Automated Extraction of Building Geometry from Mobile Laser Scanning Data Collected in Residential Environments

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ABSTRACT

Spatial data collection in urban environments for the extraction of building inventory information is important for many applications such as urban planning, storm water management, hazard mitigation, vulnerability assessment, and loss estimation to name a few. Creating and updating building inventory databases in large and developing urban environments benefits from efficient data acquisition and data processing techniques. This study leveraged and integrated the advantages of ground-based mobile laser scanning and aerial photography through an automated method to extract building inventory information. The integration of terrestrial and aerial data enables the identification of buildings in the dataset and the extraction of both roof polygons and wall footprints. The presented method was evaluated with real datasets collected from a typical residential area. The area of roof polygons extracted by the automated approach differs by less than 5% when compared to manually calculated values. Also the proposed method allows for accurate extraction of walls captured within the point cloud.

INTRODUCTION

Three-dimensional representations of urban environments and the extraction of building inventory information are important for many applications such as urban planning, storm water management, disaster management, and emergency response to name a few. Because of the need for up-to-date information in inherently intricate urban scenarios, efficient data acquisition technology and automatic data interpretation techniques have been actively studied and implemented in recent years (Maas and Vosselman, 1999; Süveg and Vosselman, 2004; Brenner, 2005; Pu and Vosselman, 2009; Awwad et al., 2010; Tang et al, 2010). In particular, the segmentation of data into individual features, automatic detection of buildings, and extraction of building ground plans and roof/wall dimensions are major tasks in these research studies.

Extensive studies have been conducted to automatically extract building information from spatial data collected with aerial sensors (Maas and Vosselman, 1999; Süveg and Vosselman, 2004; Dorninger and Pfeifer, 2008). These methods employ height and intensity information saved in airborne collected point clouds, color and texture information from aerial images, or a combination of both to detect and reconstruct buildings and extract building information. The major drawbacks of aerial data collection for building extraction are: 1) the low resolution of data compared with ground-based data collection, and 2) the incomplete representation of building walls (Elberink, 2008; Kashani and Grau, 2013). These limitations complicate the process of point cloud segmentation and object identification (e.g. discrimination between buildings and surrounding objects, such as trees) and prevent the extraction of details from building façades such as the shape of walls and façade surfaces, number and shape of windows, etc. Aerial data collection allows extracting building roof polygons; however, ground-based surveying is often needed to extract wall footprints, specifically in the presence of roof overhangs (Hammoudi et al., 2009).

Recent developments in ground-based laser scanning technologies have allowed for the acquisition of street-level 3D data in urban environments with high precision and resolution. Several studies have applied different techniques for segmentation of terrestrial laser scanning data to extract building façade components for 3D building modeling or other purposes (Pu and Vosselman, 2009; Awwad et al., 2010, Kashani et al., 2013). Although ground-based laser scanning can provide detailed façade information, data collection with stationary ground-based scanners is not efficient for large urban environments. Each stationary scan can only capture a local part of a large scene (e.g. a street scene); therefore, extensive time and effort must be spent on collecting multiple scans from various locations. Recently, the development of mobile laser scanning systems using terrestrial laser scanners mounted on vehicles have provided a technology that can rapidly collect point cloud data in urban environments; However, the development of robust methods for automatic extraction of building information from mobile laser scanning data has lagged behind the rapid technological advances.

The main challenges in processing mobile laser scanner data for building inventory information are: 1) the very large number of points and objects in a dataset, 2) the inclusion of objects other than buildings, and 3) the occlusion of roof and wall surfaces on the back sides of buildings. The point cloud collected by a mobile laser scanner includes many points belonging to different objects including buildings, trees, pedestrians, traffic signs, lighting poles, etc. Current point cloud segmentation methods developed to extract building façade surfaces are not efficient when used on large urban point clouds. Tarsha-Kurdi et al (2007) indicated that common plane fitting algorithms such as RANdom SAmple Consensus (RANSAC) (Fischler and Bolles, 1981) and 3D Hough transformation (Hough, 1962) may lead to "spurious surfaces" when they are applied to large point clouds that include multiple buildings and other objects. Therefore, before applying these plane fitting algorithms, the dataset should be segmented into points belonging to individual buildings. In addition, the mobile laser scanning data is collected by a vehicle-based device that scans buildings from a streets view. Therefore, mobile scanners are unable to scan roof or wall surfaces that are not visible from the street, and another source of information is needed to extract complete roof polygons and wall footprints of buildings.

The research presented in this paper describes a novel method to automatically extract building information from mobile laser scanning data collected in residential environments. The developed method incorporates color information from an aerial image of the scanned area to compensate for the lack of scan data on the backside of buildings and facilitates the building identification process. The integration of the aerial and terrestrial data collection allows extraction of both complete roof polygons and wall footprints. Once points of each building are identified and isolated, these points are used as input to current plane fitting methods to segment façade surfaces and extract detailed building information such as the shape and number of façade surfaces and windows.

AUTOMATED METHOD

The proposed method is comprised of three main steps: (1) identification of visible roof segments in point clouds, (2) extraction of complete roof polygons, and (3) extraction of wall footprints. The algorithms used to perform each of these steps are described in the following sections, and within the scope of one to two stories residential buildings.

Identification of Roof Segments in Point Cloud

In the first step of this method, visible roof areas, as seen from the street, are identified. The roof areas are used in the next step as seed regions to extract complete roof polygons from aerial images. A raster technique and slope-based analysis (Vosselman, 2000) are employed to filter out points belonging to the ground and other objects. The raster technique and slope-based analysis are described in the following paragraphs.

The point cloud data is first converted to a 2D raster dataset in which each raster cell saves only the Z value of the lowest point within that cell. As schematically illustrated in Figure 1(a), a point cloud collected from the street level is likely to include several points at different heights on a vertical object such as tree, light pole, or wall at a given (x,y) coordinate. But the raster saves only the Z value of the lowest point at each (x,y) coordinate and thus filters out multiple points on vertical objects. As illustrated in Figure 1(b), the Z values saved in the raster are likely to belong to the ground or roof surfaces except for a few points that remain on vertical objects, like trees.

Roof segments in the raster dataset are identified by a slope-based analysis (Vosselman, 2000). A neighborhood window, as shown in Figure 2(a), is slid on the raster dataset, and the slope of vectors connecting each raster cell to the other cells in the window is compared with a threshold value set larger than the surrounding ground surface slope. Therefore, roof cells are identified in the raster where the vector has a steeper slope than a threshold value. Some vertical objects may cause small areas not associated with a roof to remain. These small areas are filtered out using an area threshold, i.e. roofs cannot be smaller than a minimum set area value. The minimum height in a raster cell that is assigned in previous step often reduces roof areas around the edge of a roof (e.g. in existence of roof overhangs). Points located along the edge of the detected roof are checked in the point cloud, and if they are as high as the detected roof, then their area is added to the overall roof area. The identified roof area is then saved as a polygon, as shown in Figure 2(b). The roof area is then used as seed regions for image classification in the next step.

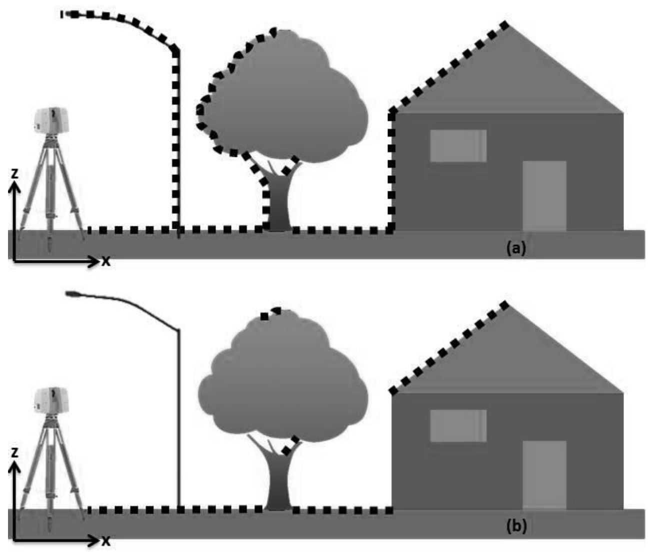

Figure 1. Schematic of point cloud data collected from street level: (a) several points with different heights on vertical objects; (b) lowest point at each (x,y) coordinate.

Extraction of Complete Roof Polygons

Due to the roof occlusion issue associated with street level mobile laser scanning, the roof polygons identified in the previous step only cover a portion of the roof that is visible from the street. Therefore, in this step, the identified roof areas are employed as seed regions for a region growing methodology that extracts a complete roof polygon from an aerial image.

Red, Green, and Blue (RGB) and intensity values are used as metrics in a region growing image classification. The set of pixels in the aerial image that overlap a roof polygon identified in the previous step is used as a sample to determine a range of RGB and intensity values for roof pixels. A buffer polygon along the street sides of a building (front, left and right side of the roof polygon), as shown in Figure 2(c), is used as a sample to establish a range of RGB and intensity values for none-roof pixels. Using the established RGB and intensity ranges and a maximum likelihood classifier, the model identifies other roof pixels within a rectangular neighborhood around the seed roof polygon. The seed roof polygon is grown by combining newly identified roof pixels until the roof polygon overlaps the entire area of the roof in the image. The result created by this method may include small regions that were misclassified and roof edges that may not be straight due to the noise, contrasts, and shadows. To improve the results, these small misclassified regions are removed and roof boundaries are smoothed and generalized by forcing the edges to be parallel or perpendicular to the main directions of the buildings. Figure 2(d) shows the resulting building polygons.

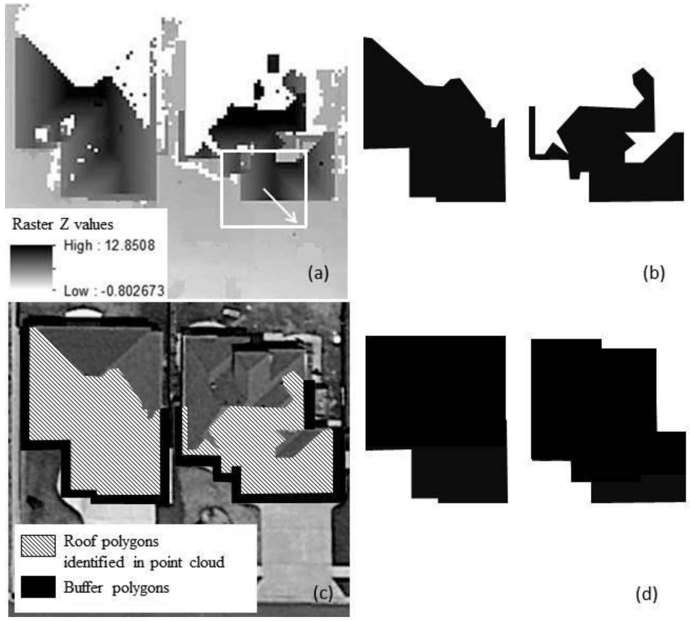

Figure 2. Extraction of roof polygons: (a) a slope-based analysis of a raster dataset after filtering vertical objects; (b) identified roof polygons in point cloud data; (c) roof polygons and buffer polygons overlaying on the aerial image; (d) complete roof polygons

Extraction of Walls

In the third step of this method, wall footprints are extracted. The roof polygons generated in the previous step are used to isolate points for each building. Then an adopted RANSAC algorithm is applied to detect vertical planar surfaces in the point cloud. The RANSAC algorithm detects the largest planar surface in a point cloud. In order to identify multiple surfaces within the same point cloud, the algorithm can be repeated, but each time the previous largest surface must be removed from the cloud. The vector normal to the surface is used to identify whether or not the detected surface is a vertical wall. Once the vertical wall surfaces are identified, the wall footprints are extracted with the projection of vertical planes on the XY coordinate surface. Figure 3 illustrates point cloud of a building, façade plane segments detected by the RANSAC algorithm, and the detected vertical planes projected on the XY coordinate surface. As seen in Figure 3, even though there was a tree in the scan that eliminated many building points, the method is still able to detect vertical planes and produce an accurate wall footprint.

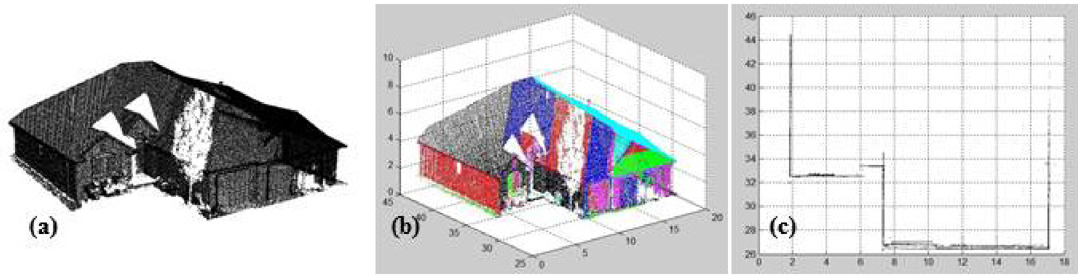

Figure 3. Extraction of wall footprints: (a) point cloud of a single building isolated from the point cloud dataset; (b) façade plane segments; (c) vertical planes projected on the XY coordinate surface

CASE STUDY

A case study using this new method was carried out on a point cloud dataset collected in a residential area with one- two-family houses. To implement the proposed method in a Geographic Information Systems (GIS) environment, custom GIS models were coded and used with ArcGIS Model Builder. The accuracy of building extraction was assessed separately for each building by comparing extracted values with manually measured values.

Since authors did not have a mobile scanner, a ground-based stationary laser scanner was employed to collect point cloud data. But to obtain point cloud data that matches mobile scanner data, 5 scans were collected from stations along the street. Therefore, scans did not include backside of the buildings. Figure 4(a) shows the locations of the scans on an oblique aerial photo. Point cloud data collected from the different locations were registered using post-processing software. Figure 4(b) shows an oblique view of the point cloud data.

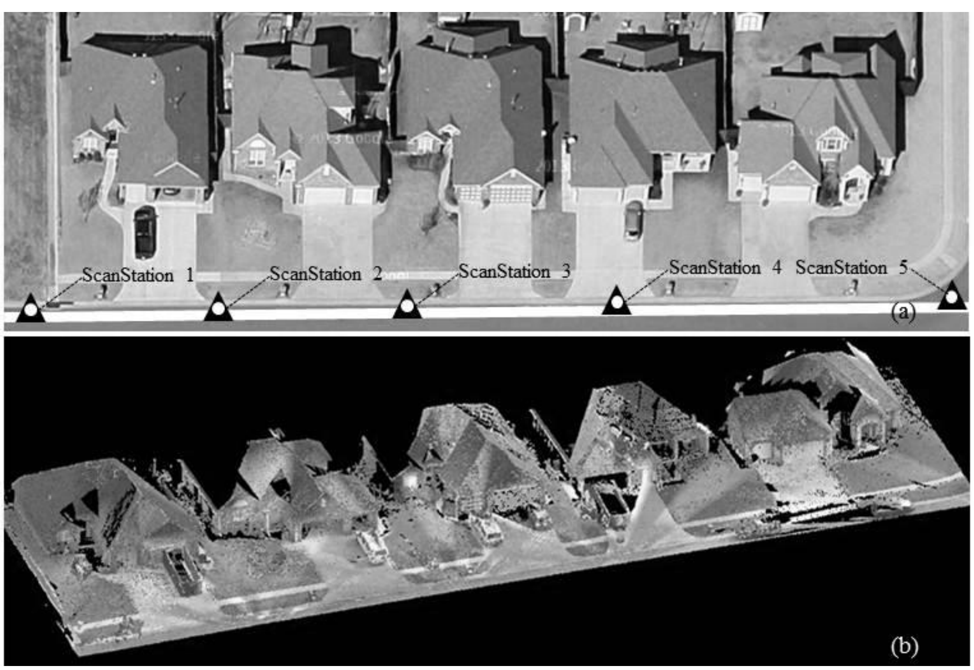

Figure 4. 3D data acquisition at a residential area: (a) Oblique view of the scanned area and locations of scan stations; (b) Point cloud of the scanned area

The point cloud dataset along with the corresponding aerial image of the scanned area were imported into ArcMap and used as inputs to the custom GIS models. Figure 5(a) illustrates the identified roof segments in the point cloud data overlaying the aerial image. The roof areas were used in the image classification step to generate complete roof polygons. Figure 5(b) shows roof polygons automatically extracted from the aerial image along with roof polygons manually drawn. Finally wall footprints were extracted by applying the RANSAC algorithm on the isolated points of each building. Figure 5(c) shows the extracted wall footprints from street-level laser scanning data along with complete footprints drawn manually.

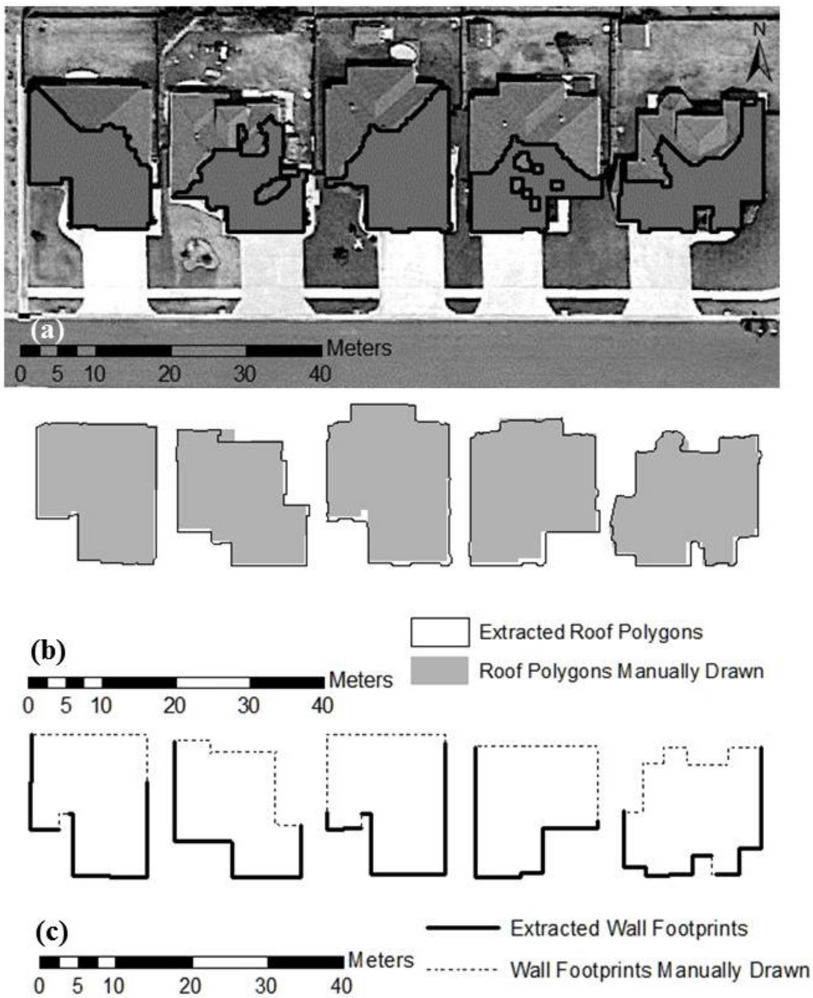

Figure 5. Outputs of GIS models: (a) Roof segments identified in point cloud overlaying on aerial image; (b) Extracted roof polygons; (c) Extracted wall footprints

The area of the roof polygons and the length of walls generated with this automated method were compared with ground truth data to evaluate the accuracy of the method. Ground truth data was captured from manual measurements performed with commercial point cloud processing software. Table 1 presents the result of the comparison. As seen in Table 1, the discrepancy between the area of the extracted roof polygons and the manual measurements are less than 5% for all buildings. Shadows on roofs, the low quality of the aerial image, and the lack of contrast at roof edges are the main causes for these discrepancies. The proposed method accurately identified wall footprints for walls within the cloud (i.e. the walls that captured by the scanner). As shown in Figure 5 (c), Walls that were not extracted, approximately 40% of walls, had been on the back of buildings and were not captured in scans. However, the footprint of missing walls on the back of a building can be estimated using the extracted roof polygons and detected wall footprints.

Table 1. The area and length of extracted roof polygons and wall footprints

Building	Area of roof polygons (m2)			Length of wall footprints (m)		
	Extracted polygons	Manually drawn polygons	Area discrepancy (%)	Extracted footprints	Manually drawn footprints	Length discrepancy (%)
1	266.12	269.13	1%	45.63	70.07	35%
2	246.08	244.23	1%	40.25	67.56	40%
3	301.29	290.72	4%	41.84	70.04	40%
4	285.78	278.60	3%	39.45	64.76	39%
5	279.63	280.24	0%	43.95	77.09	43%*

* The length discrepancy includes the length of walls in the backside of buildings that were not captured in scans

CONCLUSION

This research study developed a novel method to automatically extract building objects in residential environments through the combination of mobile laser scanning and aerial imagery supported with GIS tools. The integration of terrestrial and aerial data in the novel methodology enables the identification of buildings in the data and also allows for proper extraction of both roof polygons and wall footprints. The case study indicated that the area of roof polygons extracted by the automated method differs by less than 5% when compared to manually calculated values. Also, the method can accurately extract the footprints of walls within the point cloud. The footprints of walls on the backside of buildings, approximately 40% of walls in the case study, are not directly detectable from street-based mobile laser scanning data, however these walls can be estimated using the roof polygons and wall footprints extracted with the presented method.

LIST OF REFERENCES

Awwad, T. M., Zhu, Q., Du, Z., & Zhang, Y. (2010). An improved segmentation approach for planar surfaces from unstructured 3D point clouds. The Photogrammetric Record, 25(129), 5-23.

Brenner, C. (2005). Building reconstruction from images and laser scanning. International Journal of Applied Earth Observation and Geoinformation, 6(3), 187-198.

Dorninger, P., & Pfeifer, N. (2008). A comprehensive automated 3D approach for building extraction, reconstruction, and regularization from airborne laser scanning point clouds. Sensors, 8(11), 7323-7343.

Elberink, S. O. (2008). Problems in automated building reconstruction based on dense airborne laser scanning data. International archives of the photogrammetry, remote sensing and spatial information sciences, 37, 93-98.

Fischler, M. A., & Bolles, R. C. (1981). Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. Communications of the ACM, 24(6), 381-395.

Hammoudi, K., Dornaika, F., & Paparoditis, N. (2009). Extracting building footprints from 3D point clouds using terrestrial laser scanning at street level. ISPRS/CMRT09, 38, 65-70.

Hough, P. V. C. (1962). Method and means for recognizing complex patterns. U.S. Patent 3,069,654. Lerma, J. L. and Biosca, J. M., 2005. Segmentation and filtering of laser scanner data for cultural heritage. CIPA 2005 XX International Symposium, Torino, Italy. 6 pages

Kashani, A. G., & Grau, D. (2013). Automated Extraction of 3D Building Objects From Clustered Urban Environments with Computational Geometry and Terrestrial Laser Scanning Technologies. AWERProcedia Information Technology and Computer Science, 3.

Kashani, A. G., Biswas, S., Crawford, P., Graettinger, A., Grau, D. (2013). Automated Tornado Damage Assessment and Wind Speed Estimation Based on Terrestrial LiDAR Data. Journal of Computing in Civil Engineering, ASCE, (in review)

Maas, H.G. and Vosselman, G. (1999) Two algorithms for extracting building models from raw laser altimetry data. In: ISPRS Journal of Photogrammetry and Remote Sensing, 54 (1999)2-3 pp. 153-163.

Pu, S. and Vosselman, G. (2009) Knowledge based reconstruction of building models from terrestrial laser scanning data. In: ISPRS Journal of Photogrammetry and Remote Sensing, 64 (2009)6 pp. 575-584.

Süveg, I. and Vosselman, G. (2004) Reconstruction of 3D building models from aerial images and maps. In: ISPRS Journal of Photogrammetry and Remote Sensing, 58 (2004)3-4 pp. 202-224.

Tang, P., Huber, D., Akinci, B., Lipman, R., & Lytle, A. (2010). Automatic reconstruction of as-built building information models from laser-scanned point clouds: A review of related techniques. Automation in construction, 19(7), 829-843.

Vosselman, G. (2000). Slope based filtering of laser altimetry data. *International Archives of Photogrammetry and Remote Sensing*, *33*(B3/2; PART 3), 935-942.