

ADAPTIVE FILTERING OF AERIAL LASER SCANNING DATA

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ABSTRACT

Filtering non-terrain points from raw laser scanning data is the most important goal to improve productivity in DTM generation. Filtering algorithms are built on assumptions about what discriminates terrain points from points on other objects (e.g. buildings and vegetation). In most cases, a single measure is used to accept or reject points. In this paper a three-stage raw data classification algorithm is presented. After a preliminary interpolation to a grid, a region growing based on height differences is applied. Segments from the region growing are classified as terrain, building or vegetation, based on their geometric and topological description. Terrain grid cells are conditionally low-pass filtered, to remove low vegetation. A piece-wise approximation of the terrain surface is computed, built from the grid cells classified as terrain. Finally, raw data are accepted as terrain within a given distance from the surface. Results obtained on a ISPRS filter test data set are shown to illustrate the effectiveness of the procedure.

1. INTRODUCTION

Airborne laser scanning is today the most effective data acquisition technology for the production of high resolution, high quality DTMs (Digital Terrain Models). The only competing technique might be aerial photogrammetry with direct camera orientation by GPS/INS (Inertial Navigation Systems) and DTM generation by digital image correlation; with aerial digital cameras the automation of the workflow should not be far from that of the laser scanner. Nevertheless, the preference for the laser scanner is clear and unlikely to be reversed. Because of its characteristics (first and last pulse, penetration rate in forested areas, narrow field angles, independence on shadows and object texture), laser scanning is indeed better suited and more versatile than photogrammetry for DTM production in urban areas as well as in forested areas. Penetration of pulses under the canopy provides a key advantage over photogrammetry, since it gives the filtering algorithms a chance to succeed in getting rid of spots on vegetation while retaining terrain hits.

Due to the scanning mechanism and aircraft movement, laser spots are scattered on terrain, vegetation, buildings and on whatever target that, hit by a pulse, reflects back enough energy to be detected. The result is a point cloud that must be filtered according to the survey purpose to get rid of unwanted echos: vegetation and buildings in DTM generation, vegetation in 3D city models, both the terrain and the buildings in tree counting and modeling.

To reduce production costs and processing time, filtering is performed automatically; in addition to visual inspection of the results for quality control, manual editing is still necessary, depending on the reliability of the filtering algorithms and on the complexity of the site.

2. PREVIOUS WORK

Many filtering algorithms have been proposed in the last decade; witnessing the difficulty of the task, none performs

equally well on any kind of landscape, because assumptions on terrain characteristics or the threshold values used do not always match reality.

A first group of algorithms looks for the lowest point in a neighborhood and label it as a terrain point. This is achieved mostly by applying morphological filters (Kilian et al., 1996; Vosselman, 2000; Sithole, 2001) where the structuring element is based e.g. on height difference or slope. Wack and Wimmer (2002) use grid data in a hierarchical scheme where non-object points are detected by using a Laplacian of Gaussian.

A second group fits an interpolating surface to the data and accept individual points measuring their distance to the surface. For instance, using linear prediction Kraus and Pfeifer (1998) iteratively get rid of points above the interpolating surface, so that it gets closer and closer to the lowest data points; Axelsson's (2000) algorithm works the other way around, i.e. a minimal set of (lowest) terrain points is progressively densified in a TIN structure by slope thresholding; Brovelli (2002) analyses the residuals from spline interpolation to detect objects contours.

A third group aim first to segment the data based on one or more criteria and then try to classify them: Filin (2002) clusters points in feature space, based on curvature and height difference, classifying low and high vegetation, smooth and planar surfaces; the neighbourhood used in feature evaluation is adaptively adjusted to the slope (Filin and Pfeifer, 2006); Roggero (2002) clusters points based on connectivity and a principal component analysis using geometric descriptors; Nardinocchi et al. (2003) segment data in regions bordered by discontinuities, retrieve their geometric and topological relationships and apply a rule-based scheme to classify the segments.

Recently proposed algorithms stress the need of segmentation and of context information to improve filter robustness: Sithole and Vosselman (2005) aim to separate objects (natural or man-made) from the terrain by extracting regions raised above their surroundings and classify them using geometric and topological relationships. Tóvári and Pfeifer (2005) group points in

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segments based on consistency of normal vectors, distance to the fitting plane and distance from seed point; robust filtering of the surface is then applied, where the same weights are applied to group of points, rather than to single points. In this paper a strategy for the classification and filtering of raw laser scanning data is presented. The main building blocks of the strategy (namely, data segmentation by region growing and region classification) have already been presented respectively in (Nardinocchi and Forlani, 2001) and (Nardinocchi et al, 2003). In (Forlani et al, 2006) the capability of the method in building detection was demonstrated, in the context of building reconstruction from laser data. In the following, Section 3 presents the main features of the strategy; Section 4 reviews the segmentation and the classification, pointing to the changes now introduced to earlier versions and showing the improvements. Section 5 presents the raw data filtering, that was just sketched in the previous papers. Finally, Section 6 reports on the results. Examples and results refer to site 5 of the ISPRS laser scanning test dataset (Sithole and Vosselman, 2003).

3. OUTLINE OF THE METHOD

The classification strategy comprises three-stages (see Figure 1). In the first one, raw data are interpolated to a grid, taking the lowest elevation in the cell as grid value. In the second stage, grid data are segmented by a region growing algorithm with adaptive threshold. The geometric characteristics and the topological relationships among the segments are reconstructed and, based on a set of rules, the segments are classified as outliers, vegetation, building or terrain. Although each cell was assigned to a class, the raw data it contains must still be classified individually. In the third and last stage of the procedure, the whole set of raw data is examined. For the former, consistency is measured with respect to the elevations of the neighbouring terrain cells. For the latter, a piecewise approximation of the terrain with a continuous surface is estimated using data from cells classified as terrain; consistency is measured thresholding the distance from the surface.

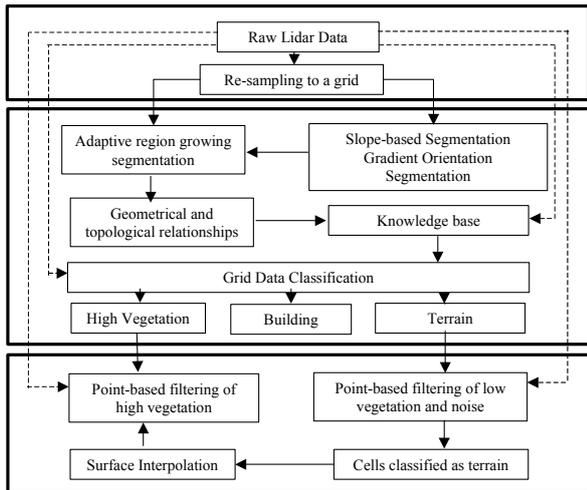


Figure 1. Components and main relationships of the framework for LIDAR data filtering. Solid lines refer to processing of grid data; dashed lines to processing of raw data

Aggregation of raw data in segments enables a richer description of geometric properties and the establishment of topologic relationships. This makes it possible reasoning about

their relationships and provides the contextual information essential to increase the probability of correct classification of single data point in the final stage. This is not to claim that the method is error free, but rather that a segment-based approach (as in feature-based matching) is more robust than just relying on point-to-point comparison in a local neighborhood (as in signal-based matching). Effective filtering cannot be separated by some sort of object recognition and identifying terrain patches or trees should not be seen as different from detecting buildings.

The final stage relies completely on the correctness of the classification of the cells labeled as terrain, since the overall approximation of the terrain is obtained only from cells classified as terrain. Some classification errors can be tolerated: small patches of low vegetation labeled as terrain are filtered out; buildings labeled as terrain, on the contrary, will not. On the other hand, the further a cell is from the nearest terrain region (or the less the terrain cells), the smaller the probability that the approximating surface will truly follow the terrain and so actually will help to correctly discriminate the point class. Data interpolation, segmentation and classification have to find the best compromise between correct labeling of the terrain regions and the attempt to extend them as much as possible, in order to penetrate into the high vegetation areas and to reduce the number of small patches of terrain that, if completely surrounded by vegetation, would be much more difficult to classify reliably.

4. DATA INTERPOLATION, SEGMENTATION AND CLASSIFICATION

In the following paragraphs the three stages of the strategy are reviewed, highlighting the changes introduced with respect to earlier versions and the improvements obtained. Attention is also paid to using First and Last pulse and how positive and negative outliers are dealt with.

The behaviour of the procedure is exemplified on the Site 5 dataset of the ISPRS Laserscanning test which offers a great variety of environments, with step edges in the terrain, slopes with different orientation, high vegetation on a steep hillside and a built up area with vegetation with a relatively low density of raw data.

4.1 Grid Data Interpolation

Grid cells are assigned the elevation of the lowest raw point in the cell (see Figure 2). The larger the grid size, the more likely this prevents the noise (such as cars, low trees and so on) to affect the aggregation process. On the other hand, increasing it

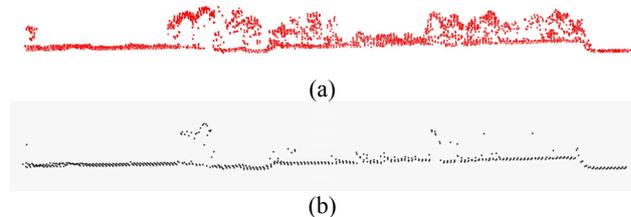


Figure 2. (a) Raw data Points; (b) Grid data Points

too much will affect the extraction of detailed information (slope, aspect, ...) from the grid, which may hamper the effectiveness of further steps. The best grid size should be between one or two times the raw data point spacing.

Empty grid cells are treated as no data, unless all 8-neighbours are non-empty: in this case, the cell value is set to the median of the 8-neighbours.

Figure 3 shows the TIN representation of the raw data (left) and of the grid data (right) in a smooth forest area. It is apparent that, due to the high penetration rate, in such cases the grid representation already constitutes a good, although noisy, approximation of the terrain.

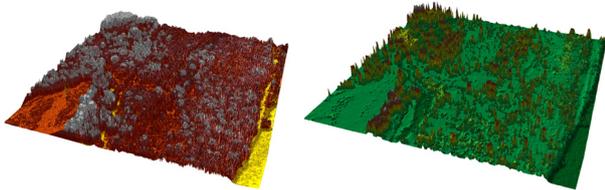


Figure 3. TIN of the raw data e TIN of the grid data on a wooded area.

4.2 Grid Data Segmentation

The region growing is the first step in data segmentation. From a seed pixel, every of the 8-connected neighbours with a height difference from the central pixel less than a threshold is enclosed in the region and becomes in turn a seed point for that region. The process goes on, until no points are added (i.e. the region border will feature a discontinuity larger than the threshold).

Although the result may depend on the cell size and the threshold, the region growing separates most of the high vegetation and of the buildings from the terrain: buildings raise above the terrain by well defined discontinuities (edges), larger than the threshold; laser spots on high vegetation get spread over many very small regions.

Unless some terrain patches are completely bordered by dense vegetation or, in case of bare earth, by a slope so steep that the threshold is exceeded, the whole terrain may end up all in a single region. This is because, from the seed point, the algorithm looks for a smooth path across all the 8-neighbours: therefore, even if in some area the terrain is steeper than the threshold would allow, the region growing may include it by “sneaking through” along a smoother path.

In the original implementation neither the choice of the seed points nor the threshold for the region growing were tied to the morphological features of the grid data. The threshold was set to 0.5 m (i.e. about two times the height error of the data), independently of cell size and terrain slope. The drawback was that, in steep roofs or in steep terrain, several narrow regions may be created, affecting the success rate of building and terrain identification. Figure 4 illustrates the problem that arose with a fixed threshold on a very steep roof.

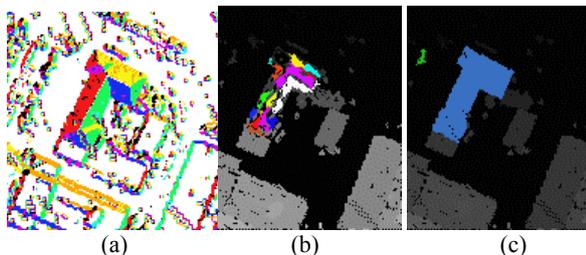


Figure 4. Steep roof segmentation. (a) Gradient orientation image; (b) region growing with fixed threshold: the roof is fragmented in several regions; (c) region growing with slope adaptive threshold: the house is included in one single region bordered by discontinuities.

For a given roof slope, the larger the cell size or the lower the point density, the likelier was a fragmented segmentation.

The same may happen with very steep terrain although, as already pointed out, in such cases the aggregation may come from a smoother adjacent terrain area.

Indeed, the region growing threshold should be coupled to the grid cell size and should also take into account evidence of surface continuity in the neighborhood. Several changes have been made to the original implementation of the method to address this problem. The region growing algorithm is now steered by both the gradient orientation of the grid heights and the slope. The seed pixels of the region growing algorithm are chosen from regions larger than 30 m² with homogeneous gradient orientation while the threshold value is adaptively adjusted to the slope of the region. Moreover, the process starts from the regions with the lowest threshold value.

In large regions with homogeneous gradient orientation the computation of the threshold will not be affected by vegetation.

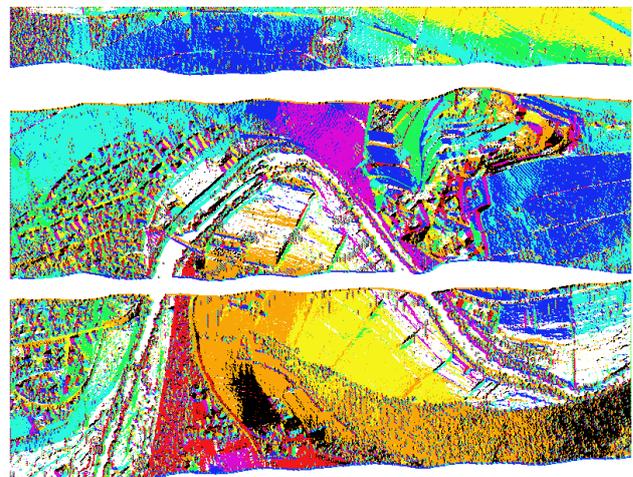


Figure 5. Gradient Orientation of the heights at Site 5. The orientation space is divided in 8 partitions.

The threshold value T for the segmentation based on height differences is computed, in each region obtained from the gradient orientation segmentation, as:

$$T = \min(T_{\max}, \max(T_{\min}, s \Delta + 2\sqrt{s^2 \sigma_{PL}^2 + \sigma_H^2}))$$

where: $T_{\max} = 2\Delta$; $T_{\min} = 0.5 \text{ m}$ $s =$ the 75th percentile of the slope distribution; $\Delta =$ cell size in m; σ_{PL} and σ_H are respectively the planimetric and height accuracy of laser data in m. With this modification the primary segmentation of the grid data becomes in fact a (bounded) slope based segmentation.

Figure 5 shows the gradient orientation (cell size = 2m). Large areas with the same colour correspond to regions having the same aspect (orientation intervals are 45° large). Data holes and flat areas are represented in white. Figure 6 shows the color coded threshold values T for the same dataset.

The seed points for the region growing based on height difference are taken from segments of the gradient orientation segmentation larger than 50 m², from the lower threshold values on. The 0.5 m fixed threshold value is applied to the remaining regions: in this way, areas with vegetation, that exhibit different gradient orientation, or very small patches with the same orientation, get separated in small regions.

Figure 7 shows the most significant segments with different colors. The red spots are very small regions (less than 3 pixels) that will be labeled as outliers or vegetation if several small regions are contiguous. Notice that segments from the region growing may encompass several regions with different gradient orientation or with different slopes.

4.3 Data Classification

Geometric characteristics of the regions and their topological relationships are computed and stored in a knowledge base. A rule-based scheme is applied to classify the regions: the outcome of the process labels each region as vegetation, building, terrain, outlier or unclassified (the last item typically being 1÷3% of the area size). Actually, each class may have sub-classes (e.g. courtyard as part of terrain); among unclassified regions, narrow regions are defined as those slender in shape. Points on high rise chimneys, towers, power line poles, etc may be classified as outliers or buildings, depending on shape, point density and cell size. Currently, no rules discriminate bridges, that are therefore included in the terrain.

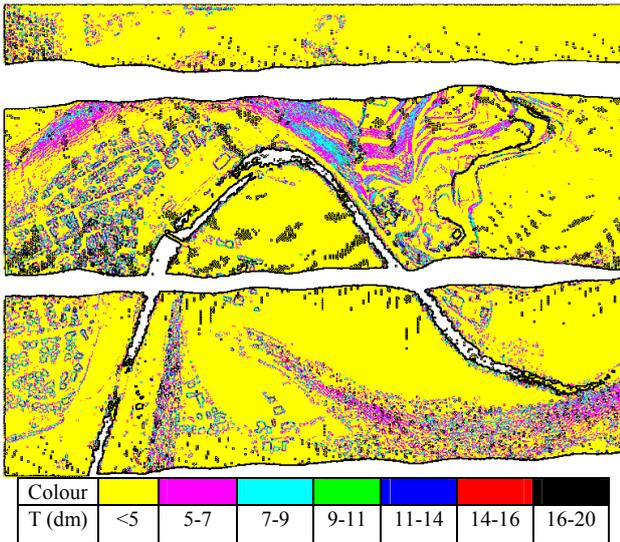


Figure 6. Color plot of the threshold values for the region growing



Figure 7. The most significant regions of the grid data segmentation by the adaptive threshold

The current set of rules has been drawn from simple models of characteristics and relationships between terrain, building and vegetation. The complexity of the task means that robustness of the rule set cannot be taken for granted and that more rules might have to be invoked in new scenarios. Most misclassification errors occur with trees labeled as buildings, buildings as terrain and terrain as buildings. The worst misclassification error is a building included in the terrain, because it will not be corrected in the next stage; on the

contrary, terrain pixels erroneously labeled as building might be recovered in the last stage. Figure 8 shows the result of grid data classification.

4.4 Using First and Last Pulse

Almost every laser scanner today provides first and last (F&L) pulse returns; the pattern of their difference is of great help in identifying vegetation. This is very important to improve both data classification as well raw data filtering: the percentage of grid points in a region where F&L pulse elevations differ is used to help the identification of terrain; raw data filtering (in terrain as well as non-terrain areas) can be robustified by this information (see Section 5).

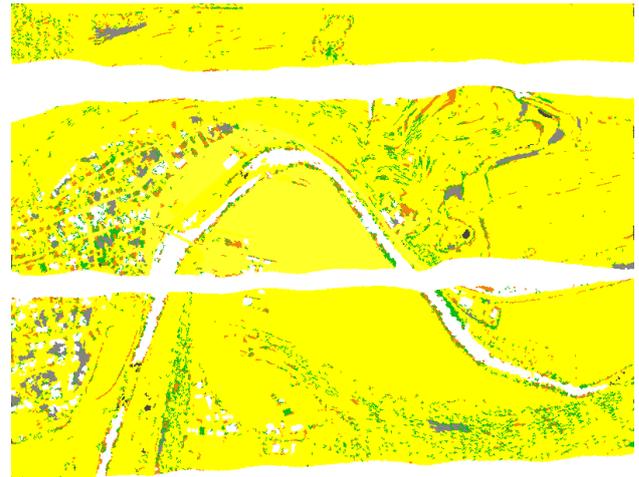


Figure 8. Grid Data Classification. Yellow: terrain; white: building; orange: narrow regions; grey: unclassified.

In the previous implementation of the strategy, cells with different height in the F&L pulses were classified as vegetation before applying the region growing and were not passed to the region growing. This led to more fragmentation of the terrain; now a terrain region penetrates much further into areas with high vegetation, because the (lowest) last pulse of the cell may have an acceptable height difference to nearby terrain cells (whether the pulse indeed hit the terrain or rather the vegetation, is to be clarified, of course).

Grid data under high vegetation are more noisy than those on bare Earth; together with F&L information, this can be used in the final filtering of raw data.

4.5 Outliers

Outliers in laser data are either “negative” (i.e. points below the surface, mostly due to multi-path) or “positive” (i.e. points above the surface, such as hits on birds, power cables, etc). The segmentation makes the classification insensitive to single cells with positive or negative outliers in two ways: if the outlier is the only point in the cell, it will be put in a 1-pixel region and classified as outlier. If there are several points in the cell, some outliers some not, the positive outliers will be recognized in the final filtering stage, because they are higher than the neighbourhood, whatever the class the cell was assigned. With negative outliers, the pixel has been labeled as outlier from the grid classification; other points of the cell may be assigned to terrain or vegetation, depending on the distance from the approximating surface.

Even in case several contiguous cells contain outliers, it is very unlikely that they end grouped in a region, because this would

happen only if they have similar gradient orientation or very small height differences.

5. EXTRACTING TERRAIN POINTS FROM RAW DATA

The output of the grid classification can be divided in two classes: terrain and non-terrain pixels (i.e. pixels classified as building, vegetation, outliers and pixels in unclassified regions). Each raw data in a grid cell is now examined to label it as terrain or as non-terrain point, comparing its distance from a reference surface with a threshold t depending on terrain slope and sensor error tolerance in horizontal and elevation.

The reference surface is computed from the local neighborhood for the former class, from a global approximation of the terrain for the latter. The reason for differentiating between the two classes is to allow more flexibility and fine-tuning for the terrain cells.

Some of or all the raw data points of a cell classified as terrain may in fact be low vegetation or noise. To check against this possibility, a reference value h_{ref} is computed from the neighborhood using a conditional averaging filter. Let m_n be the mean of the neighbouring terrain cells, h_c the elevation of the current cell and $t = 0.5$ m a threshold value for low vegetation:

$$\begin{aligned} \text{if } (h_c > m_n + t) & \quad h_{ref} = m_n \\ \text{else} & \quad h_{ref} = h_c \end{aligned}$$

Cells unclassified or classified as non-terrain may nevertheless contain raw data points that are in fact terrain points. Comparing the elevation of the raw data with the predicted elevation from a surface approximating the terrain, a decision will be made on the point class. To this aim, the most reliable information available (i.e. the raw data labeled as terrain points) is used to compute the approximating surface. The acceptance threshold is computed for each cell as a function of the slope of the surface.

Currently, the approximating surface is computed using bilinear splines with relatively short spacing (3÷4 times larger than the cell size); this may change in the future, to cope in a better way with discontinuities (see below).

Points in cells classified as building do not need filtering; a consistency check of the classification is performed, though: no point in such regions should fall in the acceptance band. If terrain points were erroneously identified as building, they might now be recognized as terrain, if close enough to the interpolating surface.

6. RESULTS ON ISPRS SITE 5

Figure 9 shows the behaviour of the raw data filtering in the forested hillside of Sample51 (ISPRS Site5). The cross-section (a) shows the reference data: terrain (pink) and vegetation (light blue). In (b) the red points are input to the spline, while the predicted value of the terrain in all cells classified as vegetation or in unclassified regions is shown in green. The approximation of the terrain is good and the ensuing raw data classification is correct. On the other hand, if the terrain shows step edges, as in the quarry in Sample53, the interpolation function typically undershoots at the bottom and overshoots at the top (see figure 10 (a)). This smoothing of sharp edges leads to rejection of true terrain points.

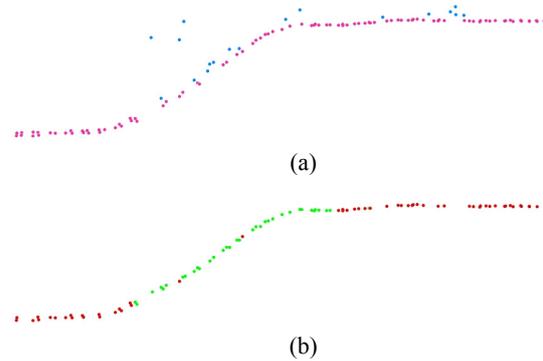


Figure 9. Cross-section of a forested area on a hill side; (a) Reference data: terrain: pink; vegetation or buildings: light blue. (b) Terrain surface approximation: spline input: red; spline prediction: green.

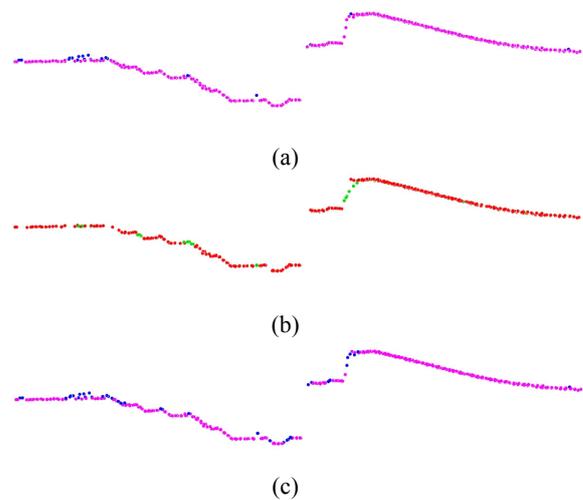


Figure 10. Cross-section of terrain with step edges; (a) Reference data: terrain: pink; vegetation: light blue. (b) Terrain surface approximation: input: red; spline prediction: green. (c) Filtering: accepted terrain points (pink), rejected points (light blue).

Figure 11 shows a cross-section in an area with buildings and vegetation (Sample54) with the same color coding as Figure 10.

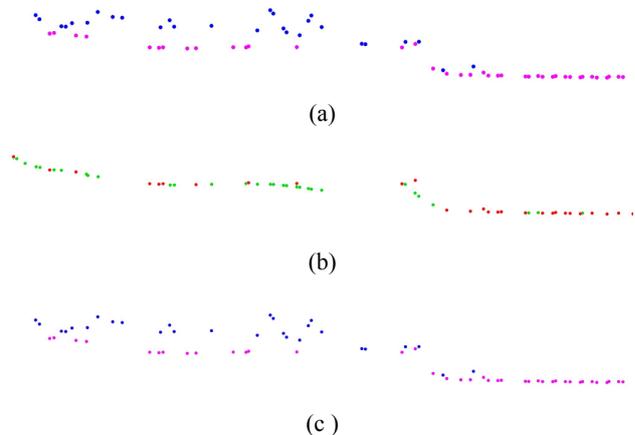


Figure 11. Cross section of an area with buildings and vegetation. (a) Reference data: terrain: pink; vegetation or buildings: light blue. (b) Terrain surface approximation: spline input: red; spline prediction: green; (c) Filtering: accepted terrain points (pink), rejected points (light blue).

Table 1 shows the overall results for the Samples available at Site 5; performance and correctness of the cell classification are measured respectively by the percentage of true terrain points with respect to the total number of terrain points in the Sample and by the percentage of misclassified points with respect to the number of cells labelled as terrain. Filtering errors are given according to the Laserscanning Test definitions.

TP: Terrain Points; TG: Grid cells class. Terrain	Terrain grid classification		Raw data filtering errors	
	#TrueTP in TG wrt #True TP in Sample (%)	#FalseTP in TG wrt #TG cells (%)	Type I	Type II
Sample 51	85.1	6.4	8.3	8.6
Sample 52	80.8	2.2	8.5	9.6
Sample 53	77.8	1.0	10.7	14.3
Sample 54	85.5	7.5	4.4	12.0

Table 1. Correctness of grid classification and terrain filtering for Site 5 Samples

Correctness of the terrain grid classification is normally high, taking into account that if a cell contains more than one TrueTP, the others were counted as errors. Classification errors on the grid are higher with high vegetation and buildings (Sample 51 and Sample 54) but filtering improved the results by more than 10% in both cases. With rough terrain, both types of filtering performed less effectively, especially the spline interpolation.

As far as raw data classification is concerned, Type I errors are good and better than most Test participants, Type II are among the largest.

7. CONCLUSIONS AND PERSPECTIVES

A strategy for classification and filtering of raw LIDAR data has been presented. The core of the procedure, i.e. the classification of data segments based on their geometric and topological relationships looks sound enough. On the ISPRS Laser Test Site 5, grid data classification led to the reliable identification of a percentage of true terrain points varying around 80%. Based on that information, a good approximation of the terrain surface can be computed. Terrain raw data close enough to the surface are also recognized as terrain, improving the percentage of success by up to 10%.

Problems arise with step edges in the terrain, because of over- and undershoot of the spline functions: alternative interpolation techniques will be tested soon (in this respect, our last stage needs a pre-filtered input as REIN (Kobler et al., 2007).

New approaches to rule definition in the grid classification are also being tried: an attempt is currently underway to automate the search for patterns in the data, using classification trees (Sutton, 2005) such as the AdaBoost algorithm.

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