Extracting Building Footprints from LiDAR data

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***Abstract*—This report presents an analytical comparison of the two solutions which focused on extracting building footprints from airborne LiDAR data. Both approaches are unsupervised and do not rely on deep learning. Building on the strengths of these methods, this work also proposes an alternative pipeline using RANSAC and DBSCAN for plane fitting and spatial clustering to generate building footprints. While conceptually promising, the proposed method achieved a significantly lower Intersection over Union (IoU) score.**

***Index Terms*—LiDAR, RANSAC, building footprints**

I. Introduction

This work is a report on understanding and analysis the top 2 solutions to the 11^{th} SIGSPATIAL Cup competition[1]. Building extraction from remote sensing data plays a critical role in a wide range of applications, including population estimation, urban planning, infrastructure management, and disaster response [1]. With the increasing availability of Airborne Laser Scanning (ALS) data, also known as LiDAR, high-resolution 3D point clouds offer a promising data source for accurate building delineation over large areas. ALS can capture the 3D structure of surface features with high spatial resolution, making it particularly suitable for building mapping tasks [2].

We analysed the methodologies mentioned in the contest papers [1] [2] and compared them based on spatial and non-spatial approaches. In addition, we propose and implement another method for building footprint extraction using RANSAC and utilize the previous works on 3D modeling of buildings using RANSAC for the provided data set.

II. Solutions

In the 11^{th} SIGSPATIAL Cup competition, 20 `.laz` files representing a LiDAR point cloud for a given area in the USA, were provided. Correspondingly, 20 GEOJSON files were also provided, which contained a list of polygons using an EPSG 3857 for self-evaluating the solutions and one set of data is visualized in Figures 1 and 2. But during this project only 9 sets of files were available. The evaluation was done by comparing the computed list of polygons to ground truth polygons labeled by humans based on aerial images, specifically by computing Intersection over Union of the areas. Now we will analyse the solutions that achieved first and second place at the competition. These are unsupervised methods, unlike the popular mapping *Microsoft Building Footprints*, which is uses deep learning.

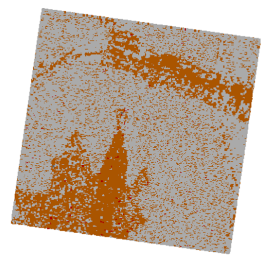

Fig. 1. A .laz file viewed in QGIS with it's classifications

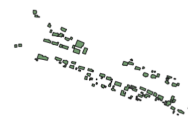

Fig. 2. A GEOJSON file viewed in QGIS

A. Challenges in Building Extraction from Airborne LiDAR Data: Ground-truth, Building Boundaries, and Evaluation Metrics

This solution uses the workflow created by the same authors [3]. The workflow begins by generating a Digital Surface Model (DSM) and a Digital Terrain Model (DTM) from raw airborne LiDAR data. The DSM captures the elevation of all surface features, while the DTM represents the bare-earth terrain by removing non-ground elements. Accurate DTM generation is critical for downstream processing, particularly to delineate building structures effectively.

Next, the Normalized Digital Height Model (NDHM) is computed by subtracting the DTM from the DSM. This isolates above-ground objects such as buildings and trees. A height threshold is applied to the NDHM to eliminate low-lying noise and vegetation, focusing on structures with significant vertical height.

The refined NDHM then undergoes four filtering operations. Water body masking removes areas with characteristics of water surfaces. Morphological filtering applies structural

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[1] https://sigspatial2022.sigspatial.org/giscup/giscup.html

operations to clean and shape detected objects. Planarity-based filtering, guided by a roughness threshold, helps identify smooth, flat surfaces typical of rooftops. Boundary refining using dilation expands and smooths object edges to better capture full building outlines.

Finally, small artifacts such as minor objects or misclassified elements are removed. This step ensures that the final building map contains only significant structures, improving both the visual quality and analytical accuracy of the output.

B. An Unsupervised Building Footprints Delineation Approach for Large-Scale LiDAR Point Clouds

The process begins by generating a Digital Terrain Model (DTM) from the lowest elevation points in the LiDAR point cloud, which represent the ground. Areas without data—empty cells in the DTM—are assumed to be the bases of buildings since buildings block laser returns. The centers of these empty cells are used to construct an α-shape (with a parameter of 1.1 meters), which delineates the boundaries of potential building footprints on the ground.

Next, a Digital Surface Model (DSM) is created by filling in the empty cells of the DTM and calculating the height of all points above this surface. To identify flat surfaces such as building rooftops, two metrics are applied: the Terrain Ruggedness Index (TRI), which measures elevation variation, and the Vector Ruggedness Measure (VRM)Terrain Ruggedness Index (TRI) measures terrain ruggedness by quantifying the elevation difference between a central grid cell and its surrounding neighborhood. Vector Ruggedness Measure (VRM) assesses terrain ruggedness by considering the variation in three-dimensional orientation of grid cells within a neighborhood. Cells with TRI and VRM values within defined thresholds are considered flat and likely part of a building roof. These flat areas are then outlined using the α-shape method.

In the final step, candidate building footprints are validated. Each detected bottom shape is assessed for rectangularity by comparing it to its minimum bounding rectangle; a high rectangularity score indicates a valid building. If rectangularity is low, the footprint is further evaluated using Intersection over Union (IoU) with the corresponding flat roof area. Footprints with sufficiently high IoU are accepted as valid building outlines.

Here, they also mention that they achieved a score of 0.62 which is greater than Microsoft Builing Footprints' 0.573.

C. Comparing the Above Approaches

Here's a comparative analysis of the methodologies used in the two papers, articulated in paragraph form:

The two papers take distinctly different approaches to handling building boundaries and planar surfaces. The first paper treats boundaries and planes jointly. In this integrated method, the detection of planar surfaces and the delineation of building boundaries inform each other, which can lead to more accurate representations of complex building shapes. Conversely, the second paper, *An Unsupervised Building Footprints Delineation Approach for Large-Scale LiDAR Point Clouds*, handles boundaries and planes in a sequential and separate manner. It first identifies the building bottom footprints independently using low-elevation (ground) points and then extracts flat roof surfaces. The separation allows for clearer modularity in the processing pipeline but may miss nuanced interactions between shape and structure.

In terms of planarity evaluation, the first paper uses Residual Thresholding (RT), which is typically based on fitting geometric models (like planes) and measuring the deviation of data points from these models. This method offers a high degree of adaptability and precision in identifying subtle variations in surface flatness. On the other hand, the second paper employs Terrain Ruggedness Index (TRI) and Vector Ruggedness Measure (VRM). These terrain analysis metrics evaluate local surface variation by comparing elevation differences or slope vectors over a neighborhood. While these measures are simpler to compute and effective in identifying large-scale flat areas, they may be less sensitive to finer structural irregularities compared to RT.

The papers also diverge in their treatment of building boundary shapes. The first paper adopts a flexible approach to boundary extraction, allowing for irregular, organic shapes that closely follow the true edges of buildings. This flexibility is beneficial in urban environments with diverse architectural styles. In contrast, the second paper emphasizes rectangularity in building footprints. Its method includes a step to assess how closely a footprint aligns with a minimum bounding rectangle, and it favors boundaries that exhibit strong geometric regularity. While this assumption simplifies the detection process and is well-suited to grid-based urban environments, it might result in inaccuracies when buildings have complex outlines.

Finally, the direction of elevation data processing differs between the two methodologies. The first paper follows a DSM-to-DTM approach. It begins with a Digital Surface Model that includes all objects (buildings, trees, etc.) and then removes non-ground elements to isolate the Digital Terrain Model. This top-down strategy aligns with workflows focused on modeling and removing features above the terrain. In contrast, the second paper applies a DTM-to-DSM transformation. It starts with a ground model and then calculates height above terrain to reconstruct building elevations. This bottom-up method leverages voids in the DTM (where buildings are located) to identify structure footprints, which may enhance detection of buildings obscured by vegetation.

III. Proposed Solution

There are multiple works on creating 3D maps of objects and buildings using RANSAC [4] [5]. So, we hypothesized that RANSAC should be good enough to replace filtering in the above methods to generate building footprints. We developed a procedure for building extraction by including the steps from the above two methods.

A. Methodology

The process begins by selecting non-ground points from the point cloud. This is achieved masking out points labeled as

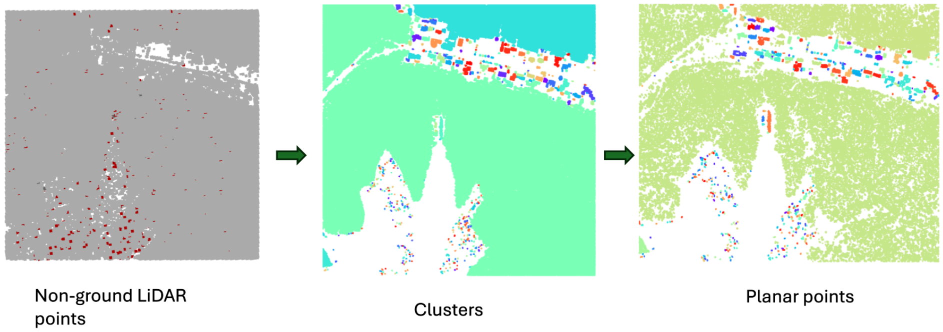

Fig. 3. Interim Steps in the Proposed Procedures

"ground" in the LAZ file which are assigned the class value of 2 as per standard. Once ground points are removed, the remaining points—classified as non-ground—are used to compute normalized heights by subtracting the ground elevation from each point, just like what was done in both of the above methods.

With normalized heights in place, the next step is to isolate the subset of points that likely represent buildings. This is done by applying a height threshold— above 2.5 meters—to eliminate low-lying features such as shrubs and fences. The filtered high points are then subjected to spatial clustering based on the coordinates using the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm. DBSCAN identifies groups of densely packed points that are separated by sparse areas, allowing it to effectively segment individual building structures from the cloud. Each resulting cluster potentially corresponds to one building or part of a building.

Once clusters are identified, the planarity of each cluster is assessed using the RANSAC (Random Sample Consensus) algorithm. RANSAC is a robust method for fitting geometric models in the presence of outliers. For each cluster, RANSAC attempts to fit one plane by selecting random subsets of points and checking how many of the remaining points lie within a certain distance from the plane. Points that conform to a planar model are considered "inliers" and are assumed to represent flat or sloped roof surfaces.

The final stage is the generation of building footprints from the filtered, planar point sets. To achieve this, the planar points are projected onto the horizontal (XY) plane, and an alpha shape algorithm is applied to create polygonal boundaries. Unlike a simple convex hull, the alpha shape method can capture concavities and complex geometries, producing more accurate building outlines. The alpha parameter was first selected as 1.1 (m) as mentioned in [2], but was later changed based on hyperparameter tuning on the dataset. Once the polygons are generated, small boundaries are filtered out based on area thresholds to remove noise and non-building features. Figure 3 shows an example of some of the steps.

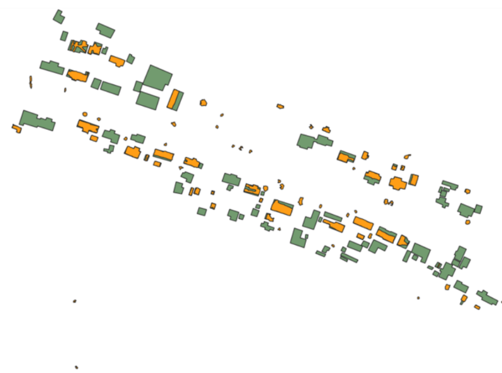

Fig. 4. An example output of the proposed procedure. This received a score of 0.2. Green area shows human annotated footprints, and orange represents the predicted polygons

B. Result

After hyperparameter tuning on the entire available dataset, we were able to achieve an average IoU score of 0.06, which was significantly less than the values mentioned in the second paper [2].

C. Scope of Improvement

We observed a lack of cloud points over the actual building polygons. Even the polygons that did overlap, the predicted shapes were irregular. The procedure did not account for buildings having multiple planes.

IV. Conclusion

This report explored and compared two leading unsupervised methods for building footprint extraction from LiDAR point clouds, analyzing their workflows, assumptions, and effectiveness. Both methods demonstrated distinct advantages in handling elevation models and building geometries, offering insights into the diversity of strategies in this domain. In addition, a novel approach using RANSAC for planar surface detection and DBSCAN for clustering was implemented, but it underperformed in terms of accuracy, with an average IoU of 0.06. The challenges faced—such as sparse point coverage and irregular building shapes highlight key areas for refinement. Future improvements could include incorporating multi-plane modeling, adaptive thresholding, or hybridizing geometric methods with learning-based techniques to improve precision and robustness in footprint delineation.

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