Measurements of forest structures by combining different point cloud data

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Abstract. It is useful to monitor forests by extracting parameters from LiDAR and aerial imagery. Reconstructing them can be challenging using only LiDAR because it is difficult to extract exact parameters. Therefore, using aerial images, we can obtain a digital surface model by matching, extract a digital terrain model by filtering, and generate a canopy height model(). In forests, we obtain a point cloud from stereo images by using a multi-view dense matching algorithm, and then fuse the results to generate a high-density digital surface model. Finally, we can extract the plant information by combining the LiDAR and matched point cloud.

Introduction

Point clouds are widely used in forest parameter extraction. However, they are usually generated using LiDAR, so have many disadvantages. In forest investigation, it is difficult to obtain a high-density point cloud (Leverl et al., 2010).

The objective of this paper is to evaluate the quality, accuracy, and feasibility of an automatic tree extraction method based on low density LiDAR point data and a dense match point cloud.

The European Spatial Data Research Organization started a benchmark on image based digital surface model (DSM) generation in February 2013. This test is based on two representative image blocks, which were processed by different groups with different software systems.

The interpretation of the benchmark results identified some scenarios that still can cause some problems during image based surface reconstruction. Some solutions showed decreasing accuracies as shadows were cast. In addition, the representative image blocks don't include the forest area (Haala, 2013).

Dense matching methods can be divided into two types: depth map fusion and object patch. One technique used to reduce the search area of matching processes in aerial images is MVLL (Multi-View Local Learning), which defines a vertical line in the object space and calculates the correlation coefficients of the two image matrices according to a point along this line (Zhang, 2005; Waser, 2008; Baltsavias, 2008; Jiang, 2004; Ming, 2009). Another method is PMVS (Patch-based Multi-View Stereo), which is a patch-based method. This method is implemented as a match, expand, and filter procedure, starting from a sparse set of matched key points, and repeatedly expanding these to nearby pixel correspondences before using visibility constraints to filter away false matches (Zhu, 2009; Furukawa, 2008; Furukawa and Jean, 2009; Furukawa et al., 2009b; Shi, Guo and Hu, 2011).

Inter-scanline inconsistencies can be resolved by techniques, which use two-dimensional constraints, like graph cut or belief propagation stereo analysis.

SGM (Semi-Global Matching), published by H.Hirschmuller in 2005, approximates global optimization by combining multiple one-dimensional optimization criteria.

Juha Hyyppa (2008) used small footprint laser scanning data to investigate the forest. This method generates a digital model first, filters the normalized digital terrain model, determines the local maximum, and then uses the growing method to segment the tree crown.

The percentage of detected trees varied between 25 to 90%, implying different capabilities in detecting suppressed trees. The best models were significantly better in separating tree groups into individual trees compared to the manual method. Surprisingly, there was no improvement in the detection rate when the pulse density was increased from 2 to 8 pt/m^2 (Shan and Charles, 2008).

Methods

This method includes accurate image orientation, DSM extraction, and tree parameter extraction. After the images were captured, they were matched to generate connection points. A bundle block adjustment was then used to obtain the accurate orientation parameter. LiDAR data were filtered to obtain a digital elevation model (DEM). The DSM was generated using dense matching. Then, the DSM and DEM were used to generate the CHM. After segmenting the CHM, then a local maximum algorithm was used to find the location and height of the trees.

Under the forest area, it is difficult to set control points. Therefore, we obtained the image orientation parameters by using a GPS-supported bundle adjustment, then a multi-view dense match to generate the dense matched point cloud. The DEM was generated by filtering the LiDAR data.

We used the calibrated bundle adjustment to obtain the orientation and camera parameters using the basic model shown in equation (1):

$$x - x_0 - \Delta x = -f \frac{a_1(X-X_s)+b_1(Y-Y_s)+c_1(Z-Z_s)}{a_3(X-X_s)+b_3(Y-Y_s)+c_3(Z-Z_s)} = -f \frac{\overline{X}}{\overline{Z}}$$

$$y - y_0 - \Delta y = -f \frac{a_2(X-X_s)+b_2(Y-Y_s)+c_2(Z-Z_s)}{a_3(X-X_s)+b_3(Y-Y_s)+c_3(Z-Z_s)} = -f \frac{\overline{Y}}{\overline{Z}} \qquad (1)$$

Where Δx and Δy are as shown in equation (2):

$$\Delta x = (x-x_0)(K_1 r^2 + K_2 r^4 + K_3 r^6) + P_1(r^2 + 2(x-x_0)^2) + 2P_2(x-x_0)(y-y_0)$$

$$\Delta y = (y-y_0)(K_1 r^2 + K_2 r^4 + K_3 r^6) + P_2(r^2 + 2(y-y_0)^2) + 2P_1(x-x_0)(y-y_0) \qquad (2)$$

Where K_1, K_2, and K_3 are radial factors, and P_1 and P_2 are tangential factors.

We used a SURE(Photogrammetric Surface Reconstruction from Imagery) algorithm to generate the dense matched point cloud. It applied the SGM algorithm to match between image pairs, and then fused the results to obtain the resulting point clouds. The SGM algorithm aims to estimate disparities across stereo pairs such that the global cost function shown in equation (3) is minimized.

$$E(\mathrm{D}) = \sum_{x_b}(C(\mathrm{x}_b, \mathrm{D}(\mathrm{x}_b))) + \sum_{x_N} P_1 T\left[\|\mathrm{D}(\mathrm{x}_b) - \mathrm{D}(\mathrm{x}_N)\| = 1\right] + \sum_{x_N} P_2 T\left[\|\mathrm{D}(\mathrm{x}_b) - \mathrm{D}(\mathrm{x}_N)\| > 1\right] \qquad (3)$$

In this equation D represents the disparity image holding estimates of all base image pixels x_b. T is an operator that evaluates whether the subsequent condition is true and is set to zero if false. x_N denotes the base image pixels in the neighborhood of x_b. The global cost function, E, is composed of a data term and two terms representing smooth surfaces. The data term is computed using pixel-wise similarity measures $C(\mathrm{x}_b, \mathrm{x}_m)$. The penalty parameters, P_1 and P_2, control the gain of surface smoothing (Rothermel et al., 2011; Rothermel et al., 2012; Wenzel et al., 2013).

Progressive densification was used for filtering. The entire point dataset was divided into tiles, and then the lowest points in each tile were used as initial ground points. Then a triangular irregular network (TIN) of those ground points was constructed as the reference surface. For each triangle, one of the still unclassified points inside was added to the set of ground points if the distance from the point to the TIN facet and the angle between the TIN facet and the line connecting the point with the facet's closest vertex did not exceed given thresholds.

The method then uses a CHM to identify local maxima using a variable size evaluation window. The window size is based on the canopy height, and is determined by the height of the surface at the center of the window using the following equation (4):

$$width = A + B*ht + C*ht^2 + D*ht^3 + E*ht^4 + F*ht^5 \qquad (4)$$

Coefficients are calculated by using locally obtained tree height and crown width measurements.

Results

The desity of the matched point cloud was 65 points/m^2. The density of the LiDAR measurements was 3-4 points/m^2. In the test area, there were many control points, and they were used to check the accuracy of the DEM of the LiDAR. The height of the trees were used to check the accuracy of the LiDAR and matched point cloud. The avgabs (average of the absolute value of the error), rms (route mean square), stddev (standard deviation), and avg (average) of the LiDAR were 8.4986, 9.58415, 4.45425, and 8.487, respectively. The avgabs, rms, stddev, and avg of the matched point cloud were 10.5831, 10.9816, 2.93263, and 10.5831, respectively. Percentage of the extraction was 30%.

Discussion

Airborne LiDAR data are often used to provide detailed information on tree canopy structure. Lower accuracy was obtained when using low density LiDAR data, as it is difficult to capture the crown shape using this method. By using the dense match method, it is possible to get a dense point cloud. However, this process is constrained by difficulties in the dense match method. In this paper, SGM algorithm was used to match image pairs, and then the result was fused to get a more accurate and dense point cloud, with a result of 65 points/m^2.

Although we have demonstrated that combining data from a dense matched point cloud and LiDAR can make up for the limitation of a low density LiDAR point cloud, the extraction result is not as good as the dense point cloud. Additional research is needed to explore additional dense match and extraction methods.

Conclusions

A method to extract forest tree parameters by integrating LiDAR and multi-view dense matched point cloud data is described here. The SURE dense match method was used to generate a point cloud, which is denser than LiDAR data. Progressive densification was used to generate the DEM.

These results show it is useful to combine the multi-view dense matched point cloud and LiDAR data to extract forest tree parameters.

Acknowledgements

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