Refining a Best of Class Pixel based Ground Filter by Virtual Surveyor based GeOBIA

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Abstract **- An existing LiDAR-based ground filter is a pixel-based approach, which classifies each pixel into one of two classes: ground or non-ground, based on the attribute information of the current pixel and its spatial neighborhood. The filters produce good results in smooth rural landscapes but perform below par in complex urban areas and rough terrains. This underperformance can be attributed to the fact that filters don't account for the context of structures in relation to their neighborhood objects (versus pixels). The current pixel-based filter must make a trade-off between making Type I errors (reject bare-earth pixels) and Type II errors (accept object pixels). In our overall approach, called Virtual Surveyor based GeOBIA, we take a state-of-the-art pixel-based filter algorithm with a parameter set that ensures the minimization of type II error. This would guarantee removal of most of the non-ground pixels, even those that correspond to objects that are small and have a relatively low height. The non-ground pixels are then fed into an object extraction algorithm. The objects are further hierarchically decomposed to their sub-objects. This results, in addition to height values, in a plethora of new information such as aggregated height values, texture, morphology, context as well as topology, which are further leveraged in the classification process. Those ground points which were mistakenly classified as object points by the pixel based classifier are extracted and relabeled, thereby reducing the type I error. To demonstrate the efficacy of the proposed method, we provide some qualitative results on a challenging dataset.**

I. Introduction

Ground filtering is a necessary step for the generation of Digital Terrain Model (DTM). Airborne LiDAR-based ground filtering is arguably superior to traditional methods for DTM extraction due to its high resolution in both horizontal and vertical directions. With the availability of higher resolution, LiDAR data gives us an unprecedented opportunity to map difficult regions such as one with a little textural variation or the one with high vegetation. Existing ground filter methods can be classified into five major classes: surface-based [1], morphology-based [2], TIN-based [3], Segmentation-based [4, 5] and Statistical analysis based [6]. Sithole and Vosselman [7] perform a comparative analysis of eight classic DTM generation method in 15 test sites. This study acts as a guideline for selecting suitable ground filter based on the terrain type of the test sites. Their study demonstrated that the algorithms proposed by Axelsson [3] and Pfeifer [1] performed better than the other methods. Based on the comparison result, no filter algorithm has proven effective for challenging terrains such as sites with rough terrain or discontinuous slope, dense forest canopies attached to rooftop edges and area with low vegetation. A more recent study of existing ground filtering algorithms is carried out by Meng et. al [8]. This research examined the performance of each class of ground filter mentioned above for a wide variety of terrain types. According to the result of accuracy assessment, Meng draws a similar conclusion as Sithole et. al [7] and suggested future directions for research aimed at developing threshold-free algorithms applicable to a wide variety of terrain types.

The inaccuracy in the filter results is defined by two statistical measure: Type I error and Type II error. A Type I error is the incorrect rejection of bare earth points whereas, a type II error is the failure to reject object points. This underperformance can be attributed to the fact that the filters don't account for the context of structures in relation to their neighborhood objects. The most filter is designed to minimize Type II errors. The filter parameter is set such that it guarantees the removal of most object points, even those objects that have a small size and a relatively low height. The disadvantage of this approach is that many ground points could be removed and thereby increase the Type I error.

Most filtering methods have one thing in common, they are all pixel-based approach. They classify each LiDAR point as belonging to an object or ground based on its attribute and its neighborhood. Consequently, the classifier in the filter algorithm has limited information to work with and is deprived of the contextual information.

Moreover, the results may contain some misclassified isolated pixels or group of pixels, which collectively known as salt and pepper noise.

Geographic Object-based image analysis (GeOBIA) framework has gained traction recently in remote sensing and geographic information science [9]. Inspired by the success of GEOBIA over pixel-based approach, we propose a solution to the aforementioned problem face by pixel-based ground filter by augmenting it with an object-based refining module. The object-based refining algorithm is based on virtual surveyor based object extraction algorithm [11]. In our approach, we start with DTM generation by one of the well-known ground filters, wherein we focus on minimizing the Type II error. The result is then fed into our object-based algorithm that further scrutinizes the extracted object points. The object-based algorithm first employs a seed growing segmentation algorithm to partition the object from its topographic background. The object is then further analyzed to reveal the image segments representing its sub-objects. This segmentation process results, in addition to spectral values, in a plethora of new information such as aggregated spectral pixel values, morphology, texture, context as well as topology. These features are then exploited in the subsequent classification process. This allows the capture of ground points that have been wrongly attributed as object point by the filter method. Thus, minimizes the Type I error.

The contributions of our work are fourfold. (1) The combination of the pixel-based ground filter with the object-based refining module renders the overall method threshold-free and is, therefore, applicable to a wide variety of terrain types. (2) The object extraction sub-algorithm of the refining module provides the classifier with the much-needed contextual information and therefore, improves the overall accuracy. (3) Partitioning of the object from its surrounding eliminates the salt and pepper noise. (4) Most filters assume that the ground surfaces are usually the lowest feature in a local neighborhood. In some cases, this assumption is wrong. For example, swimming pool, mines, an irrigation channel, construction pit etc. Our proposed approach is probably the first ground filter algorithm that is capable of filtering out man-made cavities on the ground.

II. Methodology

A. A Best of Class pixel-based ground filter

In our work, we selected the well-known surface based filter proposed by Tóvári and Pfeifer [1] as our pixel-based filter. This approach combines planar segmentation and ground filtration using a robust interpolation technique.

In the first step, a plane-fitting algorithm is used to generate planes. The planar segmentation is based on a region growing algorithm, where the seeds are placed first randomly and then in unexplored spaces to divide the target area into planar segments. Once a seed is selected, the nearest neighbor points are examined to determine whether they meet certain criteria. Neighbor points that satisfy the criteria are added to the growing region.

The next step is a robust interpolation. First, planar segments with a size larger than the largest man-made structure possible are extracted and identified as ground. These ground seeds act as ground elevation references to initiate the filtering process. Here, a surface is interpolated initially, using surface moving least squares (MLS), from all points. For each planar segment, a weight is assigned based on the average difference in the distance of the interpolated surface to the constituents observed value. These weights are considered in the next iteration and therefore, segments with a large weight have a larger influence on the run of the surface. This process is iterated until there is no object point left, i.e. their weight become zero. The procedure from [1] was modified to enable detection and filtration of man-made cavities.

B. Virtual Surveyor based refining module

Virtual surveyor based object extraction is composed of two steps (1) Seed growing segmentation, where the object is partitioned from its topographic background. (2) Hierarchical decomposition, where the constituent sub-objects are extracted and their topological relationship with the parent object is identified [10].

The segmentation capability of the Virtual Surveyor is based on the following assumptions:

(1) An object can be defined as one which introduces a distinct geometric concavity or convexity on its topographic background. This means that an object can be approximated into either of (or a mixture of) two fundamental 3D geometric structures: convex-like structure and concave-like structure. For example, buildings, drumlins, hills, trees etc. fall into the convex-like structure category, whereas, watershed, swimming pool, gully, crater can be categorized as concave-like structures.

(2) A single enclosed sloping surface will always connect the object, no matter how complex, to its topographic background. We call this sloping surface as ‘foothill slope’. An example of a foothill slope is shown in figure **1**. Mapping the foothill slope of an object will provide our desired result i.e. partition from its background.

Normal to all points in the foothill_slope of a convex object point outward whereas for the concave object, points inward. Any path which lies within the boundary of foothill_slope and encircles the object has the following characteristics:

The normal to any point of the path points inward (outward) in the case of concave (or convex) structure. We call this condition as 'foothill_slope_criteria' and the paths that obey this condition as 'path_loops'.

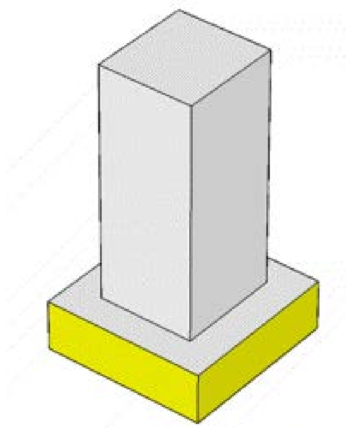


Figure 1. The sloping surface colored yellow is the foothill_slope of the building

The output from the pixel-based ground filter is fed into the refining module. The connected object planar segments are detected using connected component analysis. Each blob which represents a potential object candidates is considered individually. A number of seed planar segments are selected based on their high surface slope value and low elevation value. This is because, a seed growing segmentation algorithm that maps the slope surface of an object, which starts from a seed positioned in the vicinity of the object footprint is guaranteed to capture the foothill_slope of the object.

The foothill_slope mapping process is based on assumption 2; normal to each point of the foothill_slope surface is either pointed inward or outward. As discussed in [11], if a virtual surveyor, placed on the object, follows a locally estimated vector, called surveyor guidance vector, and forms a loop in the process then this would guarantee that the surveyor motion is restricted within the limit of the foothill_slope boundary and encircles the object. The surveyor guidance vector ($\vec{r}$) at a point is estimated using the cross-product of the vertical vector ($\hat{z}$) and the normal ($\hat{n}$) at that point. An example is shown in figure **2**.

$$\vec{r} = \hat{z} \times \hat{n} = |\hat{z}||\hat{n}|sin\theta\hat{r} = sin\theta\hat{r} \qquad \text{(i)}$$

The seed growing segmentation method accepts, into its growing region, the planar segments that lie in the direction of its constituent's surveyor guidance vector. This guarantees the mapping of the entire foothill_slope of the object.

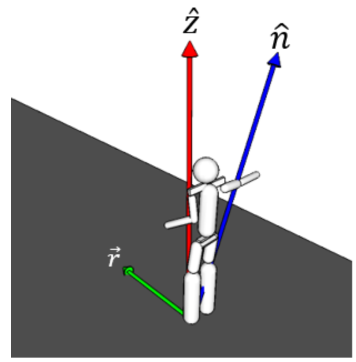


Figure 2 Surveyor standing on a slope

While mapping the foothill_slope of the object, the foothill_slope of the sub-objects (if any) are also included in the growing region. The next obvious step is to hierarchically decompose the composite object into its constituent sub-objects.

The underlying principle of the hierarchical decomposition is again based on the foothill_slope criteria, as mentioned in assumption 2. The following conclusion can be drawn:

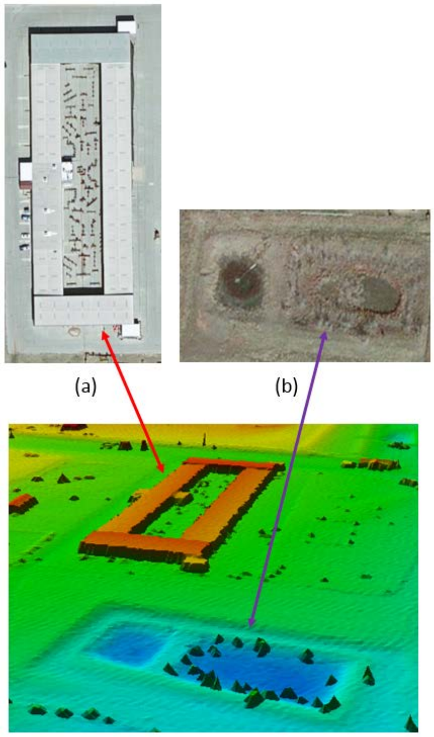
Each object in a topographic map can be represented by a set of parallel path_loops. These set of loops are easy to construct from the image segment extracted by the first step in the virtual surveyor based segmentation approach. A graph of connection is constructed, where each connection satisfies the foothill_slope_criteria. This graph is called 'complete_flow_graph'. The graph is then simplified by merging the parallel loops. This results in a circular loop for the parent object and for each of its sub-objects. The circular loop of each sub-object is connected to the circular loop of the parent object, which demonstrates the hierarchical relationship between the object and its sub-objects. Then, as described in [10], pixels of each (sub) object is associated with its corresponding circular loop. This extracts all the sub-objects present within the parent object.

The hierarchical decomposition produces the object, its constituent sub-objects, and their hierarchical relationship. Based on this contextual information and by extracting features such as shape, size etc., the object can be classified as a man-made object or the ground. The development of a rule-based classifier is a work in progress.

III Result

In this section, we discuss some of the qualitative results obtained so far.

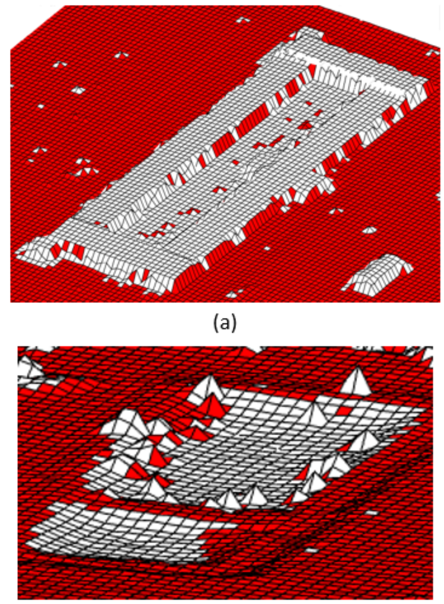
Here, two man-made structures are considered in this paper as shown in Figure 3.



(a) (b) (c)

Figure 3 Top-view RGB image of (a) complex building (b) pools and (c) elevation image

Figure 3 (a) is a complex building structure, whereas figure 3 (b) is a pair of adjacent pools. The latter is a convex structure, whereas the former is a concave structure. Figure 4 shows the corresponding results obtained by applying the Pfeifer's ground filter. The region colored red is labeled as ground. As evident from the figure, the object image is contaminated with salt and pepper noise, which is a common trait for the pixel-based ground filter. The courtyard of the building is labeled as non-ground. This is due to the fact that the ground filter has been modified to detect man-made cavities on the ground in addition to man-made convex structure. For some user, this might be undesirable as the courtyard is usually regarded as ground. In figure 4(b), it is evident that the bank of the pool, which is part of the man-made structure, has not been labeled as an object class. This interpolation based filter underperforms at the vicinity of a low-grade slope's edge.



(a) (b)

Figure 4 Pfeifer's ground filter results

Figure 5 shows the corresponding results obtained by applying the Virtual Surveyor based object extraction algorithm. As can be seen from the figure, sub-objects that lie on the foothill_slope of the parent objects are also included in the resultant segment.

Figure 6 shows the hierarchical decomposition of the extracted image object of the complex building. There is multi-level decomposition obtained at a single scale. In the first level, the image object is first decomposed into three neighboring objects: the main building and the two small rectangular block adjacent to the corner at the opposite side of the main building. The building is then further decomposed into its major components. The courtyard is clearly identified and segmented out. Here, the blue represents a convex object, whereas, the red represents concave objects.

Figure 7 shows the hierarchical decomposition of the extracted image object of the adjacent pair of pools. Here, too, multi-level decomposition is conducted without traversing through multiple scales. In the first level, the pools are separately identified and segmented out. One of the pools is further decomposed into its sub-objects. The individual trees are also revealed in the result as shown in the figure.

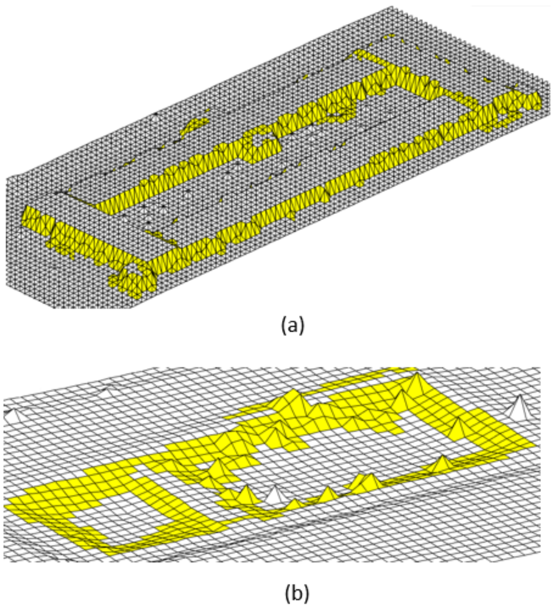


Figure 5 Virtual surveyor object extraction results

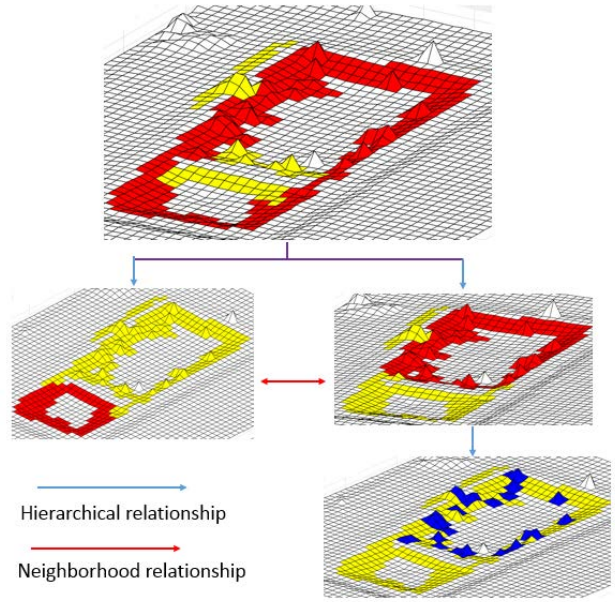


Figure 7 Hierarchical decomposition of the pair of pools

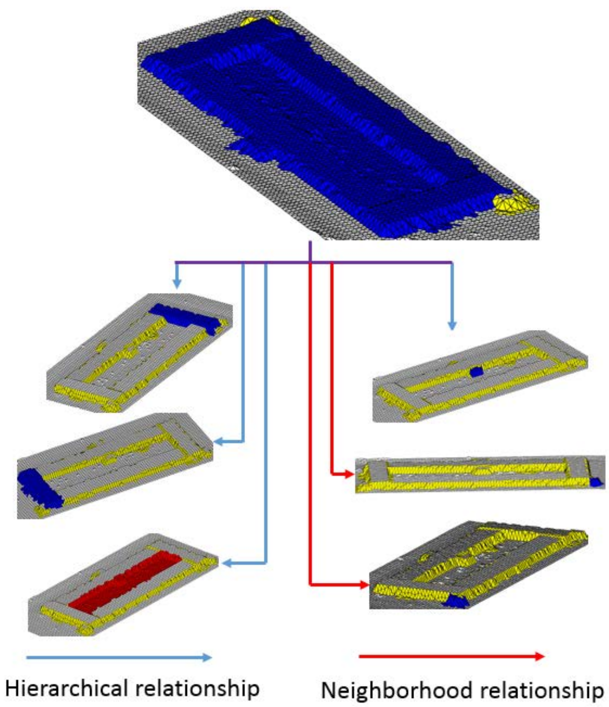


Figure 6 Hierarchical decomposition of the complex building. Blue segments represent convex structure whereas red segments represent concave structure

IV. Discussion

In this paper, we introduce a novel ground filter, which combines the pixel-based ground filter with an object-based refining module. This integration improves the robustness and accuracy of the ground filter by (1) providing detail contextual information to the classifier, (2) improving the quality of segmentation, (3) eliminating the salt-pepper noise. This approach is also capable of detecting the man-made cavities on the ground.

The work is still in the development stage but the preliminary results look very promising. The future development plan will be to construct a rule-based classifier to classify the extracted object as ground or object. The complete ground filter algorithm will be tested on a wide variety of terrain. Quantitative analysis will be performed to prove the efficacy of the algorithm.

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