Automatic Building Segmentations from LiDAR data Using Shape Plane Clustering

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ABSTRACT: Current methods of building segmentation from LiDAR depends on extraction of roof planes to segment the buildings. In our work, we propose a new method to extract buildings using the wall facades. The motivation of using wall facades is based on the rise of terrestrial LiDAR compared to aerial LiDAR. The shape property is the most important information obtained from a LiDAR file. We try to use this shape property from the LiDAR file to segment buildings from the given scene.

In the algorithm, the non-ground return points parallel to a facade of the potential building are combined to form multiple slices. These slices are parallel to the facade of a potential building. These slices are then merged based on the shape similarity and proximity to generate the footprint of the building. After generating the footprint of the building, we can also reconstruct the 3D model of the given building. The algorithm was tested both on simulated synthetic data containing different buildings and real world benchmark datasets. The results show complete segmentation of buildings from the synthetic datasets and promissory results from the real world datasets.

The algorithm proposed is versatile in nature and can be easily adapted to different datasets with minimal modifications and tweaking. Existing works involve the use of secondary datasets like satellite images, orthophotos etc in order to aid in segmentation. Our work uses only the LiDAR data and no other secondary data to identify the buildings from the scene. Demonstration have been shown to segment partial buildings in a given scene as well. Thus, the novelty of the proposed work is non-dependence on any other form of data required except LiDAR. The applications of segmenting buildings from a given LiDAR scene can be used in urban planning, resource management and monitoring tasks

1. INTRODUCTION

1.1 Literature Survey

The motivation for the work stems from the challenge to segment objects from a given scene. LiDAR is known to produce high density point cloud data, which has a lot of applications in urban planning, forestry, surveying etc. The task of tackling building segmentation is has been attempted by many people, but there hasn’t been a industry standard of automatic building segmentation. In the industry, building segmentation from such high density data is currently done mostly manually, where the automatic methods have considerable shortcomings in terms of accuracy, cost and effort. Our work is another step to solve the puzzle of segmentation. Rather than focusing on the roof extraction, we tried to focus on extracting the wall or facades of the buildings, to reconstruct the building. This technique of using facades to segment buildings will be effective in cases of fusion of both terrestrial and aerial LiDAR data.

The most important characteristic of a LiDAR dataset is the perception of shape of the object that can be derived. No other form of remote sensing data gives such high spatial freedom with regard to obtain the shape property of an object. Using this uniqueness of the shape property of the LiDAR data, a new technique has been formulated. Different methods of building extraction have been published. Most of the works involve usage of image processing techniques, like Hough transform, morphological analysis, texture analysis, contour analysis, edge detection and etc. Many of the works propose a rule based technique to extract buildings from the scene. Some works improve the detection accuracy by employing data fusion methods and composite data sources like aerial aerial images to extract buildings and 3D models. (Elaksher, 2002) segmented buildings using a transform similar to Hough transform, where voting is done in an plane parameter space and then finding a space with larger number of points.

Awrangjeb, 2010 used both LiDAR and color orthoimagery to accurately segment buildings from the scene. It defined two building masks - primary building mask and secondary building mask for the task. Here the author assumes that the buildings are only rectangle shaped or rectangle of rectangles. Canny edge detector is used to segment the lines out of the scene using a least square straight line fitting technique. Some of the shortcomings of the work include requirement of high density data, inaccurate results for high rise buildings, unable to process areas with high terrain slope. (Rottensteiner, 2002) used height thresholding and then morphological analysis similar to (Elaksher, 2002) to perform texture analysis of the given scene. The planar regions segmented from the results are grouped to obtain the building models. The building models are subsequently used to construct the 3D models of the buildings. It runs successfully in with a pre-condition that it requires dense built-up areas. (Rottensteiner, 2005a) further modified the previously devised algorithm by using data fusion techniques of Dempster-Shafer to classify objects in a given LiDAR scene. It also generated the high quality DTM model using morphological filtering to segment objects. In (Rottensteiner, 2005b) the step edges are segmented out of the LiDAR scene. These segmented edges are then combined together into polyhedral models to obtain the building. Novelty of this work is non-dependence on any 2D GIS data. Our work has similarity with it, due to its non-dependence on any form of 2D GIS data as well. (Rottensteiner, 2002b) also proposed a similar technique using an additional aerial images to segment the buildings as well.

Niemeyer, 2014 devised a new method of formulating a random forest classifier into a Conditional Random Field (CRF) framework. The CRF probabilities obtained for the classes are plugged into a Markov Random Field (MRF). The proposed method obtained results of high accuracy and completeness. (Yang, 2013) proposed a semi-automatic building segmentation using mobile LiDAR point clouds. It used image processing, RANSAC algorithm, and PCA to identify building objects from the selected coarse building footprints. The paper ended the scope with further extension to study the cylindrical and facades of complex structures. Our work, tries to carry this forward and also work on such structures. (Yang, 2013) proposed a Gibbs energy model for building objects. The benefit of this technique, is dependence with respect to only one parameter to tune, thus providing ease of use. (Pfeifer, 2007) proposed a building detection method by converting the ALS into in form of raster data. The work analyzed the different methods of segmenting buildings and studied on different ways of evaluating the accuracy of segmentation by using pixel based and object based methods.

1.2 Objective

Most of the above works, focus on extraction of roof and its different planes to reconstruct the building. In our work, we propose a new methods to extract the facade of the buildings and then use them to extract the buildings. The preliminary results were first tested on a synthetic dataset and showed positive results in real world benchmark datasets as well, with prior adjustments.

2. DATA MODEL

A synthetic dataset was created to initially verify the hypothesis. The synthetic dataset tries to simulate mobile LiDAR data. The synthetic dataset sim-lidar, contains lot of different types of buildings which is not seen in a single scene of real world data. The density of data in sim-lidar is much higher than conventional real world LiDAR data. For further testing of the algorithm on real world data, Dublin city was used. The Dublin data is a very high density aerial LiDAR based data where facades of the buildings are clearly representational and not missed due to low resolution of most of the existing LiDAR datasets.

2.1 Simulated Dataset

SimLiDAR is a synthetic dataset created for the initial proof of concept for our algorithm. The synthetic data generated primarily is a very high density point cloud data. The objects in SimLiDAR have been built with incremental complexity. The initial scenes have flat terrain, flat roofed buildings. As we increase, complexity we get buildings of different shapes and sizes like buildings with minarets, buildings with center courtyard to signify holes in the building. Some of the objects that were taken from SimLiDAR to be tested on our algorithm are:

- Simple cubic buildings
- Multiple buildings in the same scene
- Complex shaped buildings like ‘L’, ‘U’ and ‘T’ shaped buildings
- Buildings with gabled roofs
- Buildings which form a N-sided polygon
- Buildings with protrusion to signify chimneys or minarets
- Concentric buildings with an inner courtyard
- Buildings with curved walls

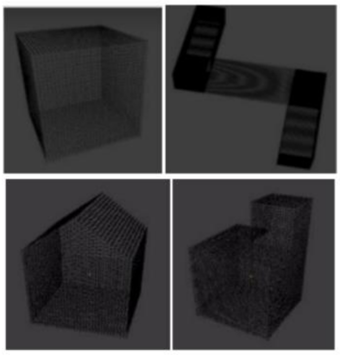

Figure 1. Sample Objects from SimLiDAR - having cube shaped, Complex Shaped, Gabled roof, Buildings with extensions

2.2 Dublin Dataset

The Dublin dataset was part of the aerial and photogrammetry survey of Dublin City. It is a very high density dataset where the points per meters^2 is 334. The dataset consists of both 3D point clouds and 3D waveform. The data consists of 1.4 billion points. For our experiments we have chosen a specific tile of the dataset. Most of the buildings in the scene aren't rudimentarily shaped. Some have curved walls, multiple extensions in the scene. As space is a big constraint in big cities, most of the buildings are connected with each other, without having separate walls to differentiate them from each other. A representation sample of the scene is shown below with both of it's aerial image and the LiDAR point cloud.

Figure 2. (a) Aerial Image of the test area (b) LiDAR point cloud of the same test area

3. ALGORITHM

3.1 Wall extraction

First step of the algorithm is to extract the different possible facades / walls in a given scene. After all the walls from a given scene is extracted. We can further process to determine if it is part of the building or not. Segment refers to a wall surface of the building. A given segment of a lidar scene is made up of multiple return points. Multiple segments combine to form a building. The segments of a building can be observed to have uniform shape and height characteristics. Whereas the height and shape characteristics of vegetation or tall trees can be seen to much more sparse, having high variance than that of buildings. Using this invariant, we retrieve different segments from the scene. Segment retrieval involves identifying set of points over the scene which have a "similar height" along a line of reference. A Point(X, Y) is chosen in the LiDAR scene having multiple return values. We call such points as seed points. Multiple such seed points combine to form a given segment. The criteria of only choosing the seed points with multiple return values in a given scene is to only extract the edge points of the objects and not the points that are in the interior or the exterior of the object. After a given seed points has been selected, we make a new frame of reference about his point. Point (X, Y) is the new origin of this new frame of reference. Now this new frame of reference is rotated at small rotation increments that is user defined. For each rotation increment we try to find all such seed points(X, Y) having the similar Z profile (height parameters) along the straight line as that of the origin.

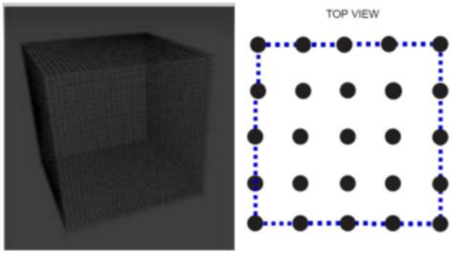

Figure 3. Shows 4 segments identified in the given LiDAR scene, shown in blue. (Top-View)

The rotation increment parameter is configurable by the user. Smaller the rotation increment, denser the set of segments, we will receive from the given scene and vice versa.

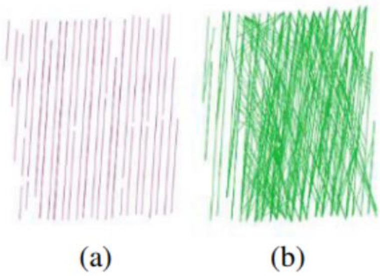

Figure 4. Showing the variation in the identified segments in case of different values of rotation increments (Top-View) (a) Rotation increment 90 degree (b) 5 degree

In real world LiDAR datasets due to occlusion errors or low resolution of the data, identifying surface points of an object is difficult. One cannot differentiate between a surface point and the interior point of the building as show in Figure 4**.** Thus, having high resolution datasets is a prerequisite for extraction of facade efficiently from a given scene.

3.2 Identifying different Blocks

Now that we have the segments signifying surfaces of the different objects in the scene. For every segment, we move along its surface normal to identify different blocks of the object having similar shape. The blocks of the object are formed by considering the 'shape planes'. Shape planes refers to the slice of LiDAR data obtained along the surface normal, perpendicular to the ground.

Consecutive sets of similar shape planes combine to give the different blocks of the object. After obtaining all such blocks of the object, they are indexed to store similar shapes together. Thus, from this sub-step of the processing pipeline we obtain a set of multi-polygons of different parts of the object grouped according to their shape (Z-profile of the shape plane).

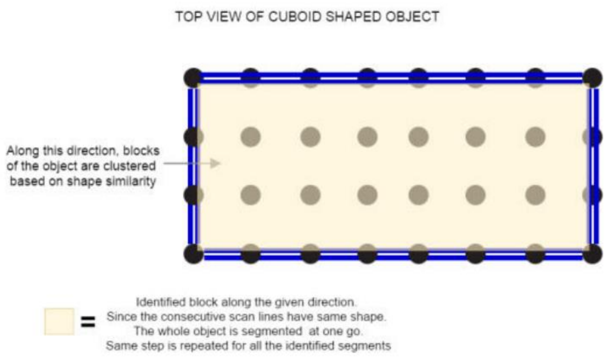

Figure 5. (a) Block Identification of a cube shaped object along a single segment presented above. (Top-view)

3.4 Shape Characteristics and Formation of Blocks

For shape similarity matching, rudimentary features are taken to segment different blocks. The features basically consider the number of perpendicular walls present in a given plane. That is it considers the histogram of number of return points at a given section in a given plane and then checks the variation in them in subsequent planes to calculate the shape similarity between two planes. If two consecutive planes are shape similar, they are combined to give the resulting block. This block continues to be added cumulatively till the consecutive planes are shape similar.

Till a new plane is encountered that is different in shape, we add it to form a new block. This process of finding different block based on similarity of the shape planes goes on till no further planes can be obtained along that direction. Further there is scope of enhancement for developing better shape features using moments to further increase the accuracy of block segmentation.

3.5 Merging Similar Blocks + Footprint creation

Now that multiple polygons are obtained for a given object, the next task is to merge the similar polygons or blocks. The merging of similar blocks is done using multiple rules like overlapping nature of the blocks, adjacency property between different blocks. Such rules are user defined and can be changed as per as data. The heuristic used to merge the different polygons is on the basis of the percentage of overlap. If the polygons overlap beyond some threshold value, they are merged together to obtain a new polygon. This step continues until we obtain only those polygons which don't have an area overlap beyond the threshold value. The final results of the merging step is a set of polygons, signifying the footprints of the 'possible' buildings. Merging step of the different blocks can be done through identifying the various features like symmetry, flatness, area etc that have already been identified by already existing works. The building extraction step involves the triangulated representation of all the points inside the given polygon. The block diagram of the algorithm is show below

4. OBSERVATIONS AND CONCLUSION

4.1 Results from synthetic dataset

The segmentation technique proposed in the paper was initially tested on the simulated set of objects. These simulated objects contain a much more variety of objects than usually seen in a real world scenario. The objects are rudimentary shaped and not that complex that are usually seen in real world scenario. The purpose of creating synthetic data set is for ease of usage in proof checking of the algorithm and easier debugging than in real world datasets. Since, the simulated objects were completely uniform with much complexities the blocks identified along each segments covered the whole building.

Peculiar case of segmentation was seen in building with minarets and the ladder shaped building. The initial segmentation of the object into different blocks resulted into multiple different sections. In the subsequent step, these blocks of the object were combined to give the final footprint of the object.

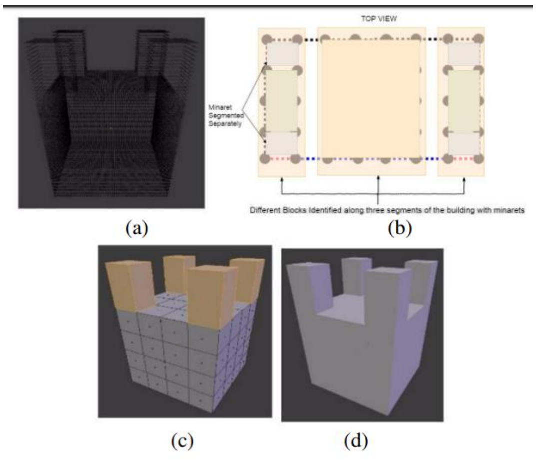

Figure 6. shows (a) LiDAR input (b) Different blocks identified from different segments (c) Selected regions not part of the same block, while rest of them are merged together to give approximate footprint of the building (d) Segmented object

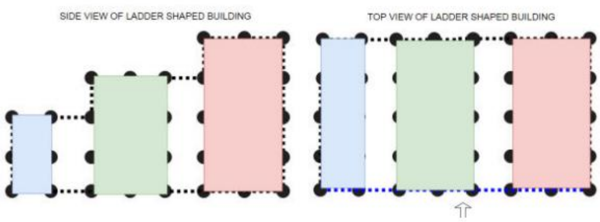

Figure 7. (a) Multiple segments are identified from the same side of the building (Side-View) (b) Different blocks identified for the same building. (Top-view)

4.2 Results from real world dataset

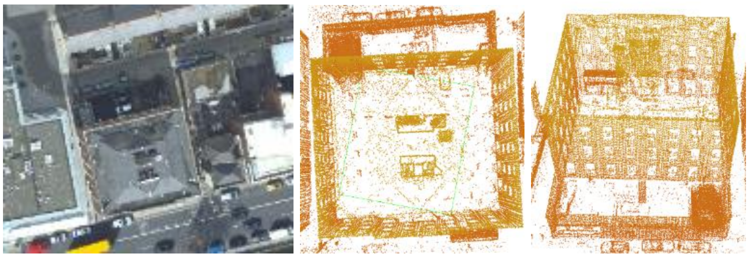

Figure 8. Shows the (a) Aerial image of the test region (b) Top view of LiDAR points (c) Side View

For subsequent testing of the proposed algorithm, a small section of Dublin dataset was chosen. This small section consists of gabled roofed building, a partial flat roofed building, vegetation consisting of high trees, ornamental bushes, roadside vegetation, cars, cables, vegetation and parks etc. At the beginning, pre-processing of data was done. Preprocessing steps involved removal of the ground points from the given scene. The baseline for finding the ground points in the given scene was referred to the method used by the popular LiDAR processing toolbox LAStools. After separating the ground points and the non-ground points, they are separately stored in two different files. The file with non-ground points was manually checked for any errors.

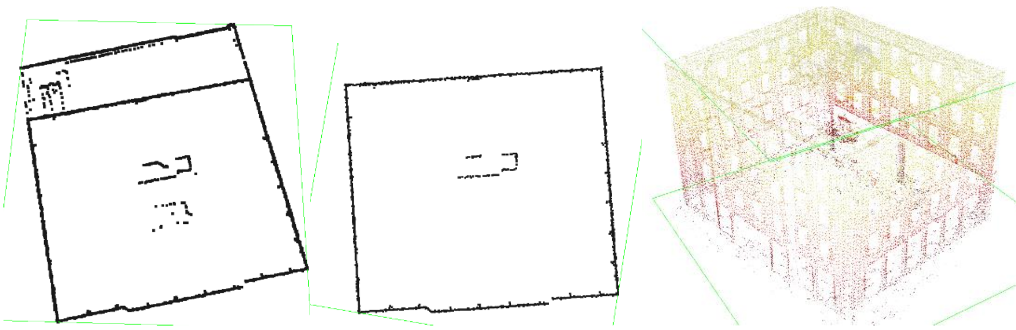

Figure 9. (a) The extracted segments overlaid with boundary segments shown in dark (b) Multiple blocks of similar shape within an object (c) 3D points inside the extracted footprint of possible building

The results from the test site gave promising results with further scope of extensive analysis and evaluation. A further post-processing step to improve the accuracy can be applied based on domain knowledge to eliminate small polygons of over segmented trees if any. The possible advantages of the proposed algorithm are explained below

4.2.1 Object segmentation from partial segments: In the given example. We can see that the only a single side of the building is been segmented out as valid segment in the given test site. It signified that the other side of the building was either missed out due to occlusion errors or it was a roof overhang, which led to non-identification of the wall. Thus, in spite of the roof overhang, our algorithm using a single segment extracted from the building footprint. Thus, even a single segment from a given scene can be used to identify the building footprint. If we miss in finding even a single segment of the building, then it is bound to skip it's segmentation leading to false negative.

4.2.2 Extraction of partial buildings: Previously in (Gaurav, 2017) we had demonstrated to extract the building footprint using similar segment extraction and cyclicity of the wall segments in a given building. One of the drawbacks of the previous work was the cyclicity assumption. Often in a given scene some buildings in the outer edges aren't completely covered in the scan. Thus they were bound to be skipped in the conventional object segmentation. Our algorithm, since it relies on partial segments from a given building to extract the building. We demonstrate in the below figure how the building inspite of being partially represented is segmented in the given scene.

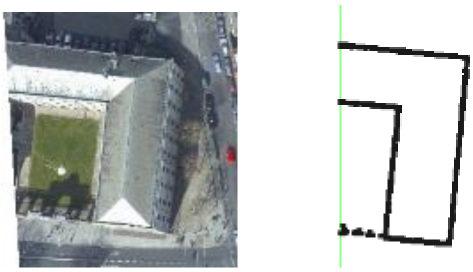

Figure 10. (a) Represents the aerial image of the partial building (b) Represents the seed points of the extracted footprint

4.3 Potential Drawbacks and Scope of Improvement

4.3.1 Parameter Tuning: The parameters involved in the algorithm consists of only three parameters in the segment extraction step that is the minimum number of return points required to be present in a given seed point, the minimum number of seed points that are required to be present in a given segment and the rotation increment. The first parameter of 'minimum number of seed points required to be present in a segment' needs to be carefully balanced. Smaller the value of the parameter, more segments will be identified and vice versa. Thus there is a scope of over segmentation if a very small number is chosen. Another parameter which is part of the segment extraction step consists of the rotation increment. Smaller the rotation increment, more segments will be identified in the scene. The advantage of our technique is that keeping a large rotation increment selects at least some of the surfaces from either sides of the building rather than all segments in the given building.

The number of parameters set are kept to minimum to ensure that the algorithm doesn't overfit based on specific dataset. While a program being more parametric ensures the flexibility and the adaptability of the algorithm depending on the data being used. Thus, there is a tradeoff in accuracy based on the parametric nature of the algorithm. The parameters are often helpful in faster debugging as the parameter often control the runtime of the program.

4.3.2 Partial building segmentation: This particular case of partial building segmentation is seen when the segments of the building, do not have complete coverage of the ground truth. This leads to partial segmentation of the building. The instances of this happening is rare and not encountered in the given test area taken.

5. CONCLUSIONS AND FUTURE WORK

The above observations successfully demonstrate the proposed algorithm of building segmentation and extraction using the facades of the building. The only precondition of the algorithm is the high density of data requirement for its proper working and efficient execution. The task of finding different block of shape similar roof planes is in fact an optimization step to mostly used "split and merge" technique of building segmentation.

The algorithm also has an adaption to low density data can also be done where the all ground points including the roof points are used for segment extraction. Here the segments over the roof planes will also be segmented leading to case of over segmentation and presumed false positives. The over segmentation in the initial step of the algorithm can lead to identification of small tree polygons being identified as buildings. Thus, higher the density of the input data better are the results of our proposed algorithm.

The results shown currently have been tested on real world data consisting of a set of buildings and vegetation. The results are very promising. The advantages of the proposed algorithm can be used to segment partial buildings from the given scene which wouldn't have been possible in the (Gaurav, 2017). Here the previous criteria of cyclicality has been removed and substituted by individual facade analysis. The requirement of higher number of planes for a given building gives a better picture of the roof planes that exist in the potential building. Thus, for a given building, more the number of walls extracted, better is the confidence of its accuracy. A confidence metric of each segmented polygon can also be computed. Thus, the criteria of identifying all walls of a given building is no more required.

The algorithm essentially creates multiple polygon which are then merged to generate the footprint. The generation of multiple polygons over the area leads to creation of different contiguous blocks of similar data. These blocks can be merged based on different feature vectors, to generate the complete building footprint. Compared to the morphological operators which require optimal tuning of window size in the split step. Our algorithm is a new way of finding such blocks using the wall facades. In our algorithm, the polygons are dictated upon the number of facades identified by the building. Thus, our algorithm is a new way of splitting a given test area into different blocks which is then merged to segment buildings. The time complexity and the execution performance advantage to the baseline of window based segmentation is a work in progress and beyond the scope of this paper.

The technique proposed is an unsupervised technique of segmentation, thus requiring no pre-training of a classifier and tuning. Thus, we demonstrated how we devised a new method of segmenting buildings out of a given scene using localized shape properties of the different planes. Such planes are perpendicular to the ground. The proposed work created a bottom-up rule based approach of segmenting buildings using the shape properties. The method proposed doesn't require any supplementary data and is unsupervised in nature, thus leading to ease of use.

The future extension of the work can involve reconstructing extensive 3D models of the buildings based on the shape variations. Another possible extension involves, using this technique to generate the accurate BIM of the buildings using the data fusion of both mobile and aerial LiDAR data to generate highly accurate buildings models, leveraging the high point density of mobile LiDAR data

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