FILTERING OF AIRBORNE LASER SCANNER DATA BASED ON SEGMENTED POINT CLOUDS

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ABSTRACT:
The extraction of points on the bare Earth from point clouds acquired by airborne laser scanning is the most time consuming and expensive part in the production of digital elevation models with laser scanning. Current algorithms for filtering point clouds assume the Earth's surface to be continuous in all directions. This assumption leads to smoothed terrain representations in case of height discontinuities as they are often found in urban environments. This paper presents a new approach to filtering point clouds in which the point cloud is segmented into smooth segments that may still contain height discontinuities. The resulting segments are subsequently classified bare earth or object surfaces based on the geometric relationships with the surrounding segments. The paper demonstrates the advantages of segment-based classification with an analysis of data sets used in the ISPRS filter test.

1. INTRODUCTION

Over the past years airborne laser scanning has become the preferred method for the acquisition of digital elevation models. The most important step in the derivation of elevation models from the point clouds acquired by laser scanners is the classification of the points into those that are part of the bare Earth surface and those that are not. Several filtering algorithms have been developed for this purpose.

Conceptually, an airborne laser scanning point cloud can be considered to be a representation of a piecewise continuous surface (the bare Earth), whose continuity is broken by objects. Essentially, all filter algorithms differ in how they measure discontinuities between surfaces from the bare Earth and surfaces from objects (like buildings). Some measures of discontinuity that are used include height difference, slope, and shortest distance to a parameterised surface.

Currently most algorithms work by searching for the lowest points in a neighbourhood and treating these as bare Earth (morphological filters, e.g., Kilian et. al. 1996, Vosselman 2000, Roggero 2001), by robustly fitting surfaces and searching for points closest to the fitted surfaces and treating these as bare Earth (e.g., Pfeifer et. al. 1998, Axelsson 2000, Elmqvist 2002), by clustering points and treating small clusters as objects (e.g., Brovelli et. al. 2004).

Some major problems identified in current filters are that they erode the bare Earth in steep sloped landscapes and at discontinuities in the bare Earth, and that they retain low vegetation and parts of large objects (Sithole and Vosselman 2004).

The erosion at discontinuities in the terrain and the problems with large objects are both due to the fact that the algorithms typically work by analysing the structure of a point cloud in a local neighbourhood. Therefore, it can not be seen whether two surfaces patches that show a discontinuity within a local neighbourhood can be connected through a smooth path outside that neighbourhood and should therefore be considered as parts of the same surface. Due to this limited context information, the higher surface path within the neighbourhood may be incorrectly classified as object surface or will at least be eroded.

In this paper we present a new approach for filtering airborne laser scanner data. A global overview is given in section 2. Instead of classifying points in a local neighbourhood, we first segment the point cloud into patches in which all points can be connected through a smooth path of adjacent points (section 3). Subsequently, these segments are classified based on their geometric relationships with the surrounding segments (section 4). In contrast to other segment based filter approaches (Lohmann, 2002, Voegtle and Steinle, 2003), the segmentation is performed on the point cloud and not in a raster image. By allowing overlapping segments, the terrain can be extracted as a continuous surface even in the presence of vegetation. In section 5 we demonstrate and analyse the potential of this technique by applying it to the data set used in the ISPRS filter test (Sithole and Vosselman, 2004) and comparing the results against those obtained by several test participants.

2. FILTERING STRATEGY

The design of the algorithm was guided by the following objectives:

- The algorithm should work on raw laser data, i.e., irregularly spaced points,
- The algorithm should apply to as many landscape types as possible.

Before a filter algorithm can be devised, a conceptual model of landscapes needs to be defined. Filtering can then be defined against this model. The simple model chosen is shown in figure 1.

The characteristics of the model are:

- The surface of each object is encompassed in one or more continuous surface segments (O1, O2, O3 and B1),
- All points in a surface segment that can be described by locally continuous shape functions belong to the same surface,
- Object segments (O1, O2, and O3) are separated from the bare Earth segment(s) (B1) by discontinuities,
- The perimeter of each object is mostly raised above its neighbourhood.

In line with the objectives of the algorithm, the model has been made as general as possible so that it accommodates most types of landscape. Emphasis is placed on establishing the topological and geometric relations between bare Earth and object surfaces. Filtering is now defined as the identification of surface segments whose perimeter is raised above their neighbourhood.

Meaningful surfaces can be reconstructed for large objects but not for small objects (too few points). Therefore, in the algorithm large and small objects are detected separately. Large objects are treated by segmentation of the point cloud, while small objects by smoothing of the point cloud in a later stage. The algorithm can be described as a procedural stripping away of objects from the bare Earth in the following sequence, large objects, bridges, and small objects. In each step of the sequence smaller and smaller objects are removed. The explicit detection of bridges is necessary to ensure the reliability of the detected bare Earth. However, bridge detection is beyond the scope of this paper and shall not be further elaborated here. Details on the removal of bridges can be found in (Sithole and Vosselman 2003).

3. SEGMENTATION OF POINT CLOUDS

The segmentation of a point cloud into smooth surfaces is the first important step of the developed filter algorithm. Two points are considered to be part of the same surface if there is a smooth path of adjacent points between them. This definition allows for discontinuities within a surface as long as there is a path around a discontinuity that connects points on both sides. According to this definition, ramps, bridges, and flyovers are considered part of the bare Earth although they also contain points with significant height difference to nearby bare Earth points.

3.1 Range data segmentation algorithms

Several segmentation algorithms have been presented in the computer vision literature. The two major classes of algorithms are scan line segmentation and surface growing (Vosselman et al., 2004).

Jiang and Bunke (1994) describe a scan line segmentation algorithm for range images. In their approach the range data is available in a raster image. The algorithm first segments the range data for each scan line (i.e. image row) separately. The range data is segmented such that the height of the pixels within one segment can be described by a linear function. Once all rows are segmented, the segments are grouped across the scan lines based on proximity criteria.
Surface growing algorithms first select seed surfaces by testing if the height of points within some distance of a point can be approximated by a smooth surface. These seed surfaces are then extended with other points adjacent to the surface that have a short perpendicular distance to the surface. While adding points to the surface, the surface parameters may be updated.

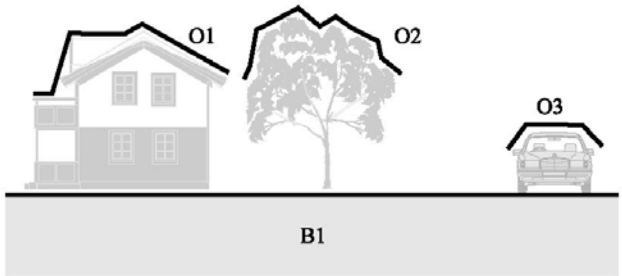


Figure 1 Conceptual model of landscapes

The growing of a surface continues until no further adjacent points are found at a short perpendicular distance to the surface. The seed surfaces are processed one after another until all points have been assigned to a surface. Surfaces with a low number of points are usually eliminated.

Hoover et al. (1996) describe a comparative study on the performance of selected algorithms. In their experiments the scan line algorithm shows the best results. A modified scan line algorithm is also adopted for segmentation of the laser scanner point clouds.

3.2 Scan line segmentation

Typical scan line segmentation algorithms only segment one set of parallel scan lines. In contrast, we define and segment scan lines with multiple orientations. For this purpose, a point cloud (exemplified by the cube in figure 2(a)) is sliced into contiguous profiles, where each slice yields a profile (i.e. our artificial scan lines). This slicing is done in several directions, figure 2(b). Once profiles have been obtained, they are segmented to get line segments that represent continuous planar curves on surfaces in the landscape.

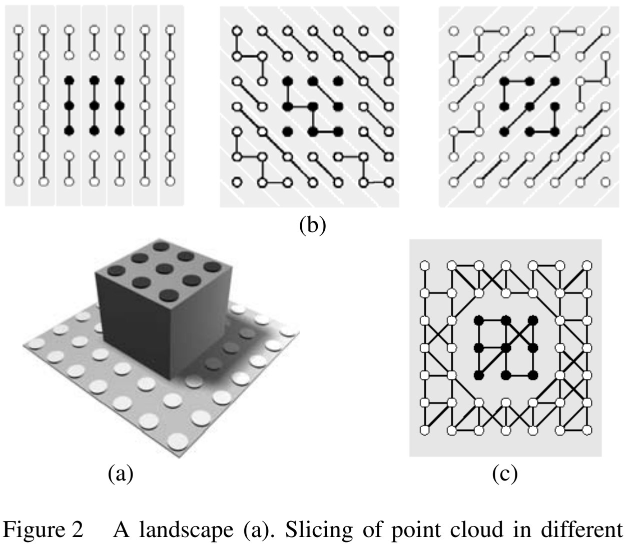


Figure 2 A landscape (a). Slicing of point cloud in different directions to get profiles, and segmenting the profiles to get line segments (b). Overlaying of profiles to get a disconnected graph (c).

The segmentation of a profile is done as follows:

- A weighted minimum spanning tree is generated for a profile, figure 3(a),

– In the minimum spanning tree all edges with a weight greater than a defined threshold are removed, figure 3(b).

The weight, w, of edges in the weighted minimum spanning tree are computed using the proximity function below:

$$w = (x_j - x_i)^2 + k(z_j - z_i)^2 \quad (1.1)$$

Where (x_i, z_i) and (x_j, z_j) are the profile coordinates of the end points i and j of an edge. The user-defined parameter $k(>1)$ scales the proximity function so that points along the x-axis are more proximal than points along the z-axis.

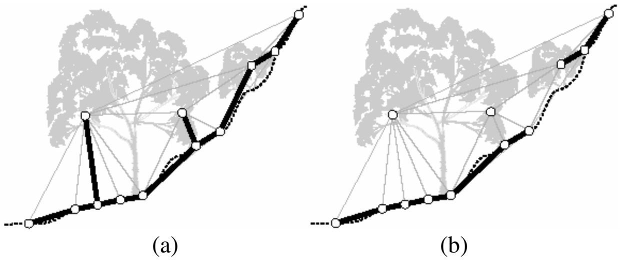


Figure 3 Weighted minimum spanning tree of a profile (a). Removal of edges with a large weight (b).

3.3 Segmentation by profile intersection

Segmentation of the point cloud is achieved by overlaying all segmented profiles. Because the line segments within profiles pass through points, the overlay yields a disconnected graph, G, figure 2(c). A surface segment is therefore a connected subgraph within G. The usage of the profiles in several directions hence provides us with an elegant way to combine the profile segmentation results to a surface segmentation. In contrast to traditional scan line segmentation algorithms (Jiang and Bunke, 1994), no decision parameters for segment proximity are needed to combine the results of adjacent profiles. Two adjacent parallel profile segments are connected only if there exists a profile segment with another orientation that contains points of both these parallel segments.

4. CLASSIFICATION OF SEGMENTS

In a profile, for any line segment, at least six topological relationships (here called shapes) can be identified between it and adjacent line segments. These are *raised*, *lowered*, *terraced*, *high*, *low* and *no shape*, figure 4. In any landscape object surface segments are mainly associated with *raised* and *high* line segments. *Lowered* and *low* line segments are mainly associated with the bare Earth surfaces. *Terraced* line segments are associated with both the bare Earth and object surface segments. Therefore, in the classification surface segments that contain a majority of *raised* and *high* line segments are classified as object.

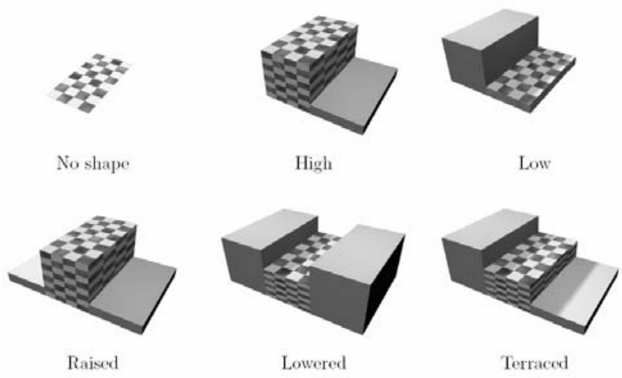


Figure 4. Topological arrangements of surfaces in a profile.

4.1 Removal of non-terrain segments

The classification begins by segmenting the point cloud with a value of k approx. equal to 4 . The generated surface segments are classified as either object or bare Earth based on the distribution of line shapes in them.

Next, all points classified as object are removed from the point cloud. The point cloud is again segmented but with a larger value of k. The surface segments generated are classified as before. This segmentation-classification step is repeated several times and the value of k is increased by a factor of 4 with each repetition, (see figure 5). The user-defined threshold is also increased by about the same factor applied to k.

The increase in the value of k serves two purposes. Firstly it simulates a search for ever-smaller objects. Secondly, as objects are removed from the point cloud, they leave behind holes. In the profile segmentation a larger value of k allows these holes to be bridged.

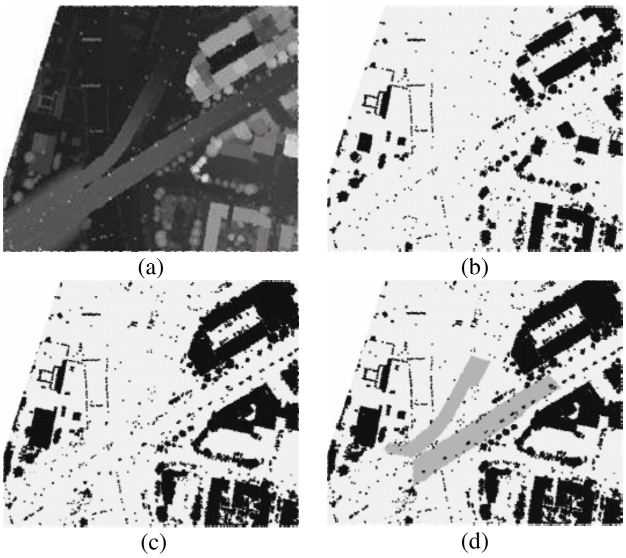


Figure 5 Classification of large objects and bridges. (a) A sample point cloud from the city of Nijmegen. The point spacing of the data is approximately 1m. The data was captured using an OPTECH ALTM system, and provided by TerraImaging. (b) Objects detected in the first classification. (c) Objects detected after the second repetition. (d) After all large objects have been detected, the bridge detection algorithm is applied.

4.2 Removal of small objects

The final product of the previous two sections is a bare Earth point cloud free of large objects and bridges. What remains in this point cloud are small objects like bushes, cars, park benches, etc.,. Removing small objects is achieved by fitting planes at every point. If a point is above the plane fitted to its nearest neighbouring (3D) points, and if the standard deviation of the residuals from fit is above a user-defined threshold, then the point is deemed to belong to a small object.

This procedure is effectively a smoothing of a point cloud. When applied to a point cloud the procedure removes the top most vegetation points. Therefore, it has to be repeatedly applied until the number of points removed in a repetition is below a user-defined threshold, e.g., 10 points.

5. EXPERIMENTS

For assessing the performance of the new filtering method, usage has been made of the reference data established in the ISPRS filter test (Sithole and Vosselman, 2004).

5.1 ISPRS filter test

In the ISPRS filter test, fifteen samples were extracted from the laser scanner data acquired by Blom Norkart Mapping AS (formerly FOTONOR AS) for the OEEPE project on laser scanning (Petzold and Axelsson 2001). The data represents sections of Vaihingen and the city of Stuttgart. The Vaihingen samples have a point spacing of 2-3.5 m. The Stuttgart samples have a point spacing of 1-1.5 m. The samples contain features that were deemed to be difficult to filter. These include steep slopes, large buildings, low vegetation, bridges, and discontinuities in the bare Earth.

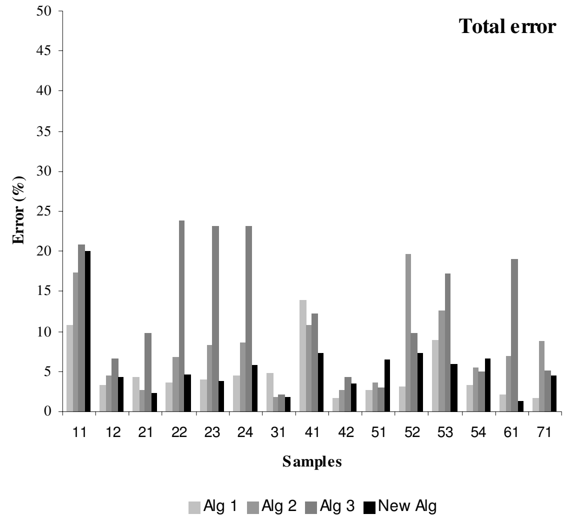
The data has been processed by eight test participants. Their results were compared against manually classified points (Sithole and Vosselman 2004).

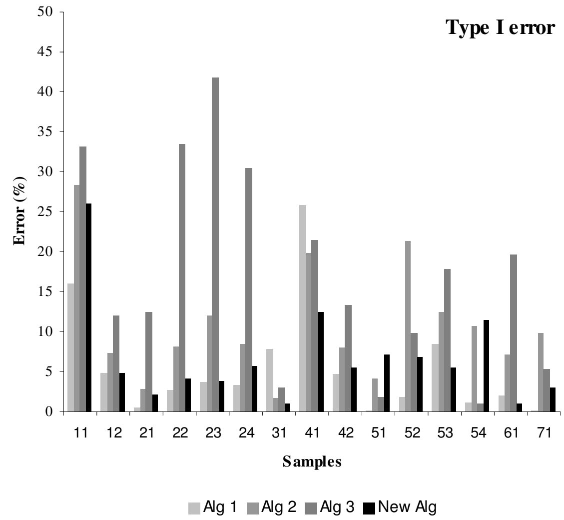
5.2 Performance analysis

The performance of the segment-based filter algorithm is measured by comparing the classifications against the same reference data as used in the ISPRS filter test. Furthermore, the performance is compared with the performances of several algorithms that were studied in that test, among them the two algorithms with the best results.

Figure 6 presents the total errors. The total error presents the number of misclassified points in a sample as a percentage of all points in the sample. Overall, the new algorithm does equally well or better than most of the algorithms tested.

Type I errors represent the number of misclassified bare Earth points in a sample as a percentage of all bare Earth points in the sample. The type I errors for the developed algorithm are relatively small (except for sample 11) and do not exhibit large variations between the sample sites. Considering that the parameters used in all the tests were nearly the same (slightly different parameters were used for the urban and rural samples), this is encouraging because it indicates that the algorithm is more robust to different landscape types, thus adding to its reliability. The large error in sample 11 is because of the heavily vegetated slopes and as can be seen all algorithms struggle with this feature. A solution to this problem is still being investigated.





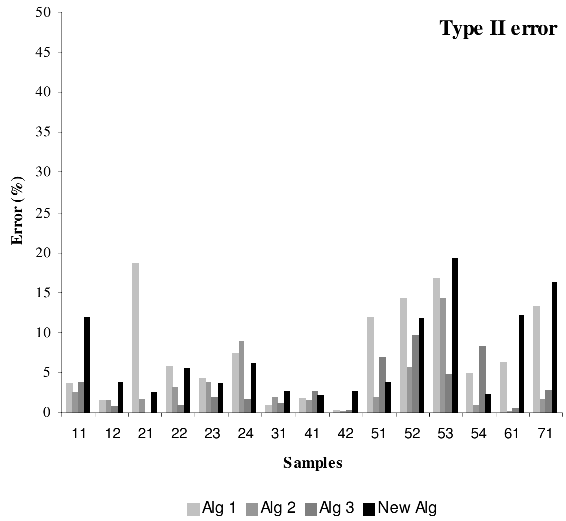


Figure 6 Comparison of the new algorithm against three tested algorithms. Percentages of total errors (top), Type I errors (middle) and Type II errors (bottom).

Type II errors represent the number of misclassified object points in a sample as a percentage of all object points in the sample. The type II errors obtained were relatively small, except for a few sites where the prevalence of low vegetation and large point spacing led to higher errors. Typically, there are more bare Earth points then there are object points hence the impact of type II errors on the total error is small.

One of the primary objectives of the research was to develop a filter algorithm that performs equally well in all landscapes. Based on the good results of the application on the algorithm on the different landscapes in the ISPRS test, the developed algorithm is deemed to succeed. A marked improvement against other algorithms was noticed in complex urban scenes (samples 12, 21, 22, 23, 24, 31, 41, 42).

This improvement is achieved because, (i) segmentation allows better discrimination of large objects, (ii) the algorithm targets specific features (e.g., large objects, bridges, etc.,) in a landscape, (iii) it is better at preserving discontinuities in the bare Earth, and (iv) the different approach to detecting small and large objects allows both type I and II errors to be reduced. The developed filter algorithm was compared against three algorithms from the test, referred to here as 1, 2 and 3. These algorithms represent three very different filtering concepts.

5.3 Detecting large and small objects

Part of the success of algorithms 1 and 2 is that they are iterative. In an iterative approach, an algorithm starts by seeking large objects and then in every repetition ever-smaller objects are sought. In every repetition algorithms 1 and 2 use the same approach but at a different scale. The developed algorithm is also iterative. However, it differs from the other algorithms in that it first distinguishes between large and small objects, based on the premise that they are geometrically and topologically different, and hence different approaches are required in their detection. The large object detection and small object detection algorithm are themselves iterative.

5.4 Discontinuities

The ability to preserve discontinuities more than any other factor contributes to the algorithm's ability to reduce type I errors. This is demonstrated by the examples in figure 7 and 8. Figure 7 (sample 22) shows an urban scene containing gangways large buildings and discontinuities in the bare Earth. Algorithm 3 has the greatest difficulty in preserving discontinuities in the bare Earth. Algorithms 1 and 2 do better and this is because they are based on finding surfaces in the point cloud. The results of the developed algorithm are only bettered by algorithm 1. Figure 8 (sample 53) shows a quarry.

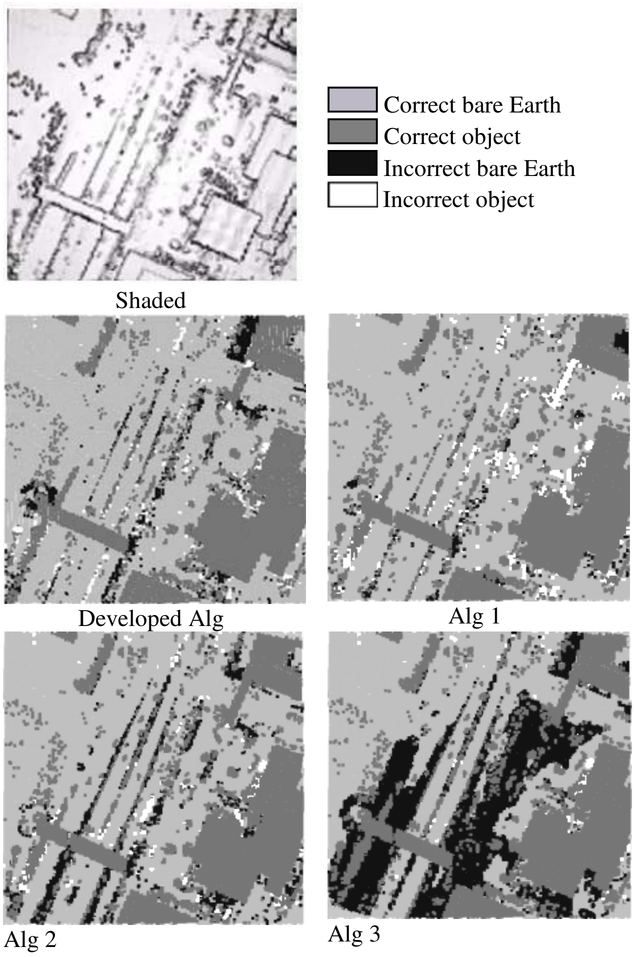


Figure 7 Discontinuity preservation in an urban landscape.

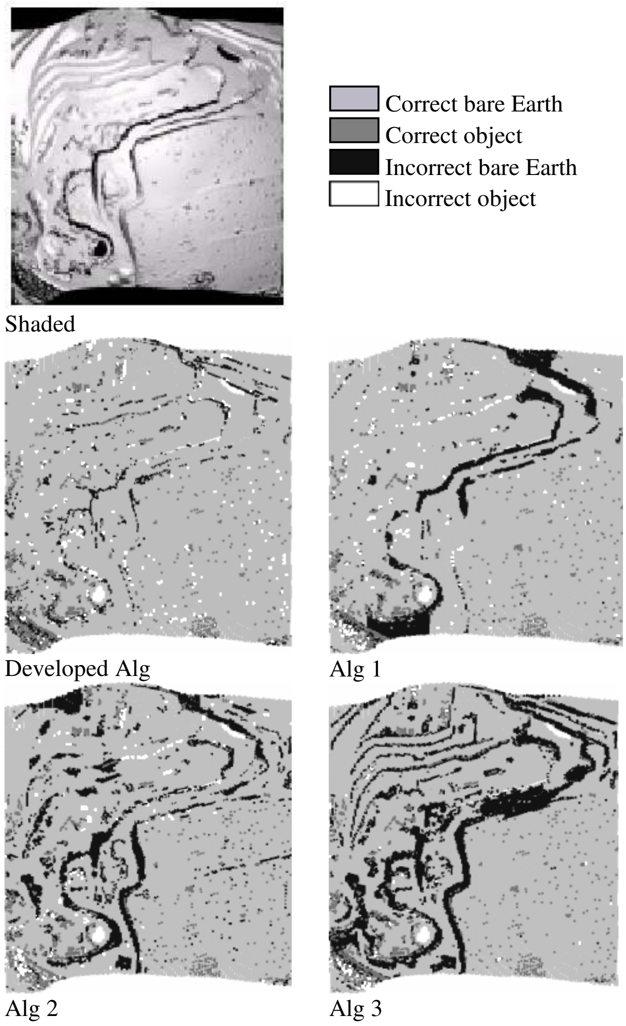


Figure 8 Discontinuity preservation in a quarry.

The developed algorithm considerably outperforms all the other algorithms. Some points on the faces of quarry edges are detected, as objects but the cost of this error in a DTM generation should be negligible. The type II errors are relatively large because of the prevalence of low vegetation.

5.5 Outliers

Laser scanner data sometimes contain isolated points that posses large systematic error. In the developed algorithm very small segments (typically 5 points or fewer) are classified as object. Therefore outlying points are detected very easily because they always yield segments with one or two points.

6. CONCLUSIONS

In this paper a new approach to filtering airborne laser scanner data was presented. Instead of a point-wise classification based on the distribution of the points within a local area, classification is performed on segments of the original point cloud. The segment-based classification allows the use of more context information and is therefore able to preserve discontinuities in the bare Earth surface. It also faces no difficulties in removing very large buildings.

Compared with other algorithms the new filter shows a reliable performance, in particular in urban areas. Ramps, fly-overs, and bridges are initially classified as part of the bare Earth, because they smoothly connect to this surface. Depending on the application the user may opt to explicitly recognise these features and remove them from the set of bare Earth points.

Currently, we only used the topological relationships between neighbouring segments for the classification. Like shown in (Voegtle and Steinle, 2003), this can be extended to other attributes like roughness or colour information.

The detection of vegetation in sloped terrain still remains a problem. Here it is difficult to find the correct trade-off between removing low vegetation and preserving small height jumps in the terrain. Operator knowledge on the smoothness of the terrain is required to find the optimal parameter settings.

The new algorithm exhibits a relatively low number of type I errors. This is considered an advantageous property, since type I errors are difficult to detect in a manual quality control procedure. If objects remain in the bare Earth dataset (type II errors), this is often easily recognised during visual inspection. Hence, minimisation of type I errors is considered more important.

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