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Terrain classification of LADAR data over Haitian urban environments using a lower envelope follower and adaptive gradient operator

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ABSTRACT

In response to the 2010 Haiti earthquake, the ALIRT ladar system was tasked with collecting surveys to support disaster relief efforts. Standard methodologies to classify the ladar data as ground, vegetation, or man-made features failed to produce an accurate representation of the underlying terrain surface. The majority of these methods rely primarily on gradient-based operations that often perform well for areas with low topographic relief, but often fail in areas of high topographic relief or dense urban environments. An alternative approach based on a adaptive lower envelope follower (ALEF) with an adaptive gradient operation for accommodating local slope and roughness was investigated for recovering the ground surface from the ladar data. This technique was successful for classifying terrain in the urban and rural areas of Haiti over which the ALIRT data had been acquired.

INTRODUCTION

Accurate three-dimensional mapping is critical for a wide variety of applications ranging from geodesy, geomorphology, and forestry to urban planning and natural hazards monitoring. Capable of acquiring elevations with centimeter-level accuracy, airborne ladar (laser radar) has had a revolutionary impact on three-dimensional imaging of the earth's surface. Data acquired by laser altimeters provide accurate measurements of the ground surface, man-made structures, and the vegetation canopy heights that can potentially be used to create separate models of bare earth, buildings, and vegetation [2, 4, 6]. Buildings can be extracted in urban areas via clustering and segmentation, and roofs and walls can then be modeled from the elevation data [2, 6]. Other man-made features such as power lines, towers, and bridges are also observable in the ladar data [1, 8]. More commonly, laser altimeters have been employed to detect vegetation [2, 6] and map the ground surface below the vegetation canopy, as the small footprint pulse penetrates openings in the vegetation canopy and reflects off lower surfaces. A map of the resulting ground surface, also called a digital terrain model (DTM), can then be used to perform hydrologic and geomorphological analyses for studying water flow, erosion, and flooding.

Classification of ladar data points as ground, vegetation, or man-made features is generally a two-step process. First, the ground and non-ground points are separated, and then the non-ground points are classified by discriminating vegetation
from man-made features. Several methods have been proposed to classify ground and non-ground points. A simple one-dimensional (1-D) approach involves processing the data points across each scan line. More sophisticated approaches use two-dimensional (2-D) surfaces and the spatial coordinates of the data. Most 2-D methods iteratively refine a 2-D surface and classify ladar data points at each iteration which is computationally intensive. Similarly, vegetation and man-made features have been extracted using a variety of 1-D and 2-D methods. Most of these techniques are based on the assumption that building roofs consist of planar surfaces, while vegetation canopies exhibit irregular patterns [2].

Axelsson [1] creates a 1-D ground surface along each scan line by constraining the amount of fluctuation in the surface using Minimum Description Length (MDL) models, constrained spline functions, snakes, or geometrical thresholds. Buildings are modeled as a series of straight-line segments with zero second derivatives separated by breakpoints with non-zero second derivatives. Vegetation is modeled assuming that the second derivatives are represented as a Gaussian distributed random variable.

Many terrain classification methods create a preliminary terrain model from the ladar data points and classify additional points in close proximity to the ground surface as terrain points. The methods developed by Hyypa, et al. [4], TopScan GmbH [7], and Haugerud and Harding [3] are examples of creating a terrain model by iteratively improving an initial terrain surface. Similarly, Kraus and Pfeifer [5] classify ladar data points based on their relation to an average surface. The average surface is updated using a weighted sum of the points based on a model of the data distribution around the average surface. Another method [8] classifies ladar points by extending an inverted bowl shaped surface around each point and tests whether the surface intersects the ground surface.

ALIRT SYSTEM AND DATA

ALIRT is an imaging laser radar system utilizing a pulsed microchip laser and a focal plane array of avalanche photodiodes operated in Geiger mode. The laser, focal plane, and system were all developed and fabricated at MIT Lincoln Laboratory. The sensor is integrated onto a Sabreliner-40 jet and typically collects imagery from 10 - 15 kft above ground level. The pointing/scanning system consists of an Applanix POS AV-610 tightly-coupled GPS/IMU system, and a large, fast, precise, and accurate scanning mirror built by National Sensor Systems in Acton, MA (now the Optical Sensor Systems group of BAE). Using the geometric information from the calibrated optical system and the range information from the focal plane array of precision timers, a 3D point is calculated for each photon detected. After many interrogations of the ground area a cloud of these 3D points is produced; this cloud is the input data to further processing algorithms and digital surface models (DSM).

The ALIRT system was tasked by the United States Southern Command (SOUTHCOM) which is a joint interagency organized to support US security issues and improve security, stability, and prosperity in the Americas. As such, SOUTHCOM’s humanitarian missions are focused on helping partners in the region prepare for and respond to natural disasters. The SOUTHCOM Haiti earthquake response, named Operation UNIFIED RESPONSE, consisted of providing resources, removing debris, establishing settlements, and creating infrastructure and resources for international relief agencies. ALIRT imagery was collected to address many specific relief and recovery objectives: a) food and water distribution – daily changes in refugee camp occupation inferred through volumetric change detection; b) transportation infrastructure — road and bridge trafficability surveys; c) security — finding helicopter landing zones and identifying mass migrations using volumetric change detection; d) temporary housing — flood plain analysis in support of refugee camp site selection; e) rebuilding — high resolution (1 m) DEMs to support longer-term infrastructure development projects. Forty-seven sorties were flown over a 25 day period, with most collections over the Port-au-Prince area. Data over regions around Cap-Haïtien, Gonaïves, Port-de-Paix, and Léogâne were also collected.
METHODOLOGY

The first step in many techniques for classifying ladar data is to create a digital surface model by gridding point cloud data. Both a one-dimensional (1-D) and a two-dimensional (2-D) implementation of the proposed Adaptive Lower Envelope Follower (ALEF) were developed for ladar classification. The 1-D implementation is described here to illustrate details of the algorithm, whereas the 2-D approach was used for operational processing of the ladar data. Gridding the data into a DSM drastically reduces the quantity of data that must be processed from either multiple discrete return or photon counting ladar systems as it results in a single statistic per grid cell. Although gridding may not be appropriate for extracting and reconstructing buildings with good fidelity or characterizing vegetation structure, it is advantageous for obtaining Digital Terrain Models over extended areas.

Lower Envelope Follower

The methodology behind the ALEF is that the ground surface forms the lower envelope of DSMs in vegetated regions, similar to a typical amplitude modulated signal. However, the DSM signal is nonstationary and is not modulated with a sine wave. First, the gridded data are detrended by applying a modified square average filter or mod-box filter (MBF) of size $n \times n$ to the $N_{i,j}$ ground height estimate data points within the box (excluding grid locations that do not contain ground height estimates). The average surface is centered between the upper and lower envelope of the gridded data and contains the low frequency content of the ground surface that represents the general topology of the area. The average surface is subtracted from the initial ground surface estimate. The residuals, which vary about zero, represent the high-pass signal for the raster surface associated with vegetation and edges of man-made objects. Locations where no data exist are flagged with zero values.

The adaptive lower envelope follower (ALEF) method for classifying ground ladar points is based on the envelope follower used to recover the message signal from an amplitude-modulated (AM) signal. In a Double Side Band Amplitude Modulation (DSB-AM) system, the amplitude of the sinusoidal carrier signal is varied according to the message signal. In 1-D, the modulated signal can be expressed as $y(t) = A(1 + m(t))\cos(\omega t)$ where $A$ is the amplitude and $m(t)$ is the message signal. Figure 1 shows an input message signal, $m(t)$ and the resulting modulated signal, $y(t)$. The upper and lower envelopes of the modulated signal rise and fall in proportion to the message signal. The modulated signal is symmetric about zero, and the two envelopes contain the same information about the message signal. The lower envelope follower recovers the message signal from the lower envelope represented as the solid black line in Figure 1. As the modulated signal decreases or slowly increases, it is tracked by the lower envelope follower. However, if the modulated signal increases quickly, the lower envelope follower decays exponentially. Thus, the lower envelope follower does not recover the signal exactly, but is a reasonable estimate derived from a relatively simple implementation.

The ALEF concept can be applied to the problem of extracting a lower envelope (i.e. a terrain surface) from ladar data, where the lower envelope represents the location of the ground in the signal. Here, the ground elevations are identified from the high-pass signal. The implementation of the algorithm requires two user inputs; the exponential decay factor and the window size to compute the initial moving average for the mod-box filter.
Figure 1. Message signal input into DSB-AM system, (a) with sine input signal (grey modulated wave) (b), and lower signal recovered from ALEF (black line).

Figure 2. 1-D representation of lower envelope follower. A) Elevations from DSM profile with the mean surface represented as the solid line. B) De-trended, stationary signal with ground envelope identified.

An example of the ALEF on a 1-D transect of ladar data is shown in Figure 2. The blue line represents the input signal and the pink line illustrates mean surface (Figure 2A) and the estimated ground envelope (Figure 2B), respectively.

**Adaptive Gradient Fill**

Although the envelope follower approximates the ground surface in vegetated regions and along the edges of man-made objects, it also follows the lower envelope of noise in areas with low relief. As such, many of the low relief elevations are removed when thresholded. Regions near building edges are also removed due to high frequency content at building edges. To reintroduce these points as terrain, the ground mask signal is augmented by data from low relief areas using a gradient flood fill operation. The gradient flood fill (GFF) grows the pixels and regions identified as ground points by filling data gaps with values from the original DSM. Here, data gaps refer to pixels in the DSM that the ALEF does not identify as ground points. If the elevation gradient between a pixel identified as a ground elevation in the ALEF and the neighboring pixel in the original DSM falls below a second threshold, the gap pixel is filled with the elevation value in the original DSM. The GFF is then applied to the new filled value. Otherwise, the gap is retained. The threshold used to evaluate the gap pixels can be user-specified, or determined adaptively.
Most methods for classification or filtering of ladar data perform poorly in areas with topographic relief, particularly if they are heavily vegetated or are occupied by buildings. When the topographic relief is roughly the same or greater than the height of the vegetation, threshold-only based algorithms do not work well. Terrain clipping is common when the threshold is too large, while low thresholds result in insufficient removal of vegetation.

The goal of the adaptive gradient flood fill operation is to account for topographic relief prior to applying the gradient-based operator. The local slope and aspect are computed from the original DSM using a Least Squares Estimate where the primary neighbors are weighted. The window size used to compute the local slope is specified by the user and typical sizes include 3x3 or 5x5. As window size increase, less localized slope information is preserved. Prior to computing the slope and aspect, a low pass filter is applied to the DSM to minimize the impacts of vegetation and buildings while preserving the large scale topographic information.

The adaptive gradient flood fill identifies terrain pixels using the following threshold:

\[ \text{threshold} > Z_i - Z_o + [\cos(\text{dir} - \text{aspect})]* \text{dist}*[\text{avg}(\text{slope}_i, \text{slope}_o)]* \text{gridsize} \]

where,

- \(Z_i\) = Elevation of pixel in question (m)
- \(Z_o\) = Elevation of center pixel (m)
- \(\text{dir}\) = relative direction of pixel \(i\) with respect to center pixel
- \(\text{aspect}\) = computed aspect (degrees) of the center pixel
- \(\text{dist}\) = distance factor from center pixel to pixel in question
  - \(\text{dist} = 1\) for primary neighbors
  - \(\text{dist} = \sqrt{2}\) for secondary neighbors
- \(\text{avg}(\text{slope}_i, \text{slope}_o)\) - used to determine the amount of relief between pixels
- \(\text{gridsize}\) = grid size of each pixel

The GFF operation is adaptive in its determination of the threshold, which is a function of the local slope and roughness based upon a 5x5 window. Thus, threshold values are different for areas of high topographic relief than for flat terrain. Any window size can be used to determine roughness and slope, however, a 5x5 window was found to give the best results for the experiments tested. This adaptive pre-processing operation increases the robustness of the method for classifying terrain points in diverse environments.

**RESULTS**

The classification methodology proposed in the previous section was tested using two subsets of ladar data acquired over Port-au-Prince, Haiti following the January 12, 2010 earthquake. Figure 3 contains a 30cm digital surface model of a portion of Port-au-Prince. Common to many third world countries, the selected area has dense housing with little ground surface apparent between housing structures. This housing configuration becomes particularly challenging when located on hillsides, such as in Figure 3a. For this data, the ALEF parameters were specified to be decay rate of 0.91 and a window size of 100 x 100 pixels. The 0.91 decay rate allowed for more topography to be identified as ground surface while still removing the majority of buildings and man-made structures within the DSM. A window size of 100 pixels is equivalent to 3000 cm or 30 m. For this subset having small structures and a terrain extent of approximately 30 m, this window size is appropriate. In urban environments with large buildings (e.g. warehouses, etc) a larger window size may be appropriate. The corresponding results of the ALEF for the selected data are shown in Figure 3b, where the ground elevations are shown as grey scale values, and black areas indicate areas not identified as terrain.
To illustrate the difference between the original DSM and the identified ground surface, a series of transects was extracted from both data sets. Two transects extracted from the DSM in Figure 3 are shown in Figure 4. Transect 1 originates at the top of the hill and passes through the dense housing to the river below. The profile of the DSM along this transect line is shown as the black line, and the underlying interpolated topography is shown as the red line. It is evident from this transect that small patches of ground between the structures are detected by the ALEF algorithm as the interpolated surface utilizes those points to generate the underlying topography. Transect 2 originates in an open patch of ground, moving across the river and passing under dense vegetation. Again, in this case, the underlying ground topography matches well with the ground data in the DSM.
A second subset of ladar data collected over Port-au-Prince was also classified using the ALEF method. For this dataset, the exponential decay factor of the ALEF was 0.96 and the window size was 300 x 300 pixels. Again, the larger window size worked well for this subset due to the dense urban area and the size of the buildings. Larger values of the decay factor result in more localized information being used in the terrain classification, which is appropriate for these dense urban areas. Figure 5a shows the digital surface model, and Figure 5b contains the classified terrain output from the ALEF. The density of buildings within the city is quite high, with occasional patches of ground between individual buildings and building clusters. As evidenced in Figure 5b, the ALEF identified ground points properly, without falsely classifying building rooftops as terrain points.
Figure 5 City block of Port-au-Prince DSM based on 30cm ALIRT ladar data. (b) Classified terrain points using ALEF method.

A transect from each dataset was extracted to further illustrate the differences between the DSM and the underlying detected topography. The transect, which traversed a city block, is shown in Figure 6. Small patches of ground (and possibly rubble) were detected as ground points which were subsequently used to estimate the underlying topography. All ground patches, which are clearly indicated in the DSM, match the underlying topography almost perfectly. This indicates that all of the ground spots were identified and valuable for the ground estimation process.

Figure 6 Digital Surface Model Port-au-Prince city block and transect indicating the buildings (black line) and underlying topography (red line).
CONCLUSIONS

Ladar data over Port-au-Prince, Haiti were collected by the ALIRT ladar system following the devastating 7.0 magnitude January 12, 2010 earthquake. The data were collected in response to disaster relief efforts by the United States Southern Command. The ALIRT system was operated to produce 30 cm DSM over the majority of earthquake impacted portions of Port-au-Prince.

The objective of this study was to develop, implement, and test a system for classifying ladar data as terrain points. The proposed technique is based on detecting the lower envelope of a 2-D signal and utilizing adaptive gradient thresholds. The contributions made by this research include an efficient method for a general classification of ladar data and the use of the 2-DALEF to detect the ground surface. The ground surface of a DSM is modeled as the 2-D lower envelope, and the 2-D envelope detector extracts this surface.

The performance of the ALEF method is related to appropriate selection of user specified input parameters. The current phase of this research is focused on adapting the ALEF code such that the parameters are selected based upon the topography and surface roughness within the scene. This adaptive methodology will further enable different portions of the digital surface model to be classified with the most appropriate parameters as conditions warrant. This extension can potentially yield a more accurate representation of terrain.

REFERENCES


