INTERPOLATION OF LIDAR DATA AND AUTOMATIC BUILDING EXTRACTION

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ABSTRACT

Laser scanning systems are frequently used to provide the digital surface models, DSM, of the earth surface. Laser scanning is a fast and precise technique for resampling the earth into irregular pattern. The large number of laser points hitting planar facades in urban areas facilitates the use of least-squares interpolation. In this paper some problems regarding interpolation and their solutions by first extracting the breaklines are presented. A procedure for building detection and extraction from the DSM is developed. A region growing algorithm based on least-squares adjustment of laser data connected by triangulated irregular network, TIN, to extract the building facades is introduced. The variance components are used to estimate the quality and the validity of the extracted parameters. Adjacent planar facades are used to extract the three dimensional breaklines, which can be stored in a vector format or can be used to separate the uncorrected segments to guide any subsequent interpolation processes or building extraction. A morphological filter is used to highlight the terrain and the non-terrain segments. The resulting classification in addition to the extracted planar facades and breaklines will be used for extracting the building parameters. The procedure is developed to work for all terrain types and for most building/roof types. The final result of this research is 3D vector representation of the buildings with the best possible accuracy. Experiments using real data are presented and show the feasibility of the suggested approach

INTRODUCTION

Many applications, such as urban planning, telecommunication and security services require 3D city models. Buildings are the objects of highest interest in 3D city modeling. Urban areas are rapidly changing mainly due to human activities in construction, destruction or extension of topographic elements such as buildings and roads. This mandates the availability of fast data acquisition technique and automatic method for detecting and extracting 3D topographic objects from the data. Airborne laser scanning is a new technology in which several sensors are integrated to obtain 3D coordinates of points on the earth. It makes use of precise GPS instruments to determine the position of the sensor, inertial navigation system (INS) to determine the attitude of the sensor, and narrow laser beams to determine the range between the sensor and the target points. Laser scanning systems are active, therefore they can work day and night. Shadows also do not affect laser data.

Large body of research had focussed on using additional data. For example, Vosselman and Dijkman (2001) are using ground plans. These ground plans reduce the search problem and eliminate the building detection problem. Other data that are used to reduce the ambiguity of the results is reflectivity data, which can be obtained in additional to the range data by some systems (Hug and Wehr, 1997). Mass and Vosselman (1999) make use of the moment to fit specific models. Building models can be used to fit the data but only after building detection. Moreover, the increased number of building models in terms of shape, size and complexity would limit the use of building models to specific areas. Other building extraction methods include extraction of planar patches. Some of which use height, slope and/or aspect images for segmentation (e.g., Morgan and Tempfli 2000, Haala at al. 1998). Interpolation is required for resampling the data into regular grid, which is accompanied with interpolation errors. Segmentation based on the raw data (e.g. Morgan and Habib 2001) such as using triangulated irregular network, TIN, would not have interpolation errors, which could affect the results.

In this paper a general strategy for handling the laser scanning data for building identification and extraction is presented. In section 2, the problem statement about the interpolation of laser data is introduced. Section 3 outlines the proposed algorithm for handling the laser data for building identification and extraction. In section 4, some experimental results using real laser data and analysis of the results are discussed. Section 5 includes the conclusions and the recommendations for future work.

RESAMPLING THE LASER DATA

Resampling has two components, namely the resampled locations and the resampled values. The former has to deal with the pixel size or the grid intervals when we want to resample into a regular grid while the latter deals with the interpolation function.

The Pixel Size

The grid intervals or pixel size have to be determined in an optimal way prior to proceeding with resampling. In order to resample the data into new locations we want to reduce the information-loss as well as keep the redundancy minimum. This can be achieved by resampling the data in such a way that each pixel/cell contains one-and-only-one laser point. More points in a cell will increase the information-loss since the cell at the end, after the interpolation, will get only one value. On the other hand, if the pixel size is very small and the number of pixels that contain no laser points becomes large, the redundancy increases as well as the storage requirements. Having n laser points distributed as grid in a unit horizontal area, the linear spacing between each two points in a row or a column is equal to $1/\sqrt{n}$ m. In order to faithfully represent the laser points in a raster array, one can use this formula as the pixel size (Morgan and Tempfli, 2000).

The above scenario considers laser points, which are regularly distributed. However, the laser data are irregularly distributed points. The above formula can still be used as far as the laser pattern is not highly irregular. As the degree of irregularity increases, the equation will not satisfy the requirements for preserving the information content and the redundancy reduction. The average or the minimum density of the laser data can be used to estimate the optimum pixel size using the above formula. One should disregard the nominal point density, but should compute it by dividing the number of laser point over the area of the horizontal convex hull.

The Interpolation Method

There are many ways for interpolation, some of which work properly in some applications and fail in others. There is no such a robust way for interpolation. The reason behind is that the interpolation is a prediction of what is not known. Most of the interpolation techniques make the prediction using the direct/close neighbors and fit them into a model. It has to be noted that, the larger the distance between the points, the less contribution in the elevation function will be. However, this function should not be continuous due to the existence of breaklines/discontinuities. Errors are always present in the data. Therefore, one should use more data than what the model requires and try to filter out the blunders, if any, or smooth the random errors in a least squares adjustment. For example, using many points on a planar area, we can estimate the plane parameters with very high accuracy because of the redundancy in the system and we can think about it as if we are smoothing the random errors. We will not consider systematic error in this paper, since they can be detected and corrected for through a calibration procedure.

Least squares local first degree polynomial (planar) fitting will be used for the interpolation. We will always use more points than that is required by the model (three points per plane) to compute the variance component as a measure of the goodness of fit between the model and the data. The interpolated values with large variance components give indication of the existence of a problem, either the assumed model or the chosen data. The model can be reparametrized by examining the eigenvalues and the data can be filtered by examining the residuals from the adjustment or as blunder detection. In the following section, another problem will be highlighted due to the existence of breaklines in the data.

The Problem of Interpolation with the Presence of Breaklines

The problem will be discussed using examples. Two examples will be shown. The first example does not have breaklines while the second example contains three breaklines. The data of the first experiment were simulated on an analytical surface without breaklines in an area of 40000 square meters as shown in figure 1(a). Normally distributed errors of zero mean and 0.1 m standard deviation were added to the elevation values. The true (since we know the ground truth about the data) interpolated surface as well as the least squares first degree polynomial fitting are shown in figure 1(b) and 1(c) respectively. For each grid location, the nearest five points were used for the interpolation. One cannot see the difference immediately by visual comparison. By analyzing the variance components as shown in figure 1(d), one cannot see any specific pattern of estimated errors. Since we know the true surface values, the interpolation errors were computed and plotted in figure 1(e). The root mean square error RMSE was 0.07 m, which is good compared to the errors associated to the raw laser data (0.1m). Again we cannot see any error pattern associated with the linear interpolation. One should notice that we do not always have the ground truth to evaluate the interpolation, otherwise the interpolation will be meaningless. However, we can always analyze the variance component due to the redundancy that we introduced to the model. By analyzing the variance component, we can reparametrize the model or alter the observation vector and update the interpolation results till we get a better estimate of the variance component. However, we will not start this “tuning” before we show the other example.

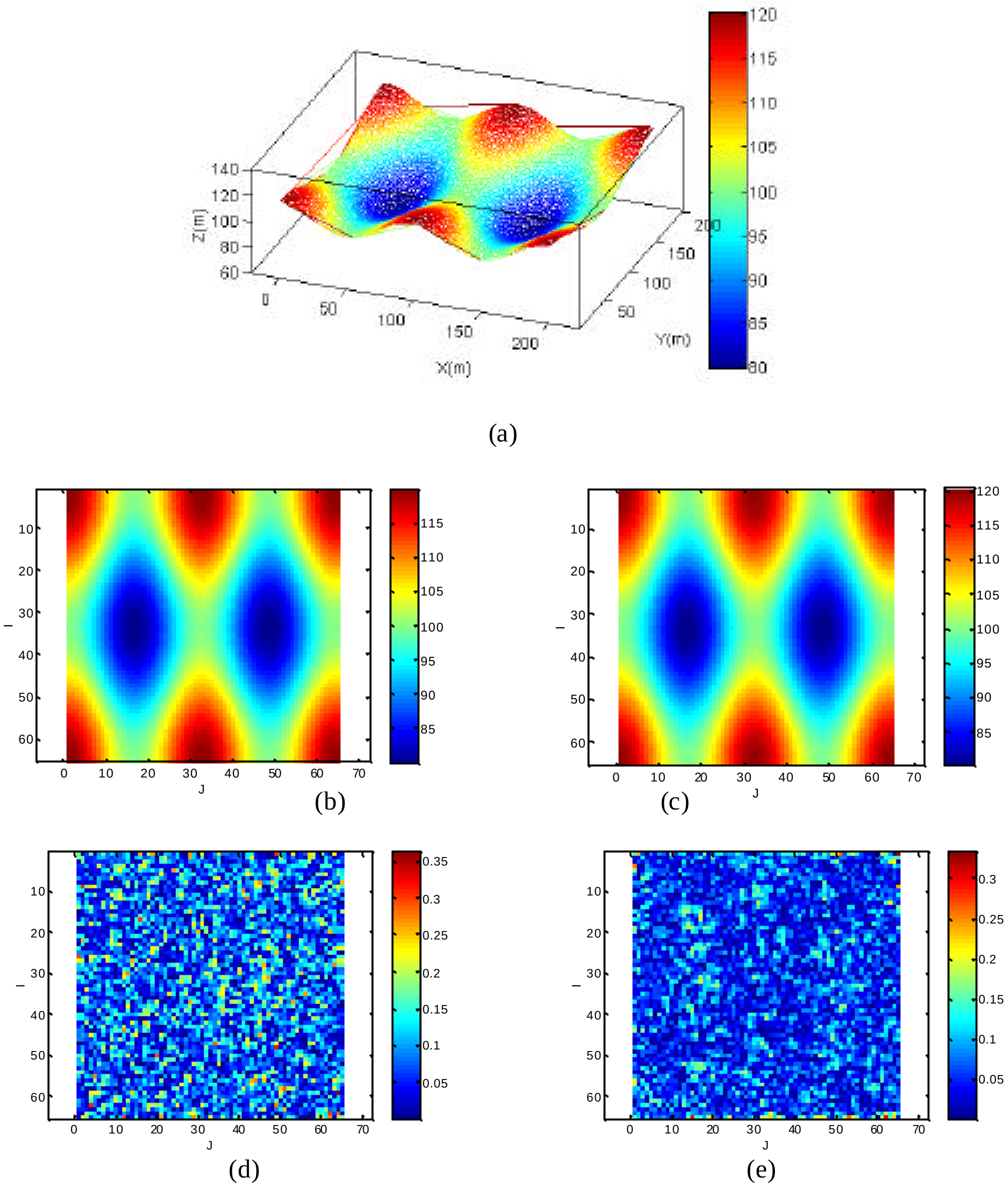


Figure 1. The true surface (a), the true interpolated surface (b), the least squares linear interpolated surface (c), the associated variance components (d), and the associated interpolation errors(e) for experiment 1.

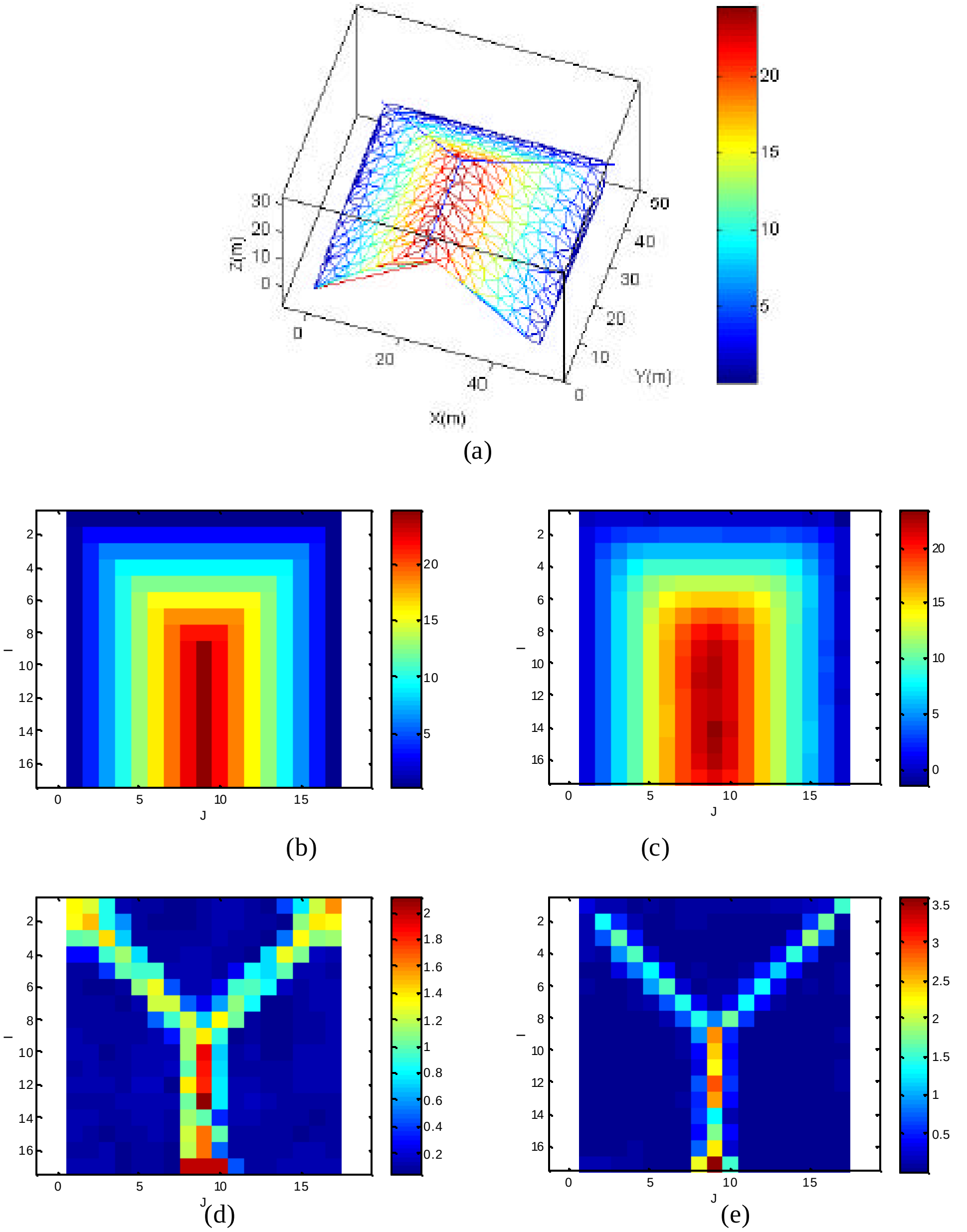
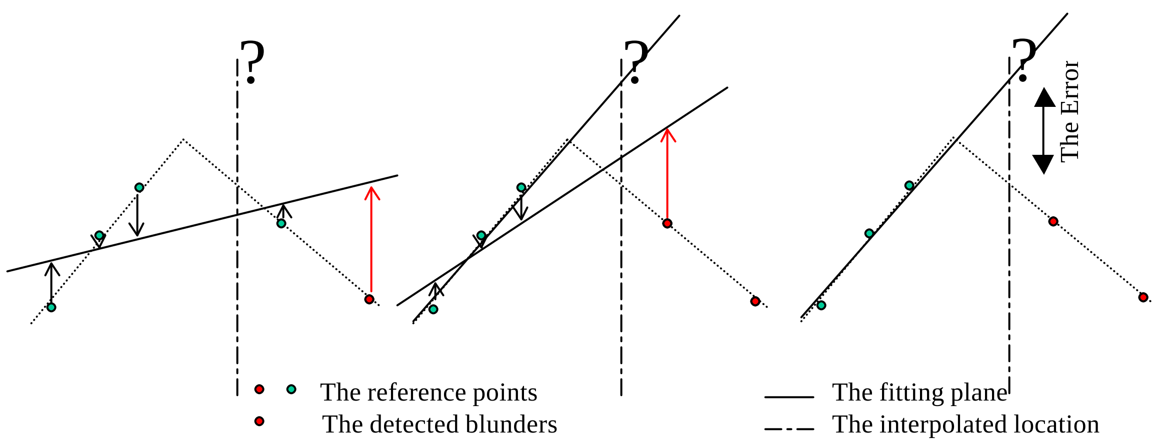


Figure 2. The true surface (a), the true interpolated surface (b), the least squares linear interpolated surface (c), the associated variance components (d), and the associated interpolation errors(e) for experiment 2.

The data of the second experiment were simulated randomly on planar saddle roof of an area of 2500 square meters as shown in figure 2(a). Normally distributed errors of zero mean and 0.1 m standard deviation were added to the elevation values. The true interpolated surface and the estimated interpolated surfaces are shown in figure 2(b) and 2(c) respectively. The variance components and the interpolation errors are shown in figures 2(d) and 2(e) respectively. The RMSE was 0.65 m, which is large compared to the elevation errors in the laser data. Moreover, we can immediately realize a pattern of large variance components associated with the breakline locations in the estimation technique. The same pattern is also shown in the interpolation error. The reason is that there is no model that can fit the data in both sides of the breakline and faithfully represent the breakline. One can think about "tuning" the data till it fits the model. However, this approach will not always work as shown in figure 3. In this figure, a sequential filtering of the blunders (or the points of the largest residuals) is shown. Figure 3(a), a linear interpolation is used to fit five data points, followed by blunder detection based on the largest residual. The point of the largest residual, the red point in the figure, will be discarded and the solution will be updated as shown in figure 3(b). Similarly, one can proceed till the variance component becomes small as shown in figure 3(c). However, the interpolation error is large.

The problem is that there are two groups of points in figure 3. Each group is on one side of the breaklines. We can assume they are uncorrelated groups of points. Therefore, the interpolation at a new location on the right side should not be influenced by any elevation values from the left side group of points and vice versa. Consequently, one should have knowledge about the breaklines in advance before starting the interpolation. Another problem in the interpolation is that neighboring interpolated locations my get contribution from same laser points which will increase the correlation between the interpolated values which in turn can alter the segmentation processes of the interpolated data.

It is very important to extract the breaklines existing in the data before applying any interpolation technique. Breaklines are also important to identify the sudden change in slope or elevation. In urban areas most of the breaklines represent parts of artificial objects such as building. Therefore, detecting breaklines will serve both interpolation and building extraction. The following section explains how to extract breaklines out of the laser data and using them into an algorithm for building detection and extraction.



(a) (b) (c)

Figure 3. The problem associated with sequential elimination of the observations of the large residuals.

BUILDING DETECTION AND EXTRACTION

The proposed algorithm for building detection and extraction has the following steps; segmentation of laser points, classification of laser segments, generation of building hypothesis, verification of building hypothesis (building detection) and extraction of building parameters. Each of these steps will be discussed briefly in the following sections.

Segmentation of Laser Points

Segmentation of laser points is to group the neighboring laser points that have common characteristics. This leads to two main issues; defining the adjacency criteria between the laser points, and defining the grouping criteria. Defining the adjacency criteria based on grid-interpolated laser data would suffer from problems as explained in section 2. Another way is to generate two or three dimensional triangulated irregular network, TIN, of the laser data points. This TIN structure can be used for providing the adjacency information between the laser points. The grouping of adjacent laser data aims at the extraction of laser points that fit analytical functions (such as planes). Hough transform is one of the method used for grouping by switching from the data space into parameter space, identifying the most probable parameters and highlighting the corresponding data (Vosselman and Dijkman 2001, NSTRCCVGS, 1993 and Hough 1962). Two problems are associated with this method, first the method does not consider the adjacency between the data points. Therefore, the adjacency between the highlighted data should be analyzed. Another problem is the determination of the pixel size in the parameter domain as well as the challenging problem of detecting the peak value(s). Therefore, analyzing the data in the spatial domain will guarantee considering both the adjacency and the grouping criteria simultaneously. Region growing is one of the methods used for grouping in the spatial domain. The grouping criterion is usually chosen as similarity of the orientation of the surface normal vectors. Due to the errors contaminating in the data, threshold values are considered when comparing two adjacent surface patches. To have a robust region growing algorithm, a comparison should be made between the orientation of the surface normal vector to be tested and average orientation of the surface normal vectors of the currently segmented surface patch. Due to the existence of the threshold, the growing algorithm may lead to unwanted results. Consider a profile of laser points located on two adjacent planes intersecting at small angle as shown in figure 4. By comparing the orientation of the surface normal vectors, the region can grow, segmenting them into one segment as in figure 4(a). It is clear that the resulting segment does not fit one plane, even if we have small angle between the two planes, because of the extent of the segmented planes. One should notice that the adaptive region growing, by comparing the orientation of the element to be tested to the average orientation of the segmented region, would not help here. By choosing the growing criteria as the small deviation from the plane fitting the growing segment, as in figure 4(b), one could overcome this problem. Moreover, as the region grows, one has to evaluate the variance component of the plane fitting problem, to decide whether to include the considered point. The deviations from the growing planes and the evaluation of variance component should be compared to the knowledge about the error contaminating in the laser data. One should not use the nominal laser accuracy, but to evaluate the accuracy based on some references, such as computing the standard deviation of the height values or computing the variance component over an interactively selected planar patch in the area mapped by the considered laser.

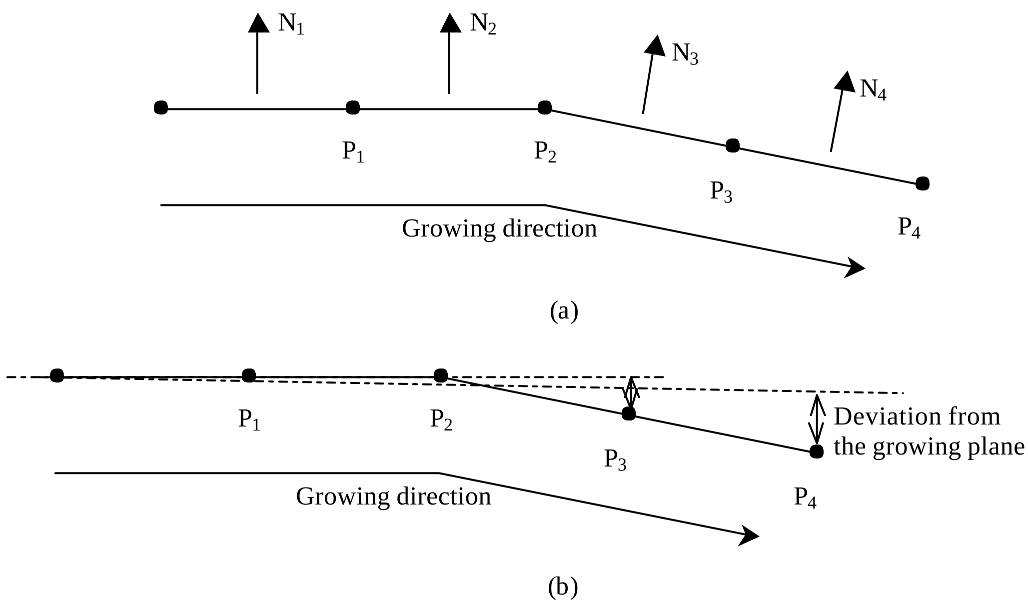


Figure 4. Region growing based on similarity in orientation of surface normal vectors (a) and the region growing based on plane fitting.

Choosing large threshold in the region growing may result in segmenting different entities in one segment, which may have the same effect as that in comparing the orientation of the surface normal vectors, which in tern needs to be followed by splitting algorithm. Splitting algorithm is another segmentation/region growing problem within one segment. On the other hand, choosing small threshold values would require further merging algorithm, which is adopted in this paper. Once again, two important criteria have to be selected; the adjacency definition between segments and the merging condition. The segments that have a significant length of common/close boundary will be considered to be adjacent (Morgan and Habib 2001). In this case the adjacency between segments depends on the ratio between the length of the segment perimeters that are close and the minimum perimeter of each of the considered segments. The merging condition is whether each of the centroids of the adjacent segments fits the other plane equation with certain tolerance.

Classification of Laser Segments

A morphological filter (Morgan and Tempfli, 2000, Hug, 1997, Hug and Wehr, 1997, Kilian et at, 1996) can be used for classification of laser points. The main concept of this filter is to classify the laser points based on the height values within a search window. Large search window would result in problems in case of high terrain variations, while small search window would misclassify laser data on building roofs. Groups of search windows of different sizes are adopted, providing that each is larger than the expected/minimum building size, which should be known as prior information. Detailed description of the morphological filter can be found in (Morgan and Tempfli, 2000). One of the problems of this method appears when having laser points on vertical or inclined facades. As shown in figure 5, points that are lower than a threshold will be classified as terrain points, even though they belong to a building. In order to overcome this shortcoming, the same morphological filter will be used based on the centroids of the planar segments, instead of dealing with isolated points. For laser with high angular field of view one expect more points belong to the vertical facades of the buildings. Even if there are no laser data on vertical facades, no side effects are expected by adapting the analysis of the segment centroids.

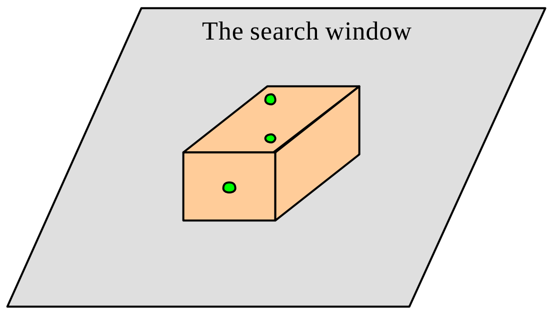


Figure 5. The problem of analyzing the height values of the raw laser data using morphological filter. The green points are classified as non-terrain while the red points are classified as terrain.

Generation and Verification of Building Hypothesis

Have the terrain and the non-terrain segment been identified, connected component labeling will be performed to connect the non-terrain segments into larger segments (building hypothesis). Each building hypotheses will be verified based on some criteria such as the size and the shape. A prior knowledge about the minimum/required size of buildings should be available, so smaller building hypothesis will be rejected. Another criterion being used is that large portion of the building hypothesis should be represented by large planar facades. For example, a hypothesis that has one or more planar façade of large size will be used for further processes, otherwise it will be rejected.

Building Extraction

After the buildings have been detected in the previous section, an algorithm for extraction of the building geometrical parameters will be performed. The algorithm has two main steps; determining the three dimensional internal building breaklines and estimating the building boundary. Internal breaklines can be determined by intersecting the adjacent planar facades within the building. The adjacency between the segments is as explained in section 3.1. It is known that the laser points are not selective, and they do not match building boundary. Therefore, one can not determine the building boundary with a high certainty unless we have more points, therefore segments, on the vertical facades that bound the building (Morgan and Habib, 2001). Other data, such as optical/imaging data could help solving the boundary problem. Having no access to such points or segments that bound the building, and using no more data other than the laser, one has to make a guess about the boundary. Figure 6 shows a portion of a building near its boundary. Some laser data points are located on the building while others are located on the terrain. It is not known how close each of the points in these two groups to the actual building boundary. Therefore, we have selected the centers of the triangles that bound the building to estimate the horizontal boundary of the building. Hough transform for detecting straight lines will be used using the horizontal coordinates of the centers of the bounding triangles. Intersecting the detected straight lines will delineate the building boundary. The building boundary in addition to the internal façade parameters and the internal 3D breaklines will be the results of the building extraction process. The topological relationships between building facades can also be stored as the adjacency between these facades had been determined in an earlier process.

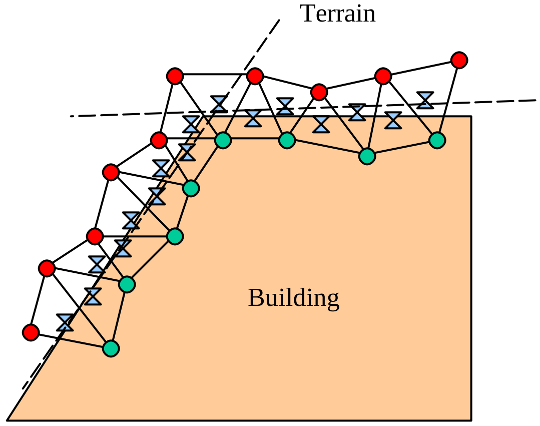
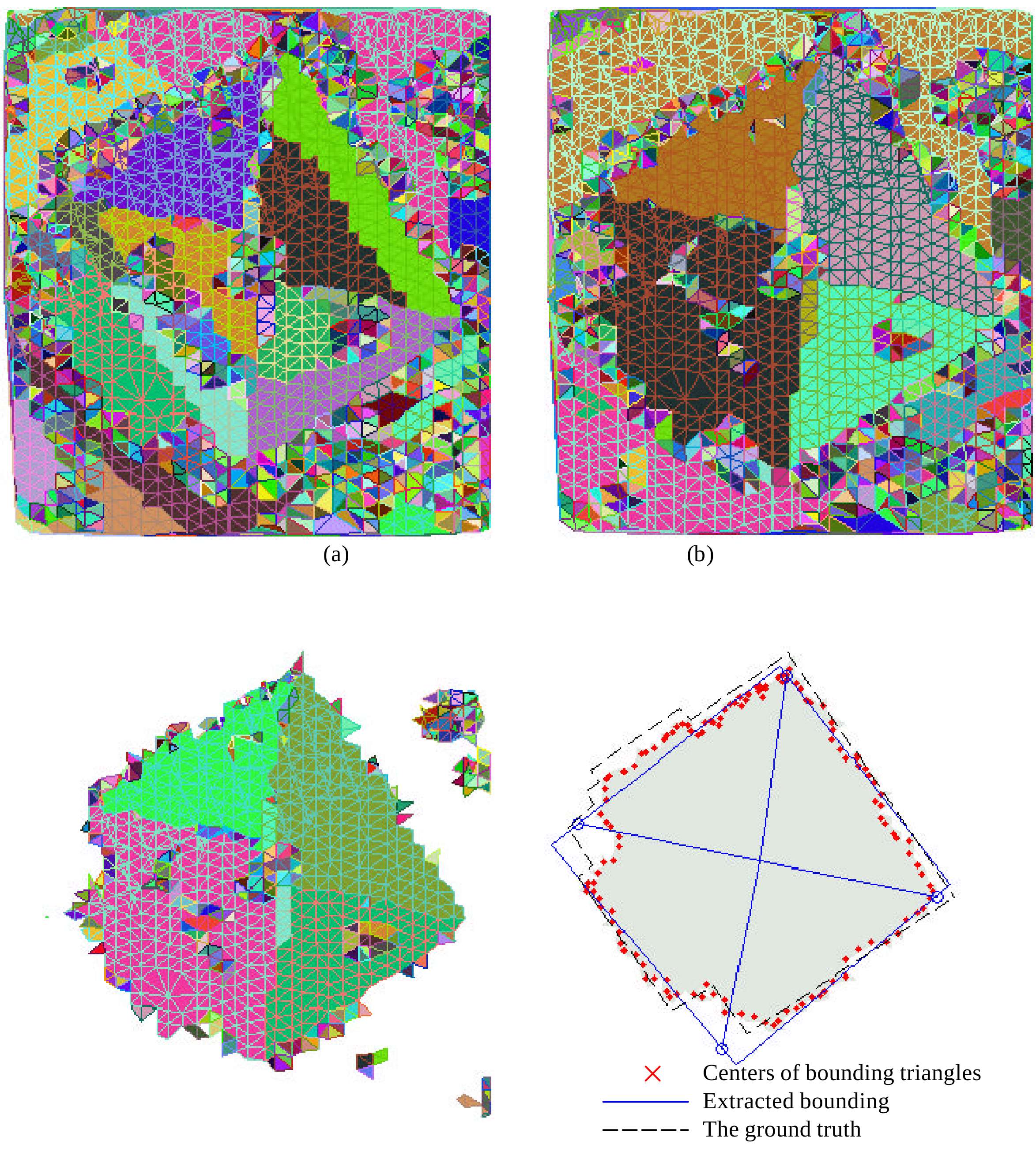


Figure 6. Estimation of the building boundary by detecting the straight lines the fit the centers of the bounding triangles by means of Hough transform.

EXPERIMENTS AND RESULTS

Real laser data had been used to test the proposed method. The density of the data is 1.5 points per square meter and the vertical precision is 0.1 m. A ground truth data is available in a form of 2D GIS layer, which is used only for the evaluation of the results. The region growing algorithm based on least squares planar fitting was performed and the preliminary planar patches are shown in figure 7(a). Figure 7(b) shows the segments after the merging procedure has been performed. One can see that segments belong to the same roof façade have been merged. The morphological filter had been applied using the centers of the extracted planar segments and the non-terrain segments have been identified and shown in figure 7(c). The connected non-terrain segments have been labeled and identified building hypothesis. Using the minimum building size as constraint in addition to the area percentage of the large planar segments in the building hypothesis were used to verify the building hypothesis. Building extraction proceeds by extracting the planar façade parameters, intersecting adjacent facades to obtain the internal breaklines, and determining straight lines delineating the centers of the bounding triangles using Hough transform. The results are shown in figure 7(d). One should notice that only four straight line building boundaries had been detected using Hough transform. That is clear due to the small number of bounding triangle centers along the short boundary lines as can be seen in the ground truth data. The larger the laser point density, the more edge triangle, the higher the success of extracting the boundary is terms of accuracy and certainty. In contrary to the extracted building boundary, the estimated variance components associated with the extracted planar facades show high certainty and accuracy regarding the quality of the internal breaklines. That can be seen, by extending both the upper and the right breaklines in figure 4(d) that are within the building. As these breaklines been extended, they will pass through corner points of the ground truth data. The quality of delineating the building can be enhanced by constraining the bounding lines to intersect at similar points on the internal breaklines. Moreover, one can constrain the bounding line extraction in two perpendicular directions. Building models can also be used to fit the detected buildings.



(c) (d)

Figure 7. The detected planar segments before the merging algorithm (a) and after the merging (b), the detected non-terrain segments (c) and the extracted building superimposed to the ground truth data (d).

CONCLUSIONS AND RECOMMENDATIONS

In this paper, a problem of interpolating laser data in urban area is presented. The solution to this problem is to detect the breaklines prior to proceeding with the interpolation. An algorithm for building detection and extraction was also presented. The automatic detection of the breaklines is one of the steps used in building detection and extraction. The algorithm makes use of two or three dimensional triangulated irregular network TIN as a basis for obtaining the adjacency between the laser points. A region growing algorithm based least squares plane fitting was introduced and tested. The quality of the extracted planar segments were evaluated based on the estimated variance component. Merging algorithm is considered to overcome the noise as well as unwanted behavior of growing algorithm. The merging is based on the adjacency between the planar segments and the overall variance component of the fitted plane to the points belong to the segments under consideration. A notion of the adjacency between segments was introduced based on the ratio between the length of the segment perimeters that are close and the minimum perimeter of each of the considered segments. A morphological filter is then applied to the centers of the considered segments to classify them as terrain or non-terrain, which is more robust than to classify the raw laser points. Connected non-terrain segments are then labeled as building hypothesis. Verification of the hypothesis is based on prior knowledge about the minimum building size and the ratio between the area occupied by large planar segments and the total area of the segment. Adjacent planar segments within the detected buildings are then intersected to extract three dimensional breaklines. These breaklines are of importance in both building identification and extraction and in interpolation of any laser data. Delineating of the building is done by performing Hough transform to the centers of the triangles that bound the building.

The Experiments performed showed the feasibility of the proposed algorithm. Building detection was done successfully. Planar building facades as well as internal breaklines were accurately identified. The building boundaries were detected with a lower accuracy. More constraints, such as parallelism, perpendicularity, using the internal breaklines as references, model fitting, can be used to increase the certainty and the accuracy of the building boundaries. Obtaining the building boundaries from other sources such as aerial photos by registering and integrating both data is recommended. More experiments using simulated and real data having variety of building and terrain types are recommended to test the algorithm.

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