coordinate space and then to segment the points of the clusters according to their positions in that space.

Few of points that locate in the intersection of two roof planes may not be clustered to their own planar cluster correctly since their normal vectors may be incorrectly inferred. To classify those points, we can apply the plane equations generated by the clustered points.

4. EXPERIMENTAL RESULTS

As the first example for demonstrating the applications of the method proposed here, a

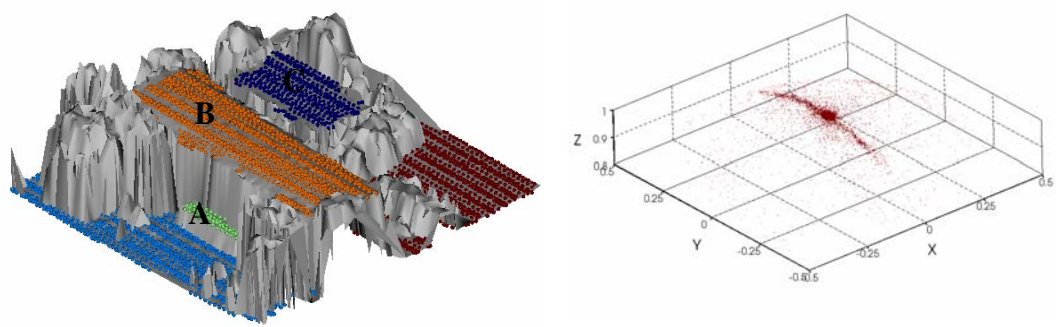
simulated data containing a building with 160° ridge angle is presented. In Fig. 3(a), the region grows by comparing the direction difference of the normal vectors at a seed point with the neighboring points. If the difference is smaller than a specified threshold, the neighboring points will be merged to the region which the seed point belongs to. Because of the small ridge angle, we get only two planes after the region growing. However, applying the density cluster method, we obtain 7 planes (Fig. 3(b)).



(a) without the density cluster method (b) with the density cluster method

Figure 3. Comparison of the region growing with / without the density cluster method

Consider an airborne LIDAR data in Fig. 4 which contains 4 planar features (the planes A, B, C and ground). The plane B is a slight curved surface. By the density cluster method, we obtain 4 planes. It is difficult to identify the points at the surroundings of the planes B and C since the influence of the noisy points on the trees. Nevertheless, the noisy points will be removed and filtered out, if we only extract the planar and line features.



(a) the result of cluster (b) normal space

Figure 4. An example of airborne LIDAR data set and the result of cluster

Ground-based LIDAR data include more variant direction information of normal vectors. The ground-based LIDAR data set given in Fig. 5 contains 11 planar features. By the method proposed here, we can only find 9 planes. The planes I and II in Fig. 5 cannot be found due to the rare point clouds there.

In addition, when two neighboring planes have the same normal vector direction, points on them will be segmented as the same cluster. To solve this problem, we add one extra condition of the height differences between points while the region growing. The height difference is defined as

the separation of the connection vector \vec{v} of two points projecting to the mean normal vector \vec{n} . If the height difference d is larger than a tolerance, we spilt them into two different planes. In Fig. 6, two planes with the same normal vector are given. After adding the extra condition mentioned above, we can get two different planes finally.

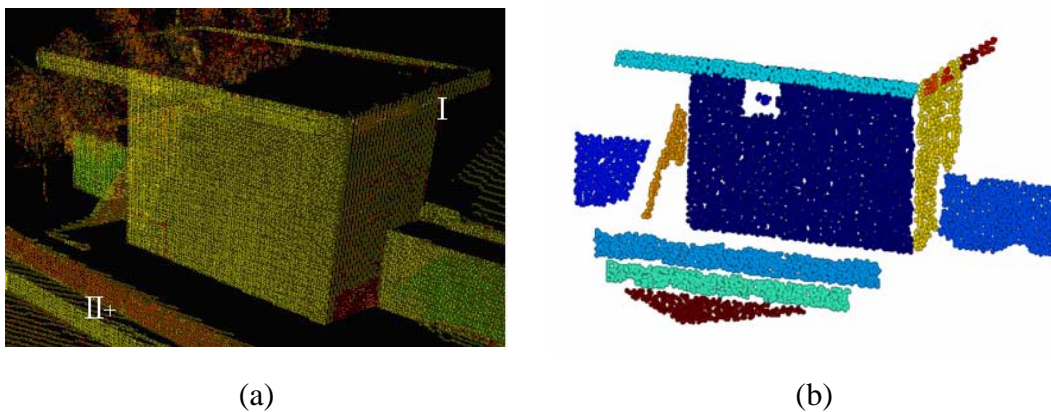


Figure 5. An example of terrestrial LIDAR data set and the result of cluster



Figure 6. Segmentation of two neighboring planes with the same normal vector by a height difference condition

5. CONCLUSIONS

In this study, the geometrical features in LIDAR data are derived by tensor analysis. The implied normal vectors of LIDAR points on planes are inferred by eigenvalue analysis of the corresponding tensors. The density cluster method is proposed for the determination of the normal clusters in the normal space. With the help of plate tensors, the normal vectors can be easily obtained without using TIN and, consequently, a tensor field for the extraction of geometric features can be established. In summary, the results of the experiments show that the current method presented in this paper is useful and effective for the feature extraction in both airborne and ground-based LIDAR data.

REFERENCES

- Filin, S., 2002. Surface clustering from airborne laser scanning data, *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. XXXIV, 3A, Graz, pp 117-124.
- Geibel, R. and Stilla, U., 2000. Segmentation of laser altimetry data for building reconstruction : different procedures and comparison, *International Archives of Photogrammetry and Remote Sensing*, vol. 33, part B3, pp. 326-334.
- Gorte, B., 2002. Segmentation of TIN-Structured Surface Models, *Symposium on Geospatial Theory, Processing and Applications*, working Group IV/6, Ottawa, Canada.
- Haala, N., Brenner, C., 1997. Generation of 3D city models from airborne laser scanning data, *Proc. EARSEL Workshop on LIDAR Remote Sensing of Land and Sea*, Tallinn, Estonia, pp.105-112.
- Hough, P.V.C., 1962. Method and Means for Recognizing Complex Patterns, U.S. Patent 3.069.654.
- Jiang, X.Y. and Bunke, H., 1994. Fast Segmentation of Range Images into Planar Regions by Scan Line Grouping, *Machine Vision and Applications* 7 (2): 115-122.
- Medioni, G., Lee, M.S., and Tang, C.K., 2000. *A Computational Framework for Segmentation and Grouping*, Elsevier.
- Vosselman, G., 1999. Building Reconstruction using Planar Faces in Very High Density Height Data, *International Archives of Photogrammetry and Remote Sensing*, vol. 32, part 3-2W5, pp. 87-92.
- Wang, M., Tang, K. P. and Tseng, Y. H., 2005. LIDAR Data Octree Structurizing for Plane Extraction, *Journal of Photogrammetry and Remote Sensing*, vol. 10, No. 1, pp. 59-70.
- Yager, R.R., Filev, D.P. 1994. Approximate clustering via the mountain method, *Systems, Man and Cybernetics*, IEEE Transactions on Volume 24, Issue 8, pp.1279~ 1284.
- You, R. J., 2000. A Study of Generation of the Digital Elevation Model in the Coast of West Taiwan with the Airborne Laser Scanning Technique, National Science Council, NSC-89-2211-E-006-080 (in Chinese).