Chapter 10
3D City Modelling from LIDAR Data

Rebecca (O.C.) Tse, Christopher Gold, and Dave Kidner

Abstract

Airborne Laser Surveying (ALS) or LIDAR (Light Detection and Ranging) becomes more and more popular because it provides a rapid 3D data collection over a massive area. The captured 3D data contains terrain models, forestry, 3D buildings and so on. Current research combines other data resources on extracting building information or uses pre-defined building models to fit the roof structures. However we want to find an alternative solution to reconstruct the 3D buildings without any additional data sources and predefined roof styles. Therefore our challenge is to use the captured data only and covert them into CAD-type models containing walls, roof planes and terrain which can be rapidly displayed from any 3D viewpoint.

10.1 Introduction

We have successfully addressed this problem by developing a several-stage process. Our starting point is a set of raw LIDAR data, as this is becoming readily available for many areas. This is then triangulated in the x-y plane using standard Delaunay techniques to produce a TIN. The LIDAR values will then show buildings as regions of high elevation compared with the ground. Our initial objective is to extrude these buildings from the landscape in such a manner that they have well defined wall and roof planes. We want to know how to extract building outlines from the triangulation when it is not available from the national mapping department. We do this by superimposing a coarse Voronoi cell structure on the data, and identifying wall segments within each.

University of Glamorgan, Pontypridd, Wales, UK rtse@glam.ac.uk, cmgold@glam.ac.uk, dbkinder@glam.ac.uk

There are two ways to examine the triangulated interior (roof) data. The first method is to find out the folding axis of the roof, but it may not be suitable for a complex roof. The second is to identify planar segments and connect them to form the final surface model of the building embedded in the terrain. This is done using Euler Operators and Quad-Edges with preserved topological connectivity. This was successfully developed by [10, 11]. In this paper, we will focus on discussing how to extract building blocks from raw LIDAR data and how to find out the roof shape of those building blocks.

10.2 What is LIDAR?

ALS (or so called LIDAR) is a new independent technology which is highly automated to produce digital terrain models (DTM) and digital surface models (DSM) [1]. It is a laser-based technology to emit and capture the returned signal from the topographical surface.

A laser scanning system, a global positioning system (GPS) and an inertial measuring unit (IMU) are the three main units in an ALS system. The laser scanning system is mounted on an aircraft, a helicopter or satellites and emits pulses toward the earth's surface and measures the distance reflected from the earth's surface and other objects on the surface back to the aircraft. IMU and GPS are important for determining the absolute position and orientation of the LIDAR sensors. The Inertial navigation system is used to correct the errors from the pitch, roll and yaw of the plane. GPS monitors the altitude and the flight path of the aircraft which observes the three dimensions data. A high accuracy GPS is installed in the plane and a ground control based station is established. Figure 10.1 shows an aircraft scanning over a piece of land.

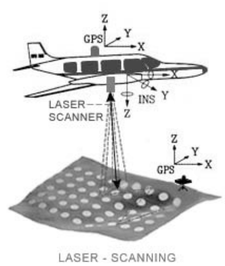

Fig. 10.1 Airborne laser scanning

10.3 Building Construction from LIDAR Data Alone

LIDAR provides an efficient way to capture 3D data; however it is not easy to extract building information from the data. Much research focuses on extracting building outlines, and they may combine different data sources, for example photogrammetric data or existing landline data [6, 7, 8, 13] . It does not work if there is no other data available. Our approach is to use LIDAR only to reconstruct the 3D buildings and remodel the roof structure without using any pre-defined models.

10.3.0.4 Building Blocks Identification

Our method is to identify building blocks from the terrain rather than searching for the building footprints directly. It separates the high-elevation data (building block) from low-elevation data (terrain surface). We make use of the duality and connectivity properties of Delaunay triangulation, and its dual Voronoi diagram.

A Delaunay triangulation is created using the original high density LIDAR data (Figure 10.2). Then we sample it to a lower resolution triangulation (Figure 10.3. In Figure 10.3 each big Voronoi cell contains many data points (about 50 - 100), some with only the ground points (low elevation) and some with only the building points (high elevation). Voronoi cells with low and high points are extracted for further modification because building segments can be found in those cells. We are using some made-up data with an L-shaped building to illustrate the method.

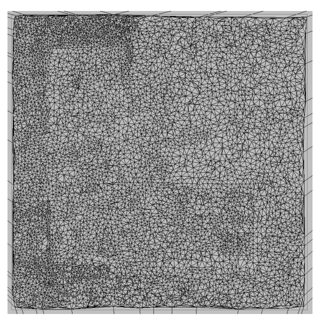

Fig. 10.2 Raw LIDAR data points

The extracted cells contain low and high points which will be split into two. The direction of the splitting line is found by calculating the eigenvalues and eigenvectors of the 3 x 3 variance-covariance matrix of the coordinates of the points within each cell. The result of three eigenvectors “explain” the

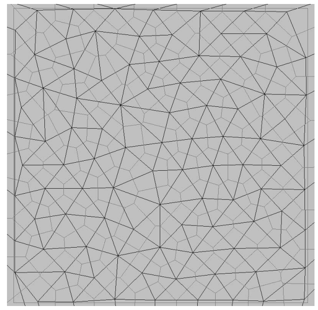

Fig. 10.3 Lower resolution LIDAR data points

overall variance, the left-over and the residue. For example, a wrinkled piece of paper might have the first eigenvector (the highest eigenvalue) oriented along the length of the paper, the second (middle eigenvalue) along its width, and the third (the smallest eigenvalue) “looking” along the wrinkles. Thus the eigenvector of the smallest eigenvalue indicates the orientation of a wall segment, if present, and looks along it. Figure 10.4 shows the eigenvector with the smallest eigenvalue which shows the orientation of the splitting line between the low and high points.

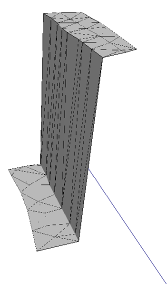

Fig. 10.4 The eigenvector with the smallest eigenvalue

With the orientation of the splitting line, the next step is to find the best location to put the line and split the cell. This is achieved iteratively, by testing various positions of the line parallel to the smallest eigenvector in order to find the greatest difference between the low and the high points. Figure 10.5 shows a thick line which separates the high points from the low points. In order to minimize the effect of sloping roofs or terrain, only those elevations close to the line are used. If this maximum difference is not sufficiently large then no wall segment was detected. Therefore walls have a specified minimum height and this height difference is achieved within a very few “pixels”.

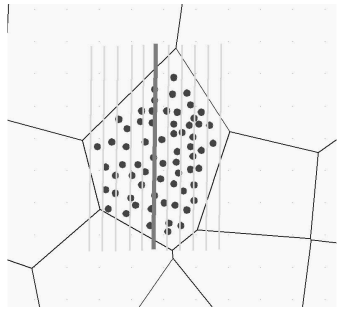

Fig. 10.5 The thick red line separates the low and high data points

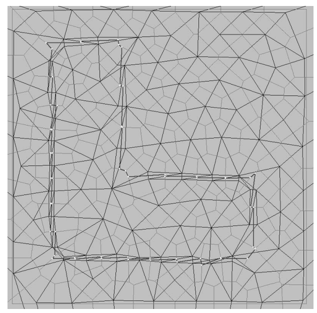

Fig. 10.6 Building segment in each Voronoi cell

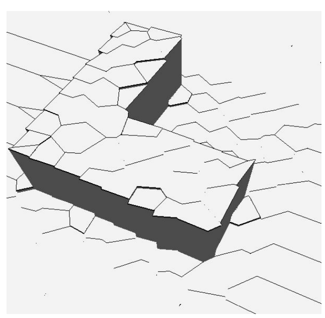

Fig. 10.7 Vertical Building Walls formed by split Voronoi Cells

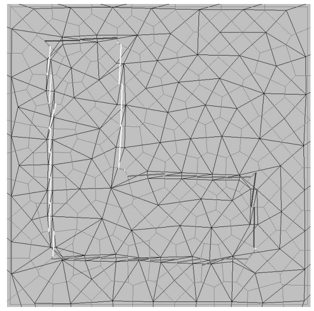

Fig. 10.8 The split Voronoi edges in six groups

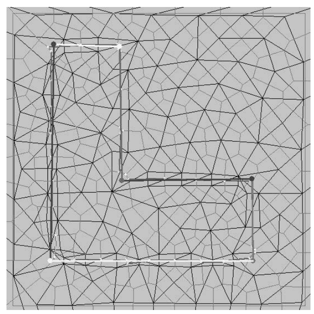

Fig. 10.9 Corners of the building

We locate the splitting line and add a generator on each side of this line, at the mid-point to split the cell. Figures 10.6 and 10.7 show the 2D and 3D view of the split Voronoi cells. A set of "high" Voronoi cells are split and surrounded by "low" ones. In Figure 10.6 building boundaries are then determined by walking around the cells and connecting the Voronoi boundary segments (the splitting line) or the immediate Voronoi edges to form a closed region. If a closed high region is found, it is considered to be a building.

The Voronoi boundary segments are used to estimate the building outline. We use the Voronoi boundary segments which are created with the eigenvector technique (but not all the Voronoi edges to form the closed high region. The Voronoi segments are clustered according to their orientation (Figure 10.8). A best fit line is found to represent each group of the clustered Voronoi segments. Figure 10.9 forms the building outline by intersecting the best fit lines.

10.4 Roof Modelling

Many systems use pre-defined building models for reconstruction [2, 5], but we would like to reconstruct the buildings without any pre-defined models. Two methods are used to remodel the roof structure. The first is simple but works only with simple gabled roofs. The second is more complicated but can solve the problem of the complex roof structure.

10.4.1 Simple Roof

No other assumptions are made about the form of the roof in our approach, except that the roof is made up of planar segments. This method may be extended to detect other basic shapes if required [14]. When the building boundary is determined, the interior points are extracted to model the roof structure. The extracted points are used to create a triangulation and each of the interior triangles has an associated vector normal (Figure 10.10. The vector normals are used to calculate and find the "smallest" eigenvector (described in the section 10.3). We project the vector normals on a right-hand coordinate system according to the "smallest" eigenvector (Figure 10.11).

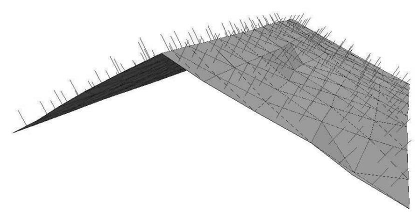

Fig. 10.10 Each of the interior triangles has an associated vector normal

In Figure 10.12 all the vector normals are plotted on a unit semicircle. The plotted vector normals are close to each other if they have the same orientation. They can be clustered into different groups (Figure 10.13). This works well even if the data is fairly noisy because the scatter of the vector normals is fairly large (Figure 10.14). If there are two or more parallel planes on the roof , these may be separated at this stage by constructing the Delaunay triangulation in x-y space for the data points of the cluster, extracting the Minimum Spanning Tree (MST), and separating the two or more parallel roof portions. The general technique is described in the next section.

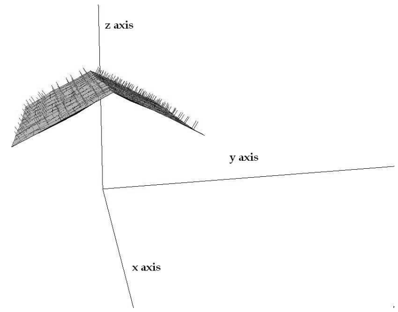

Fig. 10.11 Projected right-hand coordinate system according the smallest eigenvector

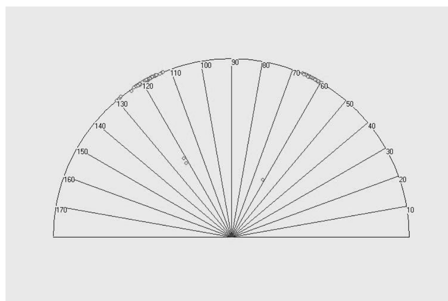

Fig. 10.12 All vector normals are plotted on a semicircle

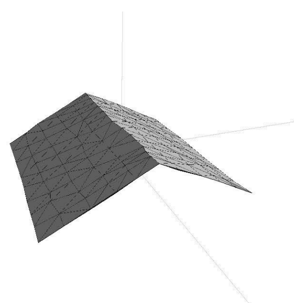

Fig. 10.13 Clustered vector normals with its associated triangle

Fig. 10.14 A clustered simple roof created by noisy data

10.4.2 Complex Roof

The above method only works for roofs with a simple axis. If the roof has many differently oriented segments, the vector normals have to be projected onto the unit hemisphere. [4] used different projections to find out the roof segments.

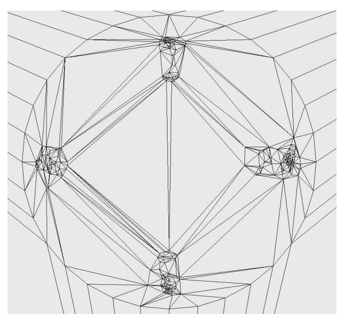

Fig. 10.15 2D view of vector normals on the unit hemisphere

A cross-hipped L-shape roof building is used to illustrate the clustering methods. The extracted data points (inside the building boundary) are used to create a Delaunay triangulation. The vector normals of the interior triangles are project onto the unit hemisphere. Figures 10.15 and 10.16 show the 2D and 3D views of projected vector normals on the unit hemisphere. Then the vector normals are clustered by their orientation and geographical location. The result is several sets of clustered triangles (vector normals) which share a single roof plane with a common description of the plane. The planar descriptions are used to form roof planes and intersect the building walls which produce the building model.

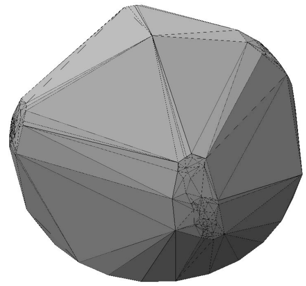

Fig. 10.16 3D view of vector normals on the unit hemisphere

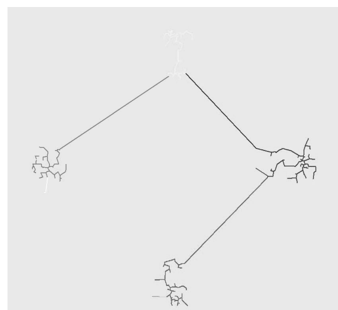

Fig. 10.17 Orientation clustering of vector normals in 2D view

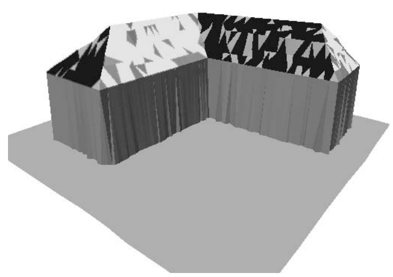

Fig. 10.18 The darker triangles face toward the same direction

Orientation Clustering is the first method used to separate the vector normals. The location of the vector normals on the unit hemisphere represent their orientation on the roof (direction). They are clustered into groups using the Minimum Spanning Tree (MST). If the vector normals are close enough, they will be assigned to the same group. Figure 10.17 shows four groups of vector normals which means the triangles face four different directions. However the roof may contain more than four roof planes which means some roof planes face the same way. Figure 10.18 shows that triangles with the same orientation are clustered. Further clustering is needed to separate the same direction roof planes.

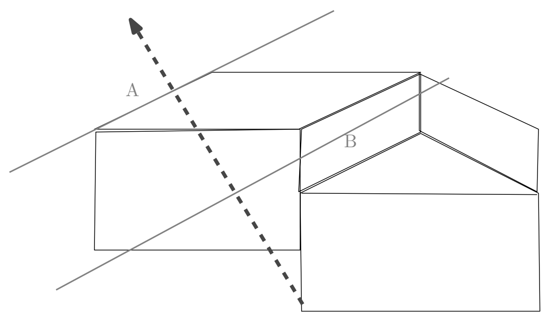

Fig. 10.19 Triangles on roof A and B projected onto the averaged vector normal (thick dash line)

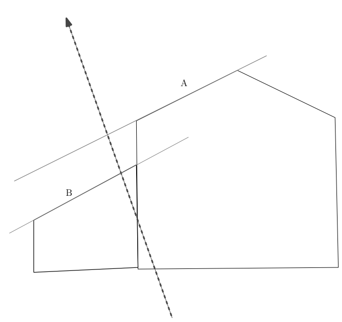

Fig. 10.20 Triangles on roofs are projected on its averaged vector normal (thick dash line)

In the second clustering method, we average the vector normals (the thick dashed line in Figure 10.19) and project the centre point of the triangles (solid thin lines in Figure 10.19) onto its averaged vector normal. They are in the same group if the projected centre points are close to each other. The same method is used to separate the building extension due to the height difference between the main and the extension buildings. In Figure 10.20 triangles on Roof A (main building) and B (extension building) are projected and clustered into two groups because of their locations.

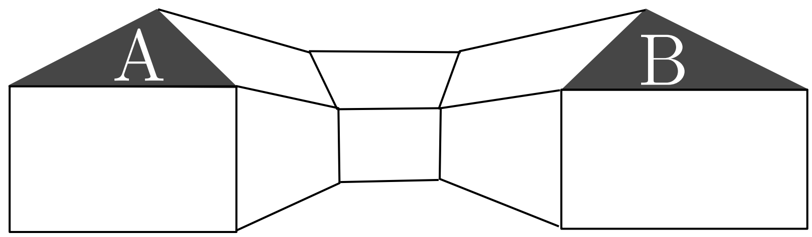

Fig. 10.21 A building with complicated hipped roofs

Figure 10.21 shows roof planes A and B in the same group after two clustering; however they are two different roof planes. The geographical clustering method is used to separate roof planes A and B. The centre points of the triangles are extracted to create a Delaunay triangulation. We then cluster the centre points using the MST. Roofs A and B will be separated into two groups.

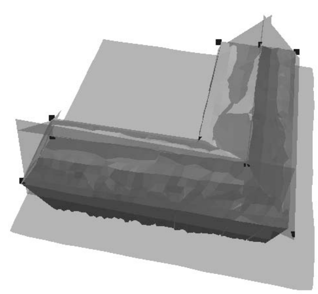

Fig. 10.22 Square points are the intersection points

Finally each cluster of triangles represents a roof plane. Once we have got all the roof planes, we need to consider the intersection of the roof planes. The relationships between roof planes may be represented as a dual triangulation. We use the dual triangulation to intersect every adjacent three to four roof planes. Figure 10.22 shows the intersection points (square points) between the roof planes and the vertical walls of the building.

10.5 Tools for Building Reconstruction

Our approach is to reconstruct a 3D city model with preserved topological connectivity. We have successfully developed a set of tools for building reconstruction [12, 9]. Few steps are used for the building reconstruction:

- Delete all the data points which are inside the building boundary.
- Insert the intersection points (include the building outline and the roof structure points) using the constrained Delaunay triangulation.
- Use Euler Operators to extrude the building to its height and remodel the roof structure.

The result of an extruded L-shape building is shown in Figure 10.23.

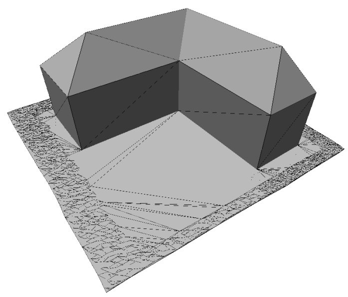

Fig. 10.23 An extruded L-shape building

10.6 Conclusion

We have outlined a procedure for the direct extraction of building exteriors from LIDAR data without any additional data sources and pre-defined building models. More complicated buildings have been built. With the help of the research of [3] may be able to model the roof like the Wales Millennium Centre which is an arch shape roof.

References

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