COMPLEX BUILDING ROOF DETECTION AND STRICT DESCRIPTION FROM LIDAR DATA AND ORTHORECTIFIED AERIAL IMAGERY

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ABSTRACT

One common and important task in urban modeling is the extraction of 3D building geometry. Detecting and describing rooftops is a key step. We propose a building roof detection and description method using airborne LiDAR data and orthorectified aerial imagery. Our approach makes no presumption of the shape that a building rooftop should exhibit. We use LiDAR to separate the building roof and its other significant features from other objects in the scene and estimate the strict outlines of these features. Imagery is processed using a robust segmentation and edge detection method to generate an edge map of the roof and then used to help refine the outlines obtained from LiDAR data. We will illustrate our approach by extracting several roof boundaries in the downtown region of Rochester, NY that exhibit simple and complex outlines.

***Index Terms*—** roof extraction, building, LiDAR, imagery, geometry

1. INTRODUCTION

Automatic 3D urban modeling has been widely studied for decades, with a primary emphasis on the detection of building rooftops using aerial data collection. When collecting nadir-looking aerial data in an urban setting, the two scene components that dominate this data are the tops of man-made structures (rooftops) and the background terrain. The detection and segmentation of these roofs from the terrain is hence a crucial step in building extraction. Often times, the outlines of these building rooftops are not just simple geometric primitives, on the contrary, they can be quite complex, making the model extraction process a challenging task. Previous approaches to this task[1][2] utilize data from only a single source, either two-dimensional imagery or LiDAR. Haala *et al.*[3] point out "the difficulties of aerial image interpretation also motivated the increasing use of three-dimensional point clouds from laser altimetry as an alternative data source". As a result, other methods[4][5] try to combine LiDAR data and geometrically uncorrected image data to obtain a synergistic effect. This information merger has advantages, however, finding correspondences between these two different types of data automatically is often problematic.

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2. OVERVIEW

The proposed methodology for complex building roof detection and description consists of the following steps (Fig.1):

1. Two-dimensional orthorectified aerial imagery and three-dimensional LiDAR point cloud data are spatially co-registered using spatial correlation information between these two different data sources.
2. Robust segmentation using the Mean Shift algorithm is accomplished by exploiting the color information present in the aerial imagery to generate a spatially accurate edge map.
3. A multi-layer elevation filter is applied to the registered LiDAR data to separate the points present on rooftops and other structural features present on these surfaces from the rest of the terrain scene elements. The LiDAR points on the rooftops are projected onto a two-dimensional plane to allow for the creation of a binary "roof" mask to be used to extract roof edges from the edge map generated above.
4. The roof outline is then extracted from the binary mask using the Douglas-Peucker line simplification technique, refining the outline by eliminating "insignificant" vertices and adjusting the remaining lines to better fit the imagery-derived roof edge map.

3. METHODS

In this section, the proposed method will be introduced.

3.1. Registration

The orthorectified imagery used in this study has been geographically tagged in the Universal Transverse Mercator (UTM) coordinate system using a WGS84 datum. The LiDAR data collected was also processed to this same map

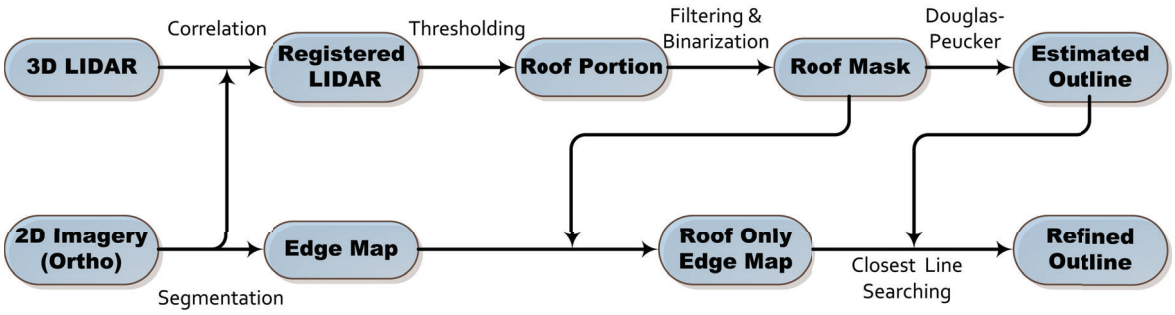


Fig. 1. Algorithmic structure and work flow of proposed method

projection. As a result of this common mapping, the LiDAR points are inherently registered to the image data. Due to system and processing errors, however, the correspondence between individual points in these two data sources is not ideal. An example of misregistration can be seen in Fig.2(a). Here we can clearly tell that Δx and Δy are the offsets which quantify the misalignment of the LiDAR and image data.

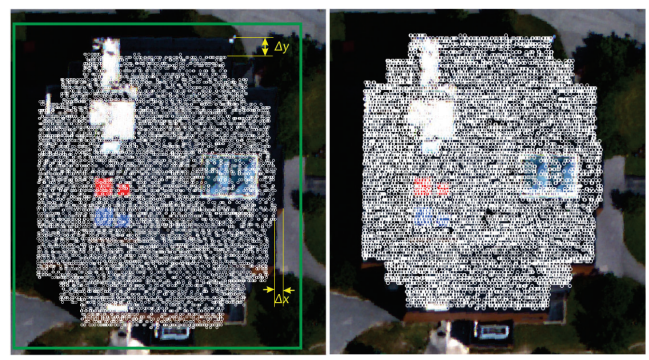
In order to address this misalignment problem, the intensity values from the LiDAR data are utilized. The intensity responses exhibit great similarities with the gray-scale image data, both depicting a visual representation of the building rooftop structure. In light of this fact, it is reasonable to compute the cross correlation between the gray-scale image data and the two-dimensional LiDAR intensity image for the purpose of refined alignment. The goal is to maximize the cross correlation by shifting one data source with respect to the other to obtain the maximum correlation response, namely

$$d = \arg\max_{d}\{Corr(\mathcal{G}, \mathcal{I}(d))\} \tag{1}$$

where $\mathcal{G}$ represents the gray-scale image, $\mathcal{I}$ represents the projected LiDAR intensity image, and d represents the horizontal and vertical shift from the initial location within a searching window. For example, the green rectangle in Fig.2 indicates a reasonable search area. Fig.3 shows the map of correlation responses for every position within the search window, with the maximum response denoted by the black circle. The corresponding Δx and Δy (in this example, Δx = 9 and Δy = -26) represent the required translation determined. Fig.2(b) illustrates the result of this alignment refining process.

3.2. Roof Detection

At this step, we will explore roof edge information from the imagery. Mean Shift [6], a well known technique for the segmentation of image data based on the inherent color information, is utilized to generate an edge map (Fig.5(c)). This is, by its nature, a pixel-based approach and as such produces a result in which the mapped edges have no knowledge of belonging to a roof outline or its contained features.



(a) Before alignment (a) After alignment

Fig. 2. LiDAR points overlaid on the orthophoto

In order to overcome this fact, the imposition of certain knowledge-level information on roof detection needs to be accomplished. LiDAR data contains elevation values for each point, so it is natural to make use of such information to aid in the detection. Fig.4 represents a profile of the three-dimensional point cloud from a plane perspective illustrating that the portion of the point cloud above the 180-meter elevation mark (above sea level) could be readily recognized as the roof. If a multiple-layer elevation filter is employed, more variant features on the roof can be extracted.

Once the non-rooftop points are filtered out, a reprojected two-dimensional point map can be further processed to obtain a binary mask. This binary mask can then be utilized along with the imagery-derived edge map in order to isolate only those edges that define the roof edge or the contained features. In order to accomplish this, the point map is convolved with a Gaussian spatial filter, producing the result illustrated in Fig.5(a). Fig.5(b) is then generated by thresholding the gray-scale filter response shown in Fig.5(a). The edge map shown in Fig.5(c) is derived from the orthorectified image data using Mean Shift segmentation method. The edges belonging to the building roof only are then isolated using the binary mask, producing the result in Fig.5(d). This process is represented as

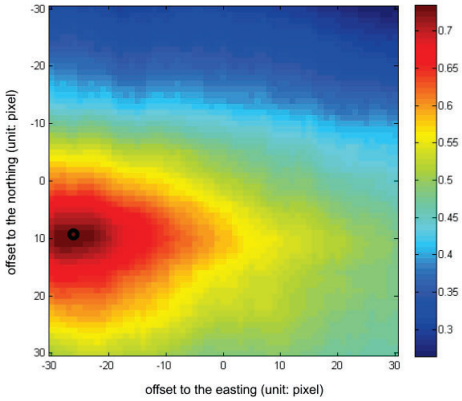


Fig. 3. Correlation map obtained within a searching window ($\Delta x \in [-30, 30]$ and $\Delta y \in [-30, 30]$)

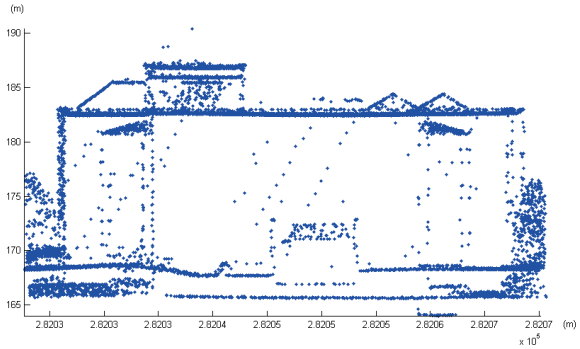


Fig. 4. Elevation profile of the LIDAR point cloud data collected of the Chester F. Carlson Center for Imaging Science building on the Rochester Institute of Technology campus, Rochester, NY, USA

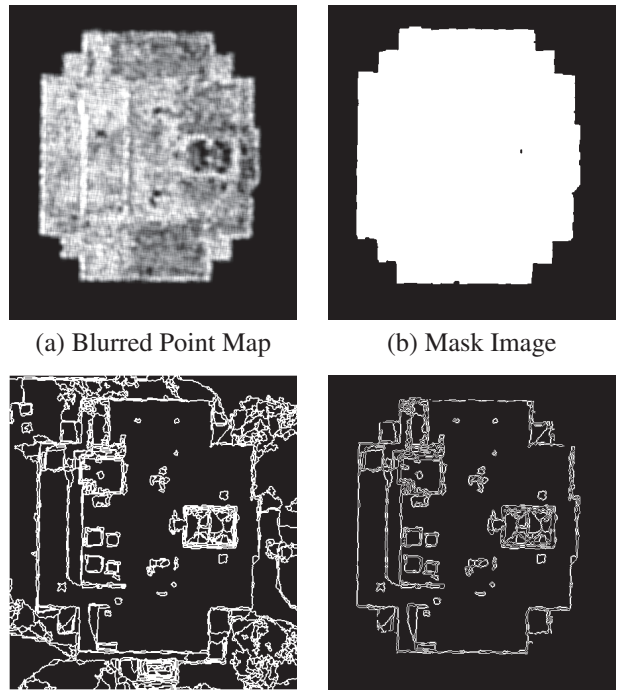
$$\mathcal{M}_{binary} = \mathcal{O}_{binary}\{\mathcal{I}_{point} * Gauss(\sigma)\} \tag{2}$$

$$\mathcal{E}_{roof} = \mathcal{E}_{all} \bigcap \mathcal{M}_{binary} \tag{3}$$

where $\mathcal{M}_{binary}$ is the binary mask, $\mathcal{O}_{binary}$ is the binarization operator, $\mathcal{I}_{point}$ is the discrete roof point map, and $\mathcal{E}_{all}$ and $\mathcal{E}_{roof}$ represent the global edge and the roof edge-only maps, respectively.

3.3. Roof Description and Refinement

An imagery-derived roof edge map, on its own, is not a sufficient geometric representation of the roof boundary. Due to the discrete, pixel-based nature of the edge detection process employed, the number of edges formed between individual pixels is large. These individual, short length edges, are often



(a) Blurred Point Map (b) Mask Image

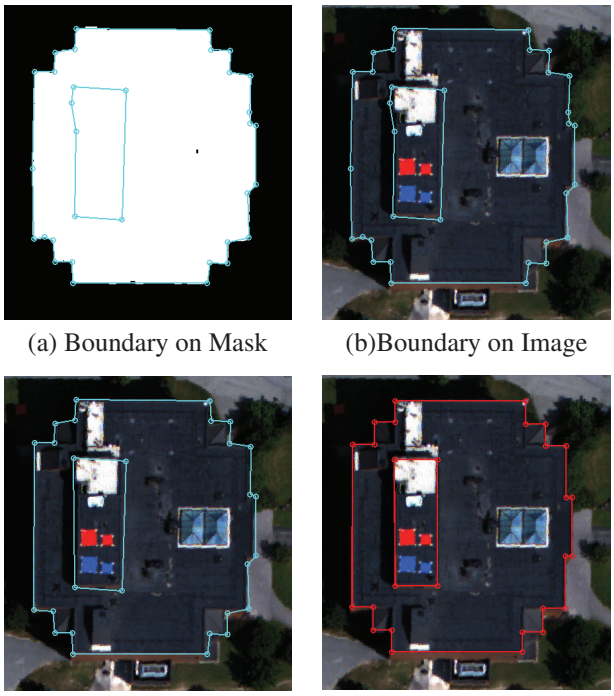
(c) Edge Map (d) Roof Edges

Fig. 5. Workflow utilized to isolate the roof and roof feature edge map from those edges derived from the original grayscale image data.

part of a longer, continuous edge feature and should be combined. In order to accomplish this, the binary mask is refined by applying a morphological "hole-filling" operator and the response is used as a first approximation of the roof boundary. The major vertices of this boundary are derived by applying a recursive Douglas-Peucker (DP) polyline simplification[7]. This simplification process reduces the number of points used to represent a similar curve. The approximated roof outline is shown in Fig.6(a)(b). An assumption is made that two adjacent lines, connected by the same vertex, found on a typical man-made structure will exhibit a significant directional change. As a result, the number of vertices on any particular edge, is significantly reduced (*c.f.* Fig.6(c)). This initially generated roof boundary, using the refined mask image, gives a rough estimation of where an edge line should be. The roof edge map continues to be used as a cue to refine this boundary further. A localized search area is defined around the current edge estimate, in which the estimate of the edge position is adjusted until it reaches its optimal location. The refined result is shown in Fig.6(d).

4. OTHER RESULTS

In the previous example, only straight lines are detected. Our method can also be applied to detect and describe the outline



(a) Boundary on Mask (b)Boundary on Image

(c) Vertices Removal (d) Refined Boundary

Fig. 6. Illustration of the workflow used to obtain the final refined roof top boundary.

of rooftops with round shapes (Fig.7).

5. DISCUSSION

In the presented workflow, registration is done prior to roof detection. All points, including the roof and the ground, are taken into account (Fig.2 depicts only a subset of these points as an illustration). The roof detection step, however, could be carried out prior to registration. In that case, only points on the roof are considered during the generation the correlation map, which does not affect the accuracy of the registration.

While conducting outline refinement, no explicit constraint is imposed to force roof corners to meet at a right angle. Most building edges in our research scene have regular orientations (e.g. vertical or horizontal directions). So, we apply a relatively simple refinement to these edges and let the orientations be vertical or horizontal. In the future, the principle direction of an urban layout needs to be determined first and then this presented refining procedure could be applied.

6. CONCLUSION

In this research, we propose a method to extract roof information from both LiDAR data and aerial imagery. LiDAR is utilized to detect rooftops and help generate rough roof outlines. A segmentation method is applied to the imagery to form an information rich edge map for the purpose of refining these outlines. A simple and fast correlation based registration method is also adopted in this research to fuse LiDAR and imagery.

(a) Rough boundary (b) Refined boundary

Fig. 7. Illustration of the round shape roof description.

7. REFERENCES

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