REFINEMENT OF FILTERED LIDAR DATA USING LOCAL SURFACE PROPERTIES

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ABSTRACT

Since the introduction of lidar technology, lidar data has been used in a wide range of applications to generate quality surface models. Accordingly, because of the importance of terrain surface models in the applications, rigorous studies have been provided to extract ground points from a mixture of ground and nonground points in a lidar point cloud. Although most filters have been shown to classify lidar points successfully with their filter parameters tuned well, however, experiments revealed that there exist certain limitations in optimizing filter parameters and the correction of all misclassified points is not a straightforward task. In this study, therefore, we propose a method to improve the quality of filtered lidar data in an automated way, which exploits surface properties occurring between immediate neighbors. The method consists of a sequence of procedures which can reduce commission and omission errors. Commission errors which may occur in low-rise objects are designed to be reduced by utilizing morphological operations. On the other hand, omission errors are reduced by adding missing points around step edges. Experimental results show that the qualities of filtered data were improved considerably with our proposed method.

INTRODUCTION

Because of its high elevation accuracy and rapid acquisition time, airborne laser scanning data has been utilized in various spatial applications such as forest inventory management, coast line change detection, and virtual city modeling. One very first step to expand its applicability to most of the applications, however, is to extract ground points from a raw lidar point cloud. Accordingly, there have been rigorous studies to filter lidar data into ground and nonground points in accurate and efficient ways. In the following, filtering methods will be reviewed and then the objectives and methodology of our proposed method will be stated.

Vosselman (2000) proposed a slope-based filter that removes nonground points above a slope profile centered at its neighboring points. The method was revised by Sithole (2001) to reduce omission errors occurring around steep ground features by adjusting slope factor adaptively according to local slopes of a preliminarily produced surface. Kilian (1996) proposed a morphological operation-based filter, where the likelihood of points as ground is weighted according to each window size and then ground points are determined in one final classification. Zhang et al. (2003) proposed a filter to preserve certain mound-like ground features while removing various sizes of nonground features, which removes certain points based on their deviations from the surfaces derived from progressively increasing morphological operations.

Local surface features such as gradients and Laplacian of Gaussian (LoG) have been utilized to distinguish ground and nonground features (Brovelli et al., 2002; Wack and Wimmer, 2002). Histogram, and surface profiles were used in Jacobsen and Lohmann (2003). Elmqvist (2002) proposed to integrate local gradient properties into an active contour model to construct intermediate base surface models for filtering. The triangular irregular network (TIN) has been taken as a based surface model in many approaches. Axelsson (2000) classified points based on the angle between points and their base triangles. Sohn and Dowman (2002) found optimal ground points which can maximize the connectivity among ground points and separability among nonground points, where those geometric characteristics are obtained from hypothesized triangulations. Kraus and Pfeifer (1998) proposed a lidar filter utilizing kriging interpolation and skewed weighting scheme. Briese and Pfeifer (2001) revised the method to speed up the filtering process and make large nonground objects be removed more efficiently.

Figure 1. Example of commission errors in filtered data. Images show the shaded relief maps of an area of 15 m \times 15 m derived from (a) raw data, (b) ground points in reference data, and (c) ground points in a filtered data. As compared with reference data in (b), filtered data in (c) is shown to have some low-rise nonground features distributed along the diagonal direction.

Figure 2. Example of omission errors in filtered data. Images show the shaded relief maps of an area of 25 m \times 25 m derived from (a) raw data, (b) ground points in reference data, and (c) ground points in a filtered data. The area contains a road in the diagonal direction. Comparing the features in (b) and (c) shows that the step edge immediately below a building and above the road has lost its sharpness in filtered data.

In accordance with the increasing number of filtering methods, some evaluations of filters have been conducted. Sithole and Vosselman (2004) compared the performance of lidar filters using filtered data with their parameters adjusted optimally and stated difficulties that test lidar filters encountered. Zhang and Whitman (2005) evaluated the performance of lidar filters which remove nonground points based on surfaces derived from different spatial operations such as minimum, slope-profile, and morphological openings.

From the previous studies, it has been shown that most lidar filters exploit the characteristics of smoothness and continuity existing in ground features under the assumption that ground features are not connected smoothly to nonground objects. Although utilizing those characteristics made the filters produce satisfactory results, however, it is not unusual to find many missing points from sharp ground features such as step edges and remaining points which were actually from low-rise objects such as shrubs and terraces in resulting filtered data. In other words, it can be stated that due to the discrepancy between the filter assumption in processing and the landscape complexity in the real world, tuning parameters would have limitations in improving the quality of filtered data. Most filtered data, thereafter, tend to have a certain amount of commission and omission errors, which may not be trivial to disregard and require subsequent correction of the filtered data for quality products. Figures 1 and 2 illustrate some examples of commission and omission errors caused by the reasons stated above. While manual correction of the misclassification can be tedious and take times significantly, however, there have been relatively few studies on improving the quality of filtered lidar data in an automated way.

Figure 3. Overall procedure to refine filtered lidar data. The steps in the shaded box show the processes in the proposed refinement method.

Hence, in this paper, we propose an automatic procedure to enhance the quality of filtered lidar data in an efficient and systematized way. The improvement procedure is accomplished through a sequence of processes in which points in a certain type of areas where commission and omission errors occur frequently are reclassified based on neighborhood surface properties. In the following, the methodology is described first in detail. Then, experimental results will be presented and the effectiveness of our approach will be discussed, followed by concluding remarks.

PROPOSED REFINEMENT METHOD

Since in general lidar filters are designed and their parameters are tuned to extract ground points from a relatively large area, most of errors in resulting filtered data are caused by not considering the deviations of local small ground features from global surface properties or the closeness of local nonground objects to the real world terrain. Hence, the strategy of our refinement method is to reduce some errors by making up for the weaknesses of general lidar filters.

For implementation of our proposed method, surface characteristics which can be derived from local areas in resulting filtered data are exploited in the procedure consisting of three steps as illustrated in . In the first step, commission errors which are likely to arise due to low-rise objects are reduced by using surfaces derived from a sequence of morphological operations. Then, in the second step, omission errors are found by comparing the elevation of points with those of neighboring points. Here, it should be noted that in the procedure the reduction of commission errors is performed before the reduction of omission errors. This orderly procedure is designed to decrease the amount of commission errors which may be newly generated while reducing omission errors. In other words, since some remaining commission errors are likely to cause addition of nonground points into ground around them during the process of reducing omission errors, commission error reduction is performed first to prevent that. Finally, reduction of commission error is performed again but with a generous condition. The purpose of this process is to suppress some commission errors which may be newly generated during the second step. In the following, each step is described in detail.

Reducing Commission Errors

The purpose of the first step of the refinement procedure is to suppress small low-rise objects such as cars and some small plants. Figure 4 illustrates an example of low-rise objects and the surface to be obtained after removing those points from low-rise objects. Those bump-like features may be detected well by finding peaks derived from topographic primal sketch (Haralick et al., 1983) or by checking points located inside enclosed contours (Seo, 2003). One simple and efficient way to discard this type of commission error points, however, is to exploit the surfaces derived from morphological opening operations as presented in Zhang et al. (2003). Their approach generates base surfaces through a sequence of morphological operations with growing windows and then removes nonground points which are displaced over a certain amount from the base surfaces that also becomes larger according to the growing window size. From the experiments, the approach was shown to have high performance to preserve well ground features while removing nonground features. Also, its implementation can be performed fast through a sequence of linear window operations for morphological opening processes.

Our refinement method adopted the approach by Zhang et al. (2003) for reducing commission errors caused by low-rise objects. However, the difference of our approach from their one is that the maximum window size is confined to a certain small value so that only objects spanning less than the value should be removed. For each window size, the maximum elevation difference (Δz_{max}) is computed by

Figure 4. Illustration of reducing commission errors. The first step of our proposed refinement procedure is designed to remove nonground points from small objects indicated by shaded circles on the dashed line, producing ground surface drawn in a solid line.

Figure 5. Discarded points from the first step of the proposed refinement procedure. With comparison to reference data, the effectiveness of the first step is visualized, where green circles represent correctly discarded points, reducing commission errors while red x-marks denotes incorrectly discarded points, increasing omission errors. (a) and (b) are results from the filtered data shown in Figures 1c and 2c, respectively. (c) shows a result for another area of 25 m \times 25 m.

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\Delta z_{\text{max}} = \varepsilon + s_{\text{max}} \cdot c \cdot hw \tag{1}
$$

where ε is a constant to allow small ground variation, s_{max} denotes maximum slope, c is the grid cell size and *hw* is half of the window size. Then, ground points deviated above this value from the base surface are reclassified into nonground points. Figure 5 presents the effectiveness of this refinement step by comparing results with reference data, where maximum slope factor in Equation 1 was set to 0.2, an elevation model of cell size 0.5 m was used, and window sizes of morphological operations was set to 3 and 5 pixels. As can be seen, many points from small peaks were discarded successfully. Meanwhile, some valid ground points were discarded and this problem will be reduced through the following processes.

Reducing Omission Errors

After commission errors being suppressed, the second step of the refinement is designed to add missing ground points around sharp ground features, in particular, step edges as presented in Figure 6. Figure 7 illustrates that the main cause of missing ground points on the top and bottom of a step edge would be the enforcement of smoothness into the geometry of filtered ground surface.

With the knowledge about the error distribution, we reduce the omission errors with the following process. A nonground point is selected and its elevation is compared with those of its neighboring ground points within a distance. If any elevation difference with neighboring points is less than a specified value, then the candidate nonground point is reclassified into ground. This can be summarized as:

Figure 6. Distribution of omission errors around edges. Edges shown in black pixels were extracted by the Canny edge operator with sigma 1.0. From the comparison with reference filtered data, omission and commission errors are displayed by red triangles and blue circles, respectively. Ground and nonground points which are correctly classified are shown in cyan and magenta dots. Many omission errors are shown to be distributed around sharp ground features.

Figure 7. Illustration of reducing omission errors around a step edge. Ground surface derived from most lidar filter is usually smooth, missing ground points indicated by shaded circles in the areas where the elevation of ground feature changes sharply. The number of missing points is reduced through the second step of the proposed refinement method, allowing the ground surface to have sharpness close to the solid line.

Figure 8. Results of the second step of the refinement procedure. Many missing points shown in green triangles along edge areas were successfully reclassified into ground, reducing omission errors, while some nonground points indicated by red x-marks were newly generated, causing a certain amount of increase in commission errors.

Figure 9. Results of the third step of the refinement procedure. Many commission error points which were generated during the second step were reclassified correctly into nonground points, shown in green circles with creation of a small number of omission errors indicated by x-marks.

class
$$
(P_i)
$$
 = {ground if $\exists P_j$, class (P_j) = ground, P_j ∈ neighborhood (P_i) , and $P_i - P_j < \Delta z_{\text{max}}$ (2)

Figure 8 shows results of this refinement process with search radius 2 m and Δz_{max} , 0.0 in Equation 2. As can be seen, many missing ground points were successfully identified. However, some nonground points were also added mistakenly into the ground class since their elevations are similar to their neighborhood elevations. The following will discuss how the problem is reduced.

Generous Reducing of Commission Errors

As stated previously, the objective of this step is to reduce the commission errors which may be caused by the second step. For example, in the second step, as indicated by x-marks in Figure 8, some points from low-rise objects which are close to sharp ground features would be mistakenly reclassified into ground by fulfilling the ground condition stated in Equation 2. Hence, in order to remove points from some bump-like features, the last step of the refinement is designed to reduce those commission errors. This step performs the same classification process as in the first step. However, this step takes a relatively large slope factor in order to preserve the sharpness of ground features obtained by the second step. Figure 9 presents some results from this refinement step. As can be seen, through the step, many nonground points were identified successfully, decreasing commission errors significantly with some acceptance of omission errors.

EXPERIMENTAL RESULTS

Test Data Description

A dataset was downloaded from a lidar filter test website published by ISPRS, which is <http://enterprise.lr.tudelft.nl/frs/isprs/filtertest/>(last accessed on November 4, 2005). The data was provided under generous and open conditions with a valuable source of test information for this study. ISPRS datasets used in this study are subsets of the lidar survey performed by FOTONOR AS with an Optech ALTM scanner in 2000. The dataset spans about 133 meters by 195meters in the x and y directions (Figure 10a). The resulting average point density and spacing are 1.04 (points/ $m²$) and 0.97 meters, respectively. As can be seen, it contains roads, vegetation, and residential buildings on steep terrain and many ground step edges aligned to the northeast direction. It is notable that the height of trees on steep terrain is low and may increase the difficulty of filtering. References for all raw points were provided by the ISPRS test site together with careful inspection of aerial photographs over the datasets and is visualized in Figure 10b. The numbers of ground points determined in the reference datasets are 16,501 from the total of 27,470 points.

Figure 10. Shaded relief maps of landscape models. (a) surface model from raw data, (b) terrain model from reference ground points, (c) terrain model from filtered lidar data, and (d) terrain model from refined classification of the filtered lidar data.

From the downloaded data, blunders were first detected and excluded at the initial step of filtering and then points were classified into ground and nonground by a set of developed programs which are based on a linear prediction method which is similar to the approach by Kraus and Pfeifer (1998) but use a constant threshold value to classify points into ground and nonground instead of the skewed weighting scheme. After testing with varying filter parameters, a good quality result of filtered data was selected as input data to evaluate the proposed refinement procedure, which is displayed in Figure 10c.

Refinement Results

For the first step for reducing commission errors, first the point cloud of input filtered data was converted into a grid of cell size 0.5 m, where the Delaunay triangulation-based cubic interpolation was applied for interpolation. Then, in this step, the maximum slope factor, 0.1 and the maximum window size, 5 by 5 pixels were set for removing low-rise nonground points based on progressive morphological operations. Then, for the second step of reducing omission errors, the maximum elevation difference parameter described in Equation 2 was set to 0.0 and the search distance to 2.0 m. Finally, for the third step of reducing commission errors which are likely to be created during the first step, the maximum slope factor was set to 0.2 with all the other parameters set to the same values as the first step.

With comparison to the given reference classification, the filtered data have the total of 3065 erroneous points while the refined data improved the classification with the total of 2315 points. Although the difference in those numbers of the errors may not appear significant, however, the comparison of resulting terrain models presented in Figures 10c and 10d shows that low-rise objects over the entire area were removed and some step edges were sharpened satisfactorily. In detail, some commission errors caused by low-rise objects indicated by C1 in Figure 10c which may be from shrubs beside a road and by C2 which may be from vehicles were removed successfully. Also, nonground low objects indicated by C3 which appear to be from small trees or vegetation plants could be completely removed. In addition, regarding omission errors, the step edges marked by O1 and O2 in Figure 10c were strengthened by capturing missing ground points around the edges, thus enabling their locations to be localized more accurately with proper elevations. As visual comparison of the three terrain models – reference, filtered, and refined ones in Figures 10b, 10c, and 10d present, therefore, enhancement of the filtered data could be accomplished over the given area by those improvements in the local areas.

Although the procedure could reduce the error amounts, however, some errors still remained and in some cases hindered the refinement procedure. For example, a group of points which seem to be from a building indicated by C4 in Figure 10c affected the refinement procedure, increasing commission errors through the processes. Also, points from some ramp edges whose elevations change with a certain width could not be classified correctly into ground in the procedure.

CONCLUDING REMARKS

In this study, we discussed the causes of the remaining errors in filtered data of airborne laser scanning data and proposed a method to reduce the errors. It was stated that filters of lidar data usually exploit the smoothness and continuity of terrain surface and thus their classification errors occur due to the lack of considerations about the sharp features of ground and the tendency of smooth connection of low-rise objects to ground surface. With these ideas, a refinement procedure was developed to reduce the amount of errors by exploiting local surface properties.

For effective refinement, commission errors were first suppressed by using morphological operations and reduction of omission errors was followed by comparing elevations of nonground points against their neighboring ground points. Further, to complete the refinement, commission errors were reduced again with more generous condition in order to preserve the ground features which were newly found in the second step. The experimental results demonstrate that the refinement method improved the quality of the terrain model in terms of the error counts and visualized shapes.

From our experiments, it was found that improvement can be obtained successfully by incorporating local surface properties in the refinement procedure, which will not only cut down the overload of interactive modification but also improve the spatial analyses in cases of immediate use of the products. Here, further developments on refinement of filtered lidar data would be possible in many ways by integrating more concepts and modeling the geometry of ground surface properties and their relationships so that the remaining problems encountered in the experiments can be resolved.

REFERENCES

- Axelsson, P., 2000. DEM generation from laser scanner data using adaptive TIN models, *International Archives of Photogrammetry and Remote Sensing*, vol. 33 (part A4), pp. 110-117.
- Briese, C., and N. Pfeifer, 2001. Airborne laser scanning and derivation of digital terrain models, *Proceedings of the 5th conference on optical 3D measurement techniques*, Vienna, Austria:80-87
- Brovelli, M. A., M. Cannata, and U. M. Longoni, 2002. Managing and processing LIDAR data within GRASS, *Proceedings of the GRASS Users Conference 2002*, Trento, Italy, 29 p.
- Elmqvist, M., 2002. Ground surface estimation from airborne laser scanner data using active shape models, *International Archives of Photogrammetry and Remote Sensing*, vol. 34 (part 3A):114-118.
- Haralick, R.M., L.T. Watson, and T.J. Laffey, 1983. The topographic primal sketch, International Journal of Robotics Research, vol.2(1):50-72.
- Kilian, J., N. Haala, and M. Englich, 1996. Capture and evaluation of airborne laser data, *International Archives of Photogrammetry and Remote Sensing*, vol. 31 (part B3):383-388.
- Kraus, K., and Pfeifer, 1998. Determination of terrain models in wooded areas with airborne laser scanner data, *ISPRS Journal of Photogrammetry & Remote Sensing*, 53:193-203.
- Seo, S, 2003. Model-Based Automatic Building Extraction from LIDAR and Aerial Imagery, Ph.D. dissertation, Dept. of Civil and Environmental Engineering and Geodetic Science, The Ohio State University, Columbus, Ohio.
- Sithole, G., 2001. Filtering of laser altimetry data using a slope adaptive filter, *International Archives of Photogrammetry and Remote Sensing*, vol. 34 (part 3/W4):203-210.
- Sithole, G., and G. Vosselman, 2004. Experimental comparison of filter algorithms for bare-Earth extraction from airborne laser scanning point clouds, *ISPRS Journal of Photogrammetry & Remote Sensing*, 59: 85-101.
- Sohn, G., and I. Dowman, 2002. Terrain surface reconstruction by the use of tetrahedron model with the MDL Criterion, *International Archives of Photogrammetry and Remote Sensing*, vol. 34 (part 3A):336-344.
- Vosselman, G., 2000. Slope based filtering of laser altimetry data, *International Archives of Photogrammetry and Remote Sensing*, vol. 33 (part B3/2):935-942.
- Wack, R., and A. Wimmer, 2002. Digital terrain models from airborne laserscanner data a grid based approach, *International Archives of Photogrammetry and Remote Sensing*, vol. 34 (part 3B):293-296.
- Zhang, K., and D. Whitman, 2005. Comparison of three algorithms for filtering airborne lidar data, *Photogrammetric Engineering & Remote Sensing*, vol. 71(3):313-324.
- Zhang, K., S.-C. Chen, D. Whitman, M.-L. Shyu, J. Yan, and C. Zhang, 2003. A Progressive morphological filter for removing nonground measurements from airborne LIDAR data, *IEEE Trans. on Geoscience and Remote Sensing*, vol. 41(4):872-882.