International Journal of Remote Sensing
Vol. 30, No. 4, 20 February 2009, 1069–1074

Letter

Improvement of the Edge-based Morphological (EM) method for lidar data filtering

QI CHEN*
Department of Geography, University of Hawai`i at Manoa, Honolulu, HI 96822, USA

(*Received 23 January 2008; in final form 22 April 2008*)

Filtering is a crucial step in lidar data processing. The Edge-based Morphological (EM) filtering method proposed by Chen *et al.* (2007, *Photogrammetric Engineering and Remote Sensing*, **73**, pp. 175–185) is fast and can be applied to different land use and land cover types. However, it requires a large number of parameters. It is challenging for average users to tune these parameters without a good understanding of the algorithm. This study introduces a new method to identify buildings so that the total number of parameters to be tuned is reduced from 7 to 2. Even with fewer parameters being tuned, it was found that the average filtering error slightly decreased compared to the original algorithm when tested with the benchmark dataset provided by the International Society for Photogrammetry and Remote Sensing (ISPRS) Commission III/WG3. This is a useful contribution to the original algorithm given that it can achieve increased accuracy in a simpler way for users.

1. Introduction

The past decade has witnessed rapid developments in lidar (Light Detection and Ranging) and its applications for terrain mapping, forest inventory, urban mapping, geomorphology, hydrology, etc. (Chen 2007). The performance of the lidar hardware (e.g. the pulse repetition rate) has significantly increased and nowadays lidar data can be acquired for a much lower cost. However, great challenges remain in designing efficient algorithms for lidar data processing and information extraction to make this technology more widely used (Chen 2007).

Filtering (i.e. extraction of ground points from lidar point cloud) is probably the most important step for lidar data processing. It plays a key role in DTM (Digital Terrain Model) generation and object height information extraction. The commercial and academic practitioners try to keep their filtering algorithms proprietary (Sithole and Vosselman 2004), although some recent studies have started to report their algorithms in more detail (Shan and Sampath 2005, Chen *et al.* 2007, Evans and Hudak 2007, Kobler *et al.* 2007, Zheng *et al.* 2007). Ideally, a good filtering algorithm should satisfy at least three criteria: (1) fast—to process enormous amounts of lidar data; (2) general—to be applied over both urban and vegetated areas; and (3) automatic—requiring little user intervention.

Chen *et al.* (2007) proposed an Edge-based Morphological (EM) filtering method. This algorithm is fast because the computation is based on raster data structure. It

*Email: qichen@hawaii.edu

International Journal of Remote Sensing
ISSN 0143-1161 print/ISSN 1366-5901 online
http://www.tandf.co.uk/journals
DOI: 10.1080/01431160802158310

can also be used over both forested and urban areas. Nevertheless, a total of seven parameters have to be specified by users. Tuning so many parameters is a serious problem given the sheer volume of lidar data. The objective of this Letter is to revisit this method and introduce a more automatic one.

2. Method

The EM method involves first removing the vegetation and objects smaller than $d_{\min}$ using a morphological opening with a circular structural element, and then detecting larger buildings using morphological openings with progressively increasing neighbourhood window sizes (see Chen *et al.* 2007 for details about other aspects such as rasterization and outlier detection). Between any consecutive openings, two opened images are subtracted to produce a height difference image *diff*. This image is then thresholded to create a binary image that consists of individual cut areas, which are either building or terrain bumps ideally. Theoretically, a cut area m_j can be classified into buildings or terrain bumps by applying a threshold to the height difference along its edge. This is based on the fact that buildings have abrupt elevation changes along their edges while terrain elevation changes smoothly.

The above criteria work well if a cut area m_j corresponds to either a building or a terrain bump exclusively. However, in practice the situation is more complicated. For example, a patch of building(s) can be contaminated by their surrounding terrain (as shown in figure 6 in Chen *et al.* 2007), which means that the edge corresponds to a mixture of building and terrain pixels. Chen *et al.* (2007) tried to solve this problem by identifying buildings using a set of heuristic rules, for which five parameters have to be specified by trial and error.

In the new algorithm, a cut area image is first produced by applying a new threshold h_{cut} of 2 m instead of 1 m over the height difference image *diff*. Such a higher threshold can make the cut areas less contaminated by surrounding terrain. Figure 1(*a*) and (*b*) show examples of the edges and their height difference values $\{diff(m_{j,b})\}$ for a building and a terrain bump area, respectively. The edge pixels are found by calculating the difference between an area from its morphologically eroded area. The structural element for erosion is a 'disk' with a radius of 1. By examining the characteristics of $\{diff(m_{j,b})\}$, the building and terrain bump can be distinguished at least by means as follows.

First, since terrain usually changes its elevation gradually, the $diff(m_{j,b})$ of some pixels must be only slightly greater than h_{cut}, depending on the slope at those edge pixels. If we assume that the minimum slope along the edge of a terrain cut area is less than a threshold $s_{\min}$, some edge pixels for a terrain area should have $diff(m_{j,b})$ values less than $h_{cut}+s_{\min}*c$, where c is the cell size. For example, if we let $s_{\min}$ be 15% and cell size c be 1, the minimum $diff(m_{j,b})$ for a terrain area will be less than 2.15. On the contrary, for buildings, the minimum $diff(m_{j,b})$ is usually greater than $h_{cut}+s_{\min}*c$ due to the abrupt elevation change. In figure 1, the minimum $diff(m_{j,b})$ values for the building and terrain areas are 2.84 m and 2.02 m, respectively.

Second, buildings and terrain show different patterns in the distribution of $\{diff(m_{j,b})\}$. For a building area, the edge pixels usually have large $diff(m_{j,b})$ values and possibly with a minority of small values if these are contaminated by the surrounding terrain. Therefore, the distribution of $\{diff(m_{j,b})\}$ is usually skewed to the left so the skewness is less than zero. In contrast, the skewness of $\{diff(m_{j,b})\}$ for a terrain area is greater than zero. The skewness of $\{diff(m_{j,b})\}$ for the building and terrain areas in figure 1 is −0.39 and 2.01, respectively.

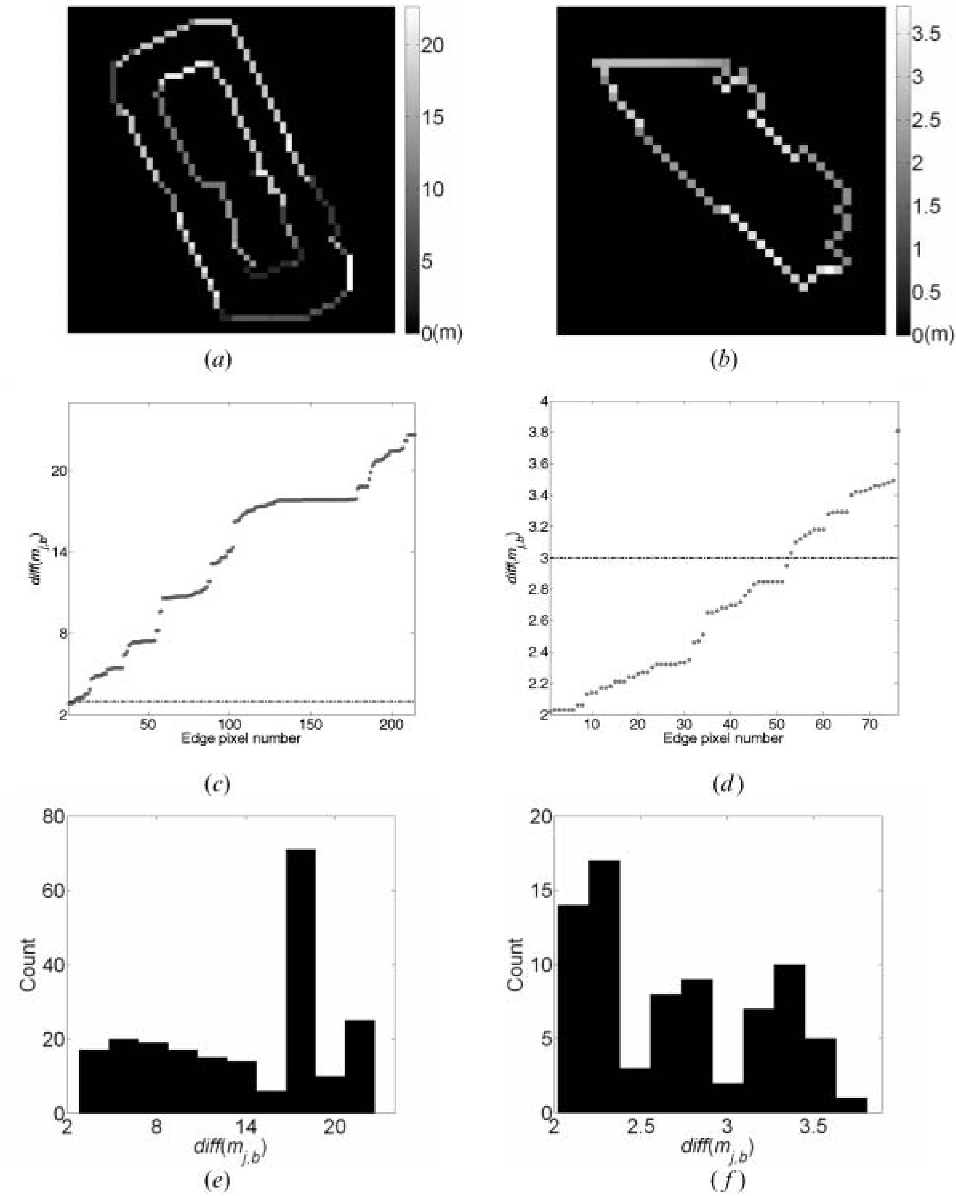

Figure 1. Edge pixels of a building and a terrain bump and their characteristics. (*a*) and (*b*) are the edge pixels and the height difference $\{diff(m_{j,b})\}$ between two consecutive morphological openings for a building and a terrain area, respectively. (*c*) and (*d*) are the $\{diff(m_{j,b})\}$ sorted from low to high for the building and terrain areas, respectively. The horizontal dashed lines indicate the value of $h_{\min,b}$, which is set to be 3 m. (*e*) and (*f*) are the corresponding histograms of $\{diff(m_{j,b})\}$.

Third, if all buildings over an area are higher than $h_{\min,b}$, then we can simply assume that most of the edge pixels for a building have $\{diff(m_{j,b})\}$ greater than $h_{\min,b}$. Based on that, if the percentage of the edge pixels with $diff(m_{j,b})$ greater than $h_{\min,b}$ is more than 50%, an area can be classified as a building; otherwise, it will be classified as a terrain area. If we set $h_{\min,b}$ to be 3 m, 98% and 32% of the edge pixels for the building and terrain in figure 1 have $diff(m_{j,b})$ values greater than $h_{\min,b}$, respectively.

In the current algorithm, if a cut area m_j satisfies any of the above three conditions (condition 1: $\min(\{diff(m_{j,b})\}) > h_{cut} + s_{\min} * c$, called the minimum height condition hereinafter; condition 2: skewness($\{diff(m_{j,b})\}$)<0, called the skewness condition hereinafter; and condition 3: $\#(\{diff(m_{j,b})\} > h_{\min,b})/\#$(all edge pixels)>50%, called the percentage condition hereinafter), it is classified as a building. Based on common knowledge of building height and terrain slope, h_{cut}, $s_{\min}$, and $h_{\min,b}$ are fixed to 2 m, 15%, and 3 m, respectively.

3. Experiments and results

3.1 *Data*

As in Chen *et al.* (2007), the International Society of Photogrammetry and Remote Sensing (ISPRS) Commission III/WG3 dataset was used to evaluate the filtering accuracy of the algorithm. There are four urban sites and three rural sites, covering different land use types such as buildings, vegetation, railroads, bridges. The laser data have point spacing of 1 m to 1.5 m for the urban sites and 2 m to 3.5 m for the rural sites. Fifteen reference samples were used to test the filtering accuracy (Sithole and Vosselman 2004).

3.2 *Results*

Figure 2 shows the building masks and relevant DEMs produced with individual conditions and the combined condition for an urban site. A comparison with the Digital Surface Models (DSMs) indicates that none of the individual conditions can completely remove the buildings in the DEM, which means that all of them can produce commission errors for identifying terrain returns in filtering. Visual inspection indicates that the percentage condition leads to the smallest commission error for this example. However, it might also have the largest omission error. For example, patches A and B in figure 2(*f*) are mainly terrain, which do not appear in the building masks produced with the minimum height or skewness condition. When the three conditions are combined, almost all buildings are identified.

Table 1 lists the total errors of filtering for the 15 reference samples. For each site, only two parameters $d_{\min}$ and $d_{\max}$ are tuned and their values are the same as the ones listed in table 2 of Chen *et al.* (2007). Being consistent with the observations in figure 2, the percentage condition produces the lowest filtering error and the skewness condition has the highest error. When the three conditions are combined, a mean error of 5.55% is obtained, smaller than the mean error of any individual condition. The error is also smaller than the mean error of 7.19% for the original algorithm in Chen *et al.* (2007).

4. Conclusions

In this Letter, an improved version of the Edge-based Morphological (EM) method (Chen *et al.* 2007) is introduced. Three new conditions are proposed to distinguish buildings from terrain bumps so that users need to tune only two instead of seven parameters. The total errors of filtering slightly decreased on average when tested with the ISPRS benchmark dataset. Therefore, this algorithm can achieve increased

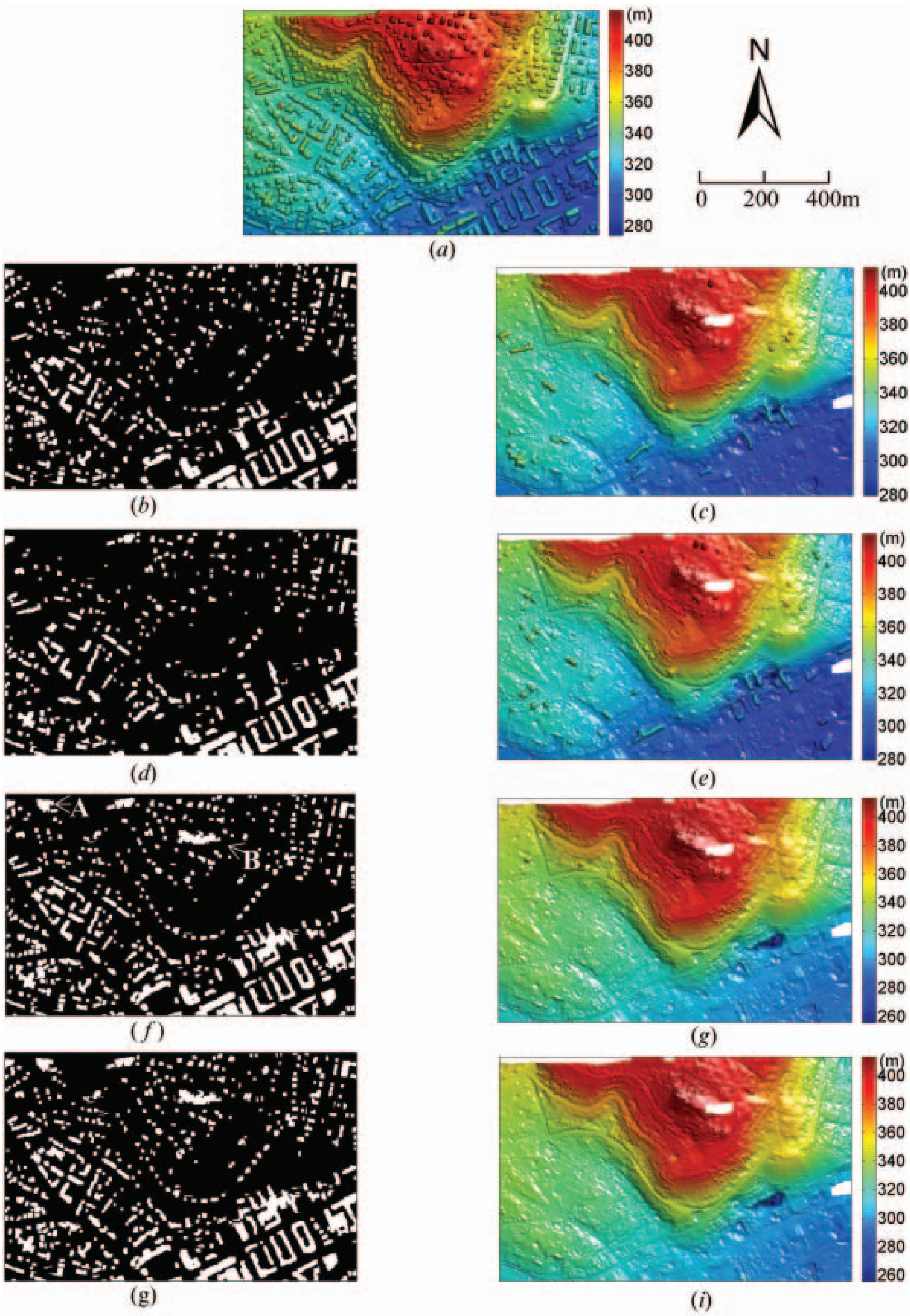

Figure 2. Building detection with different conditions. (*a*) The digital surface models of the urban site of Stuttgart city centre (all buildings and trees smaller than d_{min} have been removed). (*b*), (*d*), (*f*), and (*h*) are the building masks extracted with the minimum height, skewness, percentage conditions, and the three conditions combined, respectively. (*c*), (*e*), (*g*), and (*i*) are the corresponding DEMs, respectively.

Table 1. Comparison of total errors for all samples.

Samples	Chen *et al.* (2007) (%)	Minimum height condition (%)	Skewness condition (%)	Percentage condition (%)	Three conditions combined (%)
1 (Sample 11)	13.92	13.15	14.23	13.01	12.85
2 (Sample 12)	3.61	4.89	5.91	4.90	4.89
3 (Sample 21)	2.28	2.42	2.42	2.42	2.42
4 (Sample 22)	3.61	5.57	7.26	6.72	5.72
5 (Sample 23)	9.05	10.54	22.16	11.05	10.68
6 (Sample 24)	3.61	8.16	10.46	8.24	8.16
7 (Sample 31)	1.27	8.14	13.68	4.43	4.15
8 (Sample 41)	34.03	5.64	8.73	5.90	5.90
9 (Sample 42)	2.20	5.31	5.68	3.52	4.44
10 (Sample 51)	2.24	2.20	2.23	2.20	2.20
11 (Sample 52)	11.52	5.59	5.82	6.07	6.05
12 (Sample 53)	13.09	8.20	8.08	9.67	8.74
13 (Sample 54)	2.91	3.58	3.55	3.58	3.58
14 (Sample 61)	2.01	1.34	1.29	2.36	1.66
15 (Sample 71)	3.04	3.13	2.93	1.84	1.79
Mean	7.19	5.86	7.63	5.73	5.55

accuracy in a simpler way for users, which is useful to alleviate the time-consuming problem of lidar data filtering.

Acknowledgments
This study was supported by the College of Social Sciences Research Support Program at the University of Hawaìi at Manoa.

References

CHEN, Q., 2007, Airborne lidar data processing and information extraction. *Photogrammetric Engineering and Remote Sensing*, **73**, pp. 109–112.

CHEN, Q., GONG, P., BALDOCCHI, D.D. and XIE, G., 2007, Filtering airborne laser scanning data with morphological methods. *Photogrammetric Engineering and Remote Sensing*, **73**, pp. 175–185.

EVANS, J.S. and HADAK, A.T., 2007, A multiscale curvature algorithm for classifying discrete return LiDAR in forested environments. *IEEE Transactions on Geoscience and Remote Sensing*, **45**, pp. 1029–1038.

KOBLER, A., PFEIFER, N., OGRINC, P., TODOROVSKI, L., OŠTIR, K. and DŽEROSKI, S., 2007, Repetitive interpolation: a robust algorithm for DTM generation from aerial laser scanner data in forested terrain. *Remote Sensing of Environment*, **108**, pp. 9–23.

SHAN, J. and SAMPATH, A., 2005, Urban DEM generation from raw lidar data: a labeling algorithm and its performance. *International Journal of Remote Sensing*, **71**, pp. 217–226.

SITHOLE, G. and VOSSELMAN, G., 2004, Experimental comparison of filter algorithms for bare earth extraction from airborne laser scanning point clouds. *ISPRS Journal of Photogrammetry and Remote Sensing*, **59**, pp. 85–101.

ZHENG, S., SHI, W., LIU, J. and ZHU, G., 2007, Facet-based airborne light detection and ranging data filtering method. *Optical Engineering*, **46**, 066202.1-15.