Generation of DEM from LIDAR data
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Obtaining high resolution Digital Elevation Models (DEM)s is a critical task for analysis and visualization in several remote sensing applications. LIDAR technology provides an effective way for obtaining high-resolution topographic information. This paper presents a textured-based novel automatic algorithm for DEM generation from LIDAR data. The proposed technique uses multifractal-based textural features for object identification combined with a maximum slope filter. Although this work is concentrated on DEM generation, certain aspects of the algorithm make it suitable for classification of LIDAR data into other types of data. Some experimental results are presented to illustrate the effectiveness of the proposed algorithm.

INTRODUCTION

Obtaining high resolution DEMs as well as segmenting and classifying topographic data are critical tasks for analysis and visualization in several remote sensing applications. LIDAR technology provides an effective way for obtaining high-resolution topographic information by collecting three-dimensional, non-uniformly spaced dense point measurements over large areas of interest. Previous work on LIDAR data processing can be roughly classified into two categories: DEM generation which is essentially equivalent to classification of LIDAR data into terrain and non-terrain points, and topographic segmentation, which in general involves classification of LIDAR data into several object types including flat terrain, mountainous regions, roads, different types of vegetation, and manmade objects. In what follows, previous DEM generation and topographic segmentation techniques are discussed.

Although DEM generation requires classification of LIDAR data into only two classes, namely ground and non-ground, it is still a significantly difficult task. There are two basic errors in classifying LIDAR measurements as ground and non-ground. The first is the commission error that classifies non-ground points as ground measurements, and the second is the omission error that considers ground points to be non-ground measurements. Several approaches for separating ground from non-ground measurements exist in the literature, some of which are briefly discussed next.

Kraus and Pfeifer\textsuperscript{1,2} utilized an iterative linear least squares interpolation scheme in order to remove vegetation with the goal of generating DEMs in forest areas. This technique was extended by Pfeifer et al.\textsuperscript{3} for building-removal in urban areas. The basic idea behind the iterative linear interpolation method is that a low-degree polynomial trend surface is removed from the original elevation data to produce a set of reduced elevation values. As mentioned in Zhang et al.\textsuperscript{4}, the basic drawback of this method is that it requires the reduced elevation to be an ergodic random process, which is in general hard to satisfy, especially in urban areas where there is a significant number of manmade objects and man intervention on the natural terrain.

Vosselman\textsuperscript{4} proposed a maximum slope-based filter that identifies ground data by comparing slopes between a LIDAR point and all its neighbors in a given circle-shaped window around the point. If the maximum slope in the window was larger than a predefined threshold, the point was classified as being a non-ground point. Different thresholding choices were provided including a constant threshold and a threshold which is a function of distance. It was also mentioned that a “better” threshold may be obtained if prior knowledge about the terrain in the area of interest was available. Some additional improvements of the slope-based filter were proposed in the literature\textsuperscript{5,6}. In general, it is expected that sharp slopes correspond to buildings or trees, since sharp slopes are uncommon for ground surfaces. For a small circle-shaped window, the maximum slope filter may be effective in removing only some non-ground objects without significantly affecting the actual ground measurements. However, both omission and commission errors may be large for large windows, especially for mountainous areas where some of the slope variations may be large. Nevertheless, this method can be effective if combined with other techniques as it is illustrated in the next section.

Other DEM generation techniques include morphological filter processing for removing non-ground objects\textsuperscript{10,11}. Assuming that the LIDAR data can be represented by regular, grayscale grid images where elevation corresponds to grayscale image intensity, the shapes of vegetation and manmade objects can be determined by the change of gray tone. Mathematical morphology can be directly applicable for identifying
objects in grayscale images\textsuperscript{12}, and thus it can be used to filter LIDAR data. Zhang et al\textsuperscript{21} proposed an iterative technique using variable-size progressive morphological filters for estimating suitable elevation thresholds in local regions in order to separate terrain from non-terrain points. The main objective of this work was to develop a filter to facilitate automatic extraction of ground points from LIDAR measurements with minimal human interaction.

Haugerud and Harding\textsuperscript{8} proposed a technique for filtering trees by comparing local curvatures of point measurements. Tree vertices were removed iteratively from a triangulated irregular network (TIN) constructed from LIDAR measurements. Alternatively, ground points may be classified by iteratively selecting ground measurements from an original dataset, as proposed by Axelsson\textsuperscript{9}, where adaptive TIN models were used to find ground points by selecting seed ground points within a grid of a size greater than the largest expected non-ground objects. These seed points comprised an initial ground dataset. In the next part of the process, one point above each TIN facet was added iteratively to the ground point collection dataset if its parameters fall below a threshold. One problem associated with the adaptive TIN methods is that different thresholds have to be given for various land cover types\textsuperscript{31}.

The second category of LIDAR data processing algorithms consists of topographic segmentation techniques. Hebert et al\textsuperscript{16} have presented an outline of some classification approaches. Next, a brief discussion of some other existing techniques that classify LIDAR data into several object types is presented. Axelsson\textsuperscript{13} proposed algorithms for LIDAR data classification into three classes: terrain, buildings and electrical power lines, using multiple LIDAR data returns, and LIDAR intensity. Maas\textsuperscript{18} proposed using height texture for LIDAR data segmentation. However, the textural features used did not include some of the state-of-the-art features commonly used in texture segmentation and classification. Filin\textsuperscript{14} proposed a segmentation technique for identifying regions in LIDAR data using features such as position, tangent plane and relative height difference. The classes into which the LIDAR data were classified were high vegetation, low vegetation, smooth surfaces and planar surfaces. Song et al\textsuperscript{28} considered identifying a larger number of object types such as trees, grass, roads, and roofs based on interpolated intensity data\textsuperscript{17}. In Charaniya et al\textsuperscript{27} proposed a technique for filtering trees by comparing local curvatures of point measurements. Alternatively, ground points may be classified by iteratively selecting ground measurements from an original dataset, as proposed by Axelsson\textsuperscript{9}, where adaptive TIN models were used to find ground points by selecting seed ground points within a grid of a size greater than the largest expected non-ground objects. These seed points comprised an initial ground dataset. In the next part of the process, one point above each TIN facet was added iteratively to the ground point collection dataset if its parameters fall below a threshold. One problem associated with the adaptive TIN methods is that different thresholds have to be given for various land cover types\textsuperscript{31}.

Another subcategory of classification schemes includes identification of buildings from LIDAR data. As in the case of DEM generation, there are only two classes to be determined. However, the main goal of these techniques is not to separate ground from non-ground measurements, but to identify building locations in order to create building models\textsuperscript{7-30}. In Rottensteiner\textsuperscript{21}, it was mentioned that research teams have proposed two different ways to geometrically reconstruct buildings. First, one can instantiate parametric primitives and fit them to the data, given sufficient evidence. Second, one can detect planar segments in a surface model created from the LIDAR points and construct polyhedral building models by combining these planar segments. In Gamba and Houshmand\textsuperscript{30}, the task of extracting significant building structures in DSMs was analyzed. The original data were obtained by interferometric SAR or LIDAR techniques with different resolution and noise characteristics. This work compared the detection and information extraction abilities of the SAR and LIDAR approaches. The results show that LIDAR data provide a better shape characterization of each building not only due to the higher resolution, but also due to the shadowing/layover effects that appear in SAR imagery. Finally, some other works\textsuperscript{23-26} have been presented in the literature that deal with some other aspects of LIDAR data processing, including working directly with Laser altimeter waveforms\textsuperscript{23}, and the need for geometric corrections of the acquired LIDAR data\textsuperscript{26}.

This paper presents a textured-based novel automatic algorithm for generation of DEMs from LIDAR data. The proposed method uses advanced multiscale and textural features for object identification. Most existing texture-based techniques concentrated on simple textural features such as local variance. Although this work is concentrated on DEM generation, certain aspects of the algorithm make it suitable for classification of LIDAR data into other types of data such as buildings. Some experimental results are presented to illustrate the effectiveness of the proposed method. Finally, future work and extensions of the proposed technique are discussed.

**PROPOSED TECHNIQUE**

In this work, algorithms are investigated and developed considering features appropriate for multiscale and textural processing. Multiscale processing is required, since most often objects in LIDAR data do appear at
different sizes. Therefore, most single scale algorithms will not be effective in generating DEMs. Previous approaches dealt with multiscale processing by applying a particular algorithm multiple times, or by applying multiple passes of the algorithm while varying some of the scale-dependent parameters in order to adapt for differently sized objects. However, the disadvantage of these approaches is that if an artifact occurs due to a single pass, this will in general be amplified by the consecutive passes of the algorithm, even if the scale-dependent parameters of the algorithm vary.

One approach to solve the aforementioned problem is to perform data classification (or LIDAR image segmentation). For instance, only areas which are categorized as being vegetated areas may be processed by a particular algorithm, which is important in the case that this algorithm creates artifacts in non-vegetated areas. This direction will be further investigated in the future, since the proposed technique provides the means for data classification and object recognition in LIDAR data.

A second approach is to directly use a multiscale algorithm that is capable of identifying objects of different sizes in one pass. Of course, the classification approach and the multiscale single-pass approach can be combined for better results.

Proposed in this work is a multiscale feature extraction algorithm that borrows concepts from multifractal techniques. The algorithm is suited to the proposed LIDAR application. As mentioned above, objects appear at different sizes in LIDAR imagery. This is especially true for buildings and other manmade objects. However, a human has, most of the times, the ability to identify the properties that characterize those objects, and in addition, to simultaneously extract information at different resolutions. In this work, there is an attempt to simulate this ability.

The following formulation is usually used in multifractal analysis.

\[
<|f(x) - f(x + s)|^q> = A s^{\tau_q}, \quad s = s_i, i = 1, 2, ..., \max(i)
\]  

where \(f(x)\) is the function of interest, and \(s\) denotes the scale. The power \(q\) is used to produce different multifractal exponents \(\tau_q\). Furthermore, \(<|f(x) - f(x + s)|^q>\) is the ensemble average of \(|f(x) - f(x + s)|^q\) in a given area. Essentially, the multifractal exponents provide a measure of the rate with which \(<|f(x) - f(x + s)|^q>\) increases with respect to scale.

Although equation (1) is applicable for one-dimensional signals, it can be extended to two-dimensions as it will be discussed later. Then, if the log function is applied on both sides of equation (1), the following is obtained.

\[
\log <|f(x) - f(x + s)|^q> = \tau_q \log(s) + \log(A)
\]  

Finally, the multifractal exponents \(\tau_q\) can be calculated as follows:

\[
\tau_q : \text{slope of line} (\log(s), \log <|f(x) - f(x + s)|^q>)
\]  

In order to provide an intuitive explanation of the significance of the formulation described by equation (1), let us consider the case where \(q = 1\). In this case, the \(\tau_1\) exponent is called the Hurst exponent. The ensemble average \(<|f(x) - f(x + s)|>\) quantifies the average difference between points spaced apart by a distance equal to the scale \(s\). In the case of vegetated areas, \(<|f(x) - f(x + s)|>\) is expected to be large for both small and large scale \(s\). Therefore, the rate at which this function changes will be small for vegetated areas. In the case of (relatively flat) ground areas, \(<|f(x) - f(x + s)|>\) is expected to be small for both small and large scale \(s\). Again, this leads to a relatively small exponent. On the other hand, manmade objects, such as buildings, tend to have a relatively flat surface around their centers and sharp transitions around their edges. Therefore, although \(<|f(x) - f(x + s)|>\) may be small for small scales it will be larger for large scales, resulting in a large multifractal exponent. Thus, large non-ground objects, which most often cause problems in DEM generation for most algorithms, can be effectively detected. Based on the discussion above, this approach can be especially useful for identifying large (and small) manmade objects. Vegetation can be effectively removed by incorporating other approaches such as the maximum slope approach and small median filters.
Theoretically, another advantage of multifractals is that they provide scale invariant features that have been shown to be good descriptors of textural surfaces\(^3\). In this work, a modification of the above formulation is proposed that is more particular to the processing of LIDAR data as it will be explained below.

First, the function \( |f(x) - f(x + s)| \) is substituted by the following function:

\[
f(x) - \min_{\xi \in K_s} f(\xi), \quad K_s := \left\{ \xi \in (x - \frac{s - 1}{2}, x + \frac{s - 1}{2}) \right\}
\]

The two functions are similar since they both represent the difference at two different locations in a given area defined by the scale \( s \). Therefore, the operation that they both represent can be viewed as a highpass filter. However, extending \( |f(x) - f(x + s)| \) in two-dimensions is not as straightforward in the case of \( f(x) - \min f(\xi) \). There is some work related work in the literature, including wavelet-based approaches\(^3\). In general, these techniques are computationally complex, since several filtering operations and additional processing has to be performed. This is not appropriate for the application investigated in this work, where large amounts of data have to be processed. On the other hand, the proposed function can be easily used for one- as well for two- dimensional signals. Moreover, only max and min filters are needed which can be performed using fast techniques.

Nevertheless, there is an additional advantage of using this function. Since \( \min f(\xi) \) is subtracted from \( f(x) \), if function \( f(x) - \min f(\xi) \) is large for some scale \( s_1 \), it is also guaranteed to be large for all scales \( s_1 > s \), since \( \min \) includes \( \min_{\xi \in K_s} \). In order to illustrate the need for this property, let us consider the case where a building is surrounded by other buildings. In this case, \( |f(x) - f(x + s)| \) would first increase (due to the building’s edges), and then increase (due to the other buildings of approximately same height as the building of interest) causing the multifractal exponent value to reduce. Therefore, the building may not be identified. The proposed formulation is also motivated by the Variation method for estimating the fractal dimension\(^3\). Similarly to equation (1), the following equation can be used for calculating the multifractal exponents for two-dimensions.

\[
f(x, y) - \min_{(\xi, \zeta) \in K_{s}} f(\xi, \zeta) > = \lambda s^\tau_q(s), \quad K_s := \left\{ \xi \in (x - \frac{s - 1}{2}, x + \frac{s - 1}{2}), \quad \zeta \in (y - \frac{s - 1}{2}, y + \frac{s - 1}{2}) \right\}
\]

In contrast to the traditional multifractal analysis, equation (5) assumes that the multifractal exponent is not completely independent of the scale. This is a more realistic assumption for true data, and especially for data that include manmade structures.

If the log is applied on both sides the following is obtained:

\[
\log < f(x, y) - \min_{(\xi, \zeta) \in K_{s}} f(\xi, \zeta) > = \tau_q(s) \log(s) + \log(A)
\]

Instead of using the log-log plot and estimating the best slope for finding the multifractal exponents, the following derivative is considered:

\[
\frac{d \log(f(x, y) - \min_{(\xi, \zeta) \in K_{s}} f(\xi, \zeta))}{d \log(s)} = \tau_q(s)
\]

Based on this approach, the feature can be computed as the maximum multifractal exponent, with respect to the scale \( s \). This representation is suitable for this application because it eliminates the scale dependence of the exponents. In general, the scale dependence is eliminated also when the slope of the log-log plot is used for calculating the multifractal exponents. However, the slope eliminates local scaling properties, which are usually important for building and other manmade object recognition. For instance, manmade objects tend to have significantly sharp transitions and these can only be detected locally.

Hence, the feature used is:

\[
F_q^{(1)} = \max_s \left\{ \tau_q(s) \right\}
\]

Since the derivative cannot be performed for discrete data, the following approximation is used:

\[
F_q^{(1)} = \max_s \left\{ \log < f(x, y) - \min_{(\xi, \zeta) \in K_{s}} f(\xi, \zeta) > - \log < f(x, y) - \min_{(\xi, \zeta) \in K_{s}} f(\xi, \zeta) > \right\}
\]

Furthermore, the following feature that provides, as mentioned above, just a kind of an average representation of the multifractal exponent is used:

\[
F_q^{(2)} = -\frac{\log < f(x, y) - \min_{(\xi, \zeta) \in K_{s}} f(\xi, \zeta) >}{\log(s)} \cdot \log < f(x) - \min_{(\xi, \zeta) \in K_{s}} f(\xi, \zeta) >
\]
As mentioned previously, feature \( F^{(3)} \) is useful for identifying points that correspond to large buildings even the ones which are close to the center of the building as long as the building is included in the processing window. Since some average behavior of the multifractal exponents may be useful in order to characterize the data, the second feature is also used.

It should be mentioned that the multifractal exponents do not simply measure the elevation transitions in the LIDAR data as the maximum slope approach does. The proposed features find the rate with which the elevation differences vary which is more meaningful especially when both textural and structural objects are present.

There is an additional modification used in order to be able to recognize manmade structures. In general, a ground point may be located nearby some relatively sharp ground elevation variations. However, in general sharp transitions do not occur all around a ground point. On the other hand, a building regardless of its shape can generally be included in a “box”. This implies that there will be sharp transitions in all 360\(^\circ\) around the object. For that purpose, the multifractal features proposed above can be extracted from different neighborhoods. Each neighborhood can concentrate in a specific direction around the object in order to examine the object’s directional properties. An example of four neighborhoods oriented in 0\(^\circ\), 90\(^\circ\), 180\(^\circ\) and 270\(^\circ\) is shown next. Each neighborhood is represented by a different gray level.

Based on this approach, four features instead of a single feature \( F^{(3)} \) can be obtained first, namely \( F_{q}^{(1)}, F_{q}^{(2)}, F_{q}^{(3)}, F_{q}^{(4)} \) (one feature per direction). Then, the feature \( \hat{F}_{q}^{(3)} \) is finally calculated to be the minimum out of the four features. In the case of a building, all these four neighborhoods should provide large multifractal exponents, therefore the minimum of these four features should still be large. On the other hand, a ground area will not result in large exponents for all four directions, therefore the minimum of the four features will tend to be small.

![Figure 1. Extracting the multifractal exponents](image)

The overall system is shown in Figure 2 next.

![Figure 2. The overall proposed system](image)
In the above discussion, it is assumed that the data is gridded from an irregular spaced cloud of point measurements. In this work, the minimum elevation of all the irregularly spaced points that fall in a specific grid point \( f(x,y) \) is used to represent the value of \( f(x,y) \). Following this approach, there may be some points in the grid located at, say \((x,y)\), that are not filled in, since there was no measurements that correspond to \((x,y)\). In order to complete the grid, a median filter is applied. Only empty grid points are filled in with the median of the nearby grid point values. This process is applied multiple times using increasing median window sizes until the whole grid map is filled in.

**EXPERIMENTAL RESULTS**

Some sample data were also used from the Maryland Department of Natural Resources (MDNR), which is collecting and distributing several LIDAR-derived elevation data products, some of which is available for download. The samples of the LIDAR products, including LIDAR first and last returns, and intensity imagery, are taken from an area near Salisbury, MD, and have been provided for experimentation purposes. Figure 3 shows the last returns of the sample area provided by the MDNR. This area has been chosen for illustration purposes since it contains most of the commonly expected types of objects such as buildings (small and large), roads, vegetation, water, and flat terrain and terrain with relatively fast transitions.

Figure 4 shows the result of processing using the maximum slope approach presented in Vosselman. However, only one pass of the algorithm is performed. It can be seen that most of the vegetation has been removed, and most of the small buildings. The large buildings have not been removed but just reduced in size. Multiple passes of the algorithm will result in complete removal of the buildings. However, any artifacts produced by unnecessary usage of the algorithm over areas that do not require processing will be increased for those regions.

Figure 5 shows the LIDAR map after removing the man-made objects identified with red in Figure 5. The areas that were occupied by those objects are filled in with surrounding terrain information. It is interesting to notice that most of the non-ground objects remaining in the map correspond to vegetation.

Figure 6 shows the final filtered result following the procedure described in Figure 2. This includes one pass of the maximum slope algorithm, and one pass of the proposed algorithm. The maximum slope algorithm has been used with significantly small windows so that there are no artifacts produced. Finally, a small median-type filter is used to remove any isolated non-ground points that may have not been removed from the previous steps.

The basic idea in this work is to automatically remove the larger areas of non-ground objects by identifying those individual objects first. These objects in general cause a problem in the DEM generation for most algorithms since they may be confused with, for instance, mountainous regions with relatively flat tops. The other small non-ground objects, including vegetation, can be mostly removed using simpler techniques. However, more efficient and effective techniques still need to be investigated for vegetation identification as well as classification of different vegetation types.

Figure 8 shows the final DEM result provided by MDNR. This has been produced using automatic and manual methods. It can be noticed that the main differences are the areas where the some smaller buildings were originally located. In any case, these are areas for which not much can be said. However, it can be seen from Figure 6 that the proposed algorithm being fully automatic better eliminates those objects, as the provided LIDAR map shows some spots at where the remaining objects where located. Another observation is that the proposed technique did not remove bridges. This can however be incorporated in the algorithm.
Figure 3. Unfiltered grid

Figure 5. Grid after manmade-like objects are removed.
Figure 6. Final filtered result

Figure 7. Manual/automatic processed image provided.
CONCLUSIONS

This paper introduced an automatic technique for DEM generation. The proposed work opens the way for several extensions and future applications of LIDAR data processing. For instance, the work can be extended to object classification not only into vegetation and manmade objects, but also into different types of vegetation. This has been traditionally done with SAR data. However, it can perhaps be performed more effectively, using LIDAR data due to high resolution capabilities and multiple returns.

Furthermore, the work can be extended to combine LIDAR data with other data, such as aerial imagery, in order to assist in DEM generation or data classification. For instance, aerial imagery may be more appropriate for road detection because the road elevations may be similar to the elevation of the surrounding area. On the other hand, LIDAR data may be more suitable for building detection since buildings and vegetation produce obstructions and shadows in aerial imagery.

REFERENCES


