Modelling complex building structure (LoD2) using image-based point cloud

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***Abstract*— A method designed to reconstruct outdoor 3D building models automatically from a point cloud is presented in this paper. The proposed approach starts with building detection using spectral and spatial data from the UAV point cloud to remove non-building features. RANSAC, modified convex hull, and line growing algorithms are used to extract main roof planes and their boundaries. Roof planes are adjusted to each other using geometrical constraints, the height of each plane is estimated and a 3D model for the whole structure is constructed with LoD2. The key contribution of this approach is using a hybrid approach of model-driven with statistical analysis for modeling complex structures from a noisy point cloud. The reconstructed model shows that the workflow is sufficient to describe the whole building structure in the required LoD.**

Keywords—UAV, RANSAC, Model Driven, LoD2, Outdoor Modeling

I. INTRODUCTION

Nowadays, 3D building models have an increasing demand for multiple applications' scale such as urban planning, urban environmental modeling, computer gaming, virtual tourism, and disaster management [1]. Due to this demand; many scholars are working on the derivation of building models to reduce the amount of data used, extract and reconstruct objects from unstructured 3D point clouds, and fit in semantics to buildings [2].

Data acquisition for building reconstruction is done using light detection and ranging (LiDAR), or aerial camera for large scene data collection. The tendency for low-cost surveying, an unmanned air vehicle (UAV) emerged to collect images for using them in creating point cloud for building reconstruction. The main issue of using this point cloud is its high level of noise which makes the reconstructing polygonal structures an open problem [1], [3].

Most of the researchers are working on building reconstruction with different aspects of 2D mapping and 3D as well. Different approaches were adopted to tackle the obstacles in a point cloud for extracting building boundaries, and for more details modeling different roof segments for the building. These different approaches dealt with buildings with simple roof structures. In congested cities which consist of high-rise buildings with complex layout planes and their roof planes are not simply designed which could be full of air condition or green plants, the problem of modeling these different roof structures is found. Our proposed approach manages to deal with noisy point cloud for complex structures and model it with Level of Detail (LoD) 2. The remainder of this paper is organized as follows: Previous Work which has been conducted using existing approaches for modeling, Methodology that is proposed for the developed framework, Experiment and discussion to evaluate the adopted approach, and Conclusion and future work are the last part.

II. PREVIOUS WORK

In the recent two decades, there was a plethora of research achieved in the field of building modeling using remote sensing data. There are several data sources that are appropriate as a contribution to building modeling in the remote sensing community. Many scholars used airborne LiDAR data [4]–[8], due to its high quality and wide area of collecting information. High-resolution satellite images registered with LiDAR data for better detection and extraction of buildings [9], [10]. On the other hand, the high altitude causes low collected information about the façade, so scholars use terrestrial laser scanners for building facades segmentation [11], [12]. Aerial vertical and oblique images [13]–[16] are another choice for collecting information about building structures due to its advantages of horizontal and spectral resolution, but the main issue is dealing with occluded parts to extract building boundaries[17]. Towards low-cost survey and required safety, UAV images are widely used for collecting data [1], [3], [18]–[20]. Moreover, the UAV images are more robust against occlusion due to multiple images from different sides and the ability to change flying heights giving the benefits of collecting building façade information. Despite these benefits of UAV images, the use of non-metric cameras in collecting data leads to a high level of noise to be processed [21].

Despite different data sources, the results of the final work aim to model man-made structures. Because of the diversity of shapes and details of the structure, it is essential to select the appropriate model. Five levels of detail were discussed by [22]: LOD0 which is related to extraction and mapping of buildings with no height details [1], [9], LOD1 which represents average height of the building as block model, with adding details of roof structures and textures that will be LOD2 [3], [5], [8], [13], [23], LOD3 denotes for detailed façade structures [20], LOD4 denotes for adding interior structures to LOD3.

The availability of these different data sources encouraged scholars to develop many approaches for reconstruction of urban scenes from point cloud data. They are mainly divided into data-driven approaches and model-driven approaches. In data-driven approaches, the point cloud is used to create very dense surface models [5], [8], [24], but it requires the raw data to be free of outliers which are not guaranteed in data acquisition using image-based point cloud. In model-driven approaches [1], [3], [13], the structure is simplified to its main objects under some constraints then combined to form the whole model.

Model-driven approaches are reviewed here, as it is related the adopted workflow. Reference [1] proposed a line growing algorithm to extract line segments from the point cloud, then proposed a right side constraint algorithm to outline building boundaries. Building edges were regularized and final building footprint was generated. The proposed approach could extract LoD0 for traditional building structures and did not deal with complex structures. Reference [25] proposed a workflow to reconstruct building models from a point cloud assuming a Manhattan-world scene and using generated candidate box by using RANSAC algorithm to detect planar segments, Markov random field was used to select the appropriate candidate box. The proposed approach requires precise estimation of normal direction, as wrong normal direction will lead to false structure model. Moreover, roof with vegetation might lead to false volume detection as well. Reference [20] presented workflow for building modeling using a developed stochastic method for roof model selection based on the segmented planes from the point cloud. Reference [23] constructed a 3D building model by extracting roof points using reversed iterative mathematic morphological method, then point-based segmentation by using smoothness was used for extracting different roof patches. Horizontal direction layer-connection was created for different patched, building patches were connected and model was built for each building. That approach was effective to build LoD2 for complex building layouts, but it required high quality data and free of vegetation. Reference [13] presented workflow of extracting and modeling 3D structures using local regression window, roof segmentation, and reconstruction. Reference [19] presented workflow for modeling structures by applying RANSAC algorithm to detect planes. Symmetry was assumed for building roof planes and geometrical constraints were used.

In general, in order to overcome lack of information in building structures, some researchers used high-cost equipment ([13], [23], [25]) with simplified approaches of modeling and other researchers modeled simple buildings ([1], [19], [20]) with low-cost surveying equipment. Modeling structures of complex layout and congested roof patches of different objects (air condition & green plants) is not addressed yet. Our goal is to model complex structures using low-cost surveying equipment.

III. METHODOLOGY

In this paper, LOD2 building modeling will be deduced following three main stages: building detection, roof detection and outlining, and topology adjustment and model reconstruction from the image-based point cloud as shown in Fig. 1. The first stage, both spatial and spectral information from image-based data will be used for building detection. In the second stage, different planes will be detected using random sample consensus (RANSAC) algorithm [26], then two steps algorithm will be followed to determine the main roof planes. For each roof plane, the boundary points will be traced based on modified convex hull shape, then line growing algorithm [1]will be used to detect collinear points and line parameters. Then, three steps algorithm will be followed to modify the line segments and enhance the final results. For the detected final lines, one main dominant direction is adopted, and other line's direction adjusted. In the last stage, topology analysis will be considered to adjust planes to each other considering geometrical constraints. Then the height of each roof will be estimated from the relative raw data and the final structure will be created as LOD2.

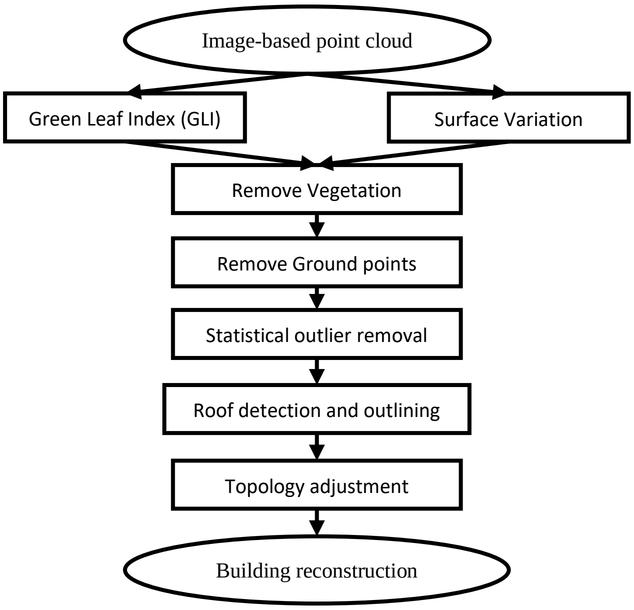


Fig. 1. Proposed workflow

A. Building Detection

To isolate the building from the surrounded unwanted vegetation regions, green leaf index (GLI) [27] is calculated from the spectral data.

$$GLI = \frac{(g-b)+(g-r)}{(g+b)+(g+r)} \quad (1)$$

Where g: green band, r: red band, and b: blue band.

Moreover, surface variation [curvature] (σ) is calculated from the spatial data based on eigenvalues [11].

$$\sigma = \frac{\lambda_1}{\lambda_1+\lambda_2+\lambda_3} \quad (2)$$

Where λ_1, λ_2, and λ_3 are eigenvalues.

Both GLI and curvature are used with predetermined threshold to detect and isolate vegetation regions. After removing vegetation from the point cloud, point cloud related to the ground is eliminated using a minimum building height threshold as the UAV image-based point cloud axes are aligned to ground axes.

B. Roof detection and outlining

Using building raw data for modeling is not sufficient, as the it is full of noise. Preprocessing of this raw data has a crucial impact on the final results, as it is required for eliminating noise, and removing outliers. Two types of filters are applied: down-sampling and statistical outlier removal respectively.

Down-sampling is done using voxelization which implemented by a k-d tree search, which creates adaptive partitions and is efficient for large-scale data, and that point is replaced by the desired characteristic X which is equivalent to the arithmetic average as described by equation (3) [28].

$$\mathrm{X} \,|\, \mathrm{P} = \sum_{i}^{n} \mathrm{X}_i / n \quad (3)$$

After the dataset is down-sampled, it may contain some outliers as sparse points collected from the scanner, or misalignment point detected from the point densification from images. Those points are detected based on their local distance to their neighbors [29]. To remove outliers from the dataset, statistical analysis will be made using location and scale parameters which are median & mean absolute deviation (MAD) instead of mean & standard deviation as it shows robust detection of outliers[30].

The main planar segments are detected by applying RANSAC several times and using the general formula for the plane equation in 3D.

$$A*x+B*y+C*z+D=0 \quad (4)$$

Where A, B, C, D are plane parameters, x, y, and z are point coordinates.

Since we are interested in roof planes. the detected planar segments will be refined by applying the two-step algorithm. Firstly, planes, with normal direction that exceeds predefined threshold with vertical direction, are discarded. Moreover, planes within distance threshold will be represented by plane of maximum points. Besides, the projection of the whole points in the same direction is used as one more plane.

For each roof plane, boundary points are traced using a modified convex hull algorithm [31]. circle neighborhood space as in image-based point cloud there is no flight direction. The algorithm starts with determining the minimum point in (y) direction to be the starting seed boundary point, then point with a minimum angle with the x-axis is selected as the next seeding point. By following counter-clockwise (CCW) order all points will lie on the left side of the line connecting these two points. After this step, the last two points are used as a new reference line for the new detect direction and all nearby points are sorted with an angle (CCW) and point with a minimum angle to the reference line will be select as the next border point. Due to the high level of noise in photogrammetric point cloud two constraints are added to that method: a constraint on angle threshold, and constraint on a minimum number of neighbors to guarantee the proceeding of the line in the same direction and select boundary points.

After boundaries' tracing, the construct of boundary segments is the next step. Line growing algorithm produced by [1] is used to detect collinear points with their corresponding lines using the least square method. The process starts with picking the first two points from the boundary points as these points are exported with their order. Then using least square to define the parameters of the line model using the formula on equation (5), points are added to the new line and model parameters also adjusted based on perpendicular projected distance threshold (PPD) using the formula on equation (6). Otherwise, a new line is starting with selecting tow new points, and repeat the procedures till there is no point remained.

$$A * x + B * y + 1 = 0 \quad (5)$$

$$PPD = \frac{|A * x + B * y + 1|}{\sqrt{A^2 + B^2}} \quad (6)$$

The extracted lines are filters based on two different thresholds (number of points, and line length). If a number of points on one line are less than point threshold, this line is discarded. Moreover, if this selected line length is less than length threshold it is discarded as well. Finally, the dominant lines are used to detect building boundary lines. The filtered lines are used to construct lines of the dominant roof plane based on the fact that most of the man-made building structures often have two dominant directions that are orthogonal[1]. One main dominant direction will be selected supported by its maximum length from all other lines, then all other lines will be angularly adjusted to be parallel or perpendicular to that one. With the same order of the line points, any consecutive lines with the same inclination will be represented by the longest line. To make the selection more robust, another condition is added. If two lines with the same length and inclination, the line with a minimum difference of angle to a dominant direction will be selected. After determining the all line segments with their parameters, boundary corners is estimated as the intersection point between any two consecutive lines using equation (5).

A. Topology Adjustment and model reconstruction

As for one building structure, more than one roof plane could be obtained, the geometrical constraint is used to help to modify all planes together and recognize small roof shapes. The maximum area plane is used as a reference plane to adjust other planes' segments using the minimum length threshold in equation (5). Different small roof patches were segmented, and each plane is used to extract polygonal points and estimate its own height from statistical analysis. Then LOD2 of the proposed building is created.

I. EXPERIMENT AND DISCUSSION

A. Datasets and study area

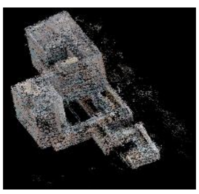
Our approach is validated on complex building structure at The Hong Kong Polytechnic University. The data was collected using DJI Phantom UAV, and the collected images were processed using commercial software (Pix4Dmapper) [https://pix4d.com/] for point cloud creation and densification. For the need to use the created point cloud in 3D building modeling, the created dataset was scaled compared to the same points in a small scene created using a laser scanner (Leica). Three different lengths were selected in three different directions and the scale was estimated, then final point cloud was detected as shown in Fig. 2.a.

B. Analysis and discussion

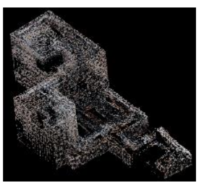
Building detection was implemented using GLI and flattening to remove unwanted features as shown in Fig. 2.b, then the minimum building height was used to remove other features as shown in Fig. 2.c. At final, the point cloud was filtered to remove outliers using statistical outlier removal as shown in Fig. 2.d.

Raw point cloud

Remove vegetation



Ground point filtering



Statistical outliers' removal

Fig. 2. Building Detection

RANSAC was used to detect main roof plane structure for boundary tracing and detection, and two main roof planes were detected besides the whole boundary, and boundary tracing was completed using modified convex hull algorithm, the results are shown in Fig. 4.

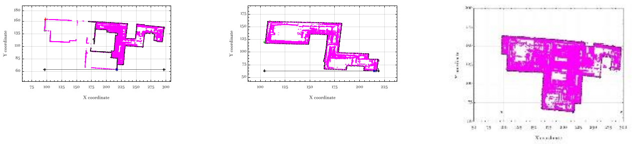
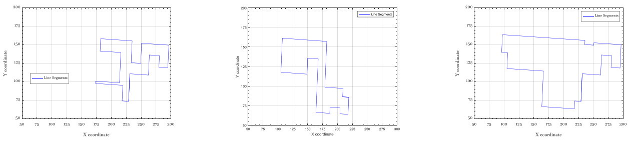


Fig. 3. Boundary tracing using modified convex hull algorithm (raw points in magenta color, traced boundary in black color and green color for connected line)

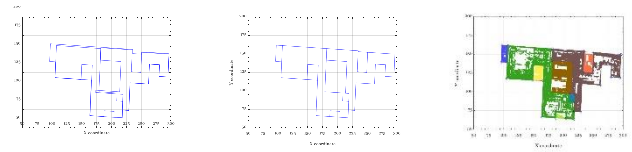
After boundary tracing, the line segments for each boundary was detected using line growing algorithm [1], and intersection points estimated as shown in Fig. **4**.



Plane 1 Plane 2 Plane 3

Fig. 4. Boundary line segments and intersection points

After the final boundary lines were detected, point topology analysis was implemented to adjust the connection of points on different planes using geometrical constraint and Dijkstra algorithm. As shown in Fig. 5. the planes before and after topology analysis.



Before adjustment After adjustment Different roof planes

Fig. 5. Topology analysis

Then the adjusted planes were used to determine the inner point cloud, and these points used to estimate the height of each plane. As shown in Fig. 1 the final building model created from these planes coincides with the image-based point cloud. The results were compared to existing planes and profiles for the building as shown in TABLE I. There were eight roof planes out of 10 planes which were detected. The average error in lengths was 0.5 meter and some lengths with 1.2 meter. The two models were oriented to each other with the maximum length, and the orientation error to other lengths was found with a maximum error of four degrees and an average of 1.5.

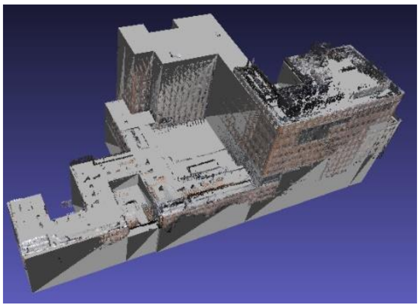


Fig. 6. Three D. building model with image point cloud

TABLE I Quantitative results from the reconstructed model

	Average Error	Max Error	Min Error
# of roof planes (%)	20	--	--
Lengths (m)	0.5	1.2	0.1
Orientation (degrees)	1.5	4	0

II. Conclusion and Future Work

In this paper, the pipeline for modeling complex building structure was presented by modeling primitive features. Roof planes were selected from the whole scene after applying RANSAC, then tracing boundary line segments using a modified convex hull algorithm. Line growing algorithm was adopted to detect mainline segments for each roof plane, then topology analysis using geometrical constraint and Dijkstra algorithm to define and correct small patches. Finally, height was detected for each plane, and LOD2 was constructed.
This method was applied to image-based point cloud which is noisy data and assumed horizontal and parallel roof planes. As future work, the plan to extend the work to model different structures and consider façade modeling as LOD3.

Competing Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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