Airborne LiDAR for DEM generation: some critical issues

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Abstract: Airborne LiDAR is one of the most effective and reliable means of terrain data collection. Using LiDAR data for DEM generation is becoming a standard practice in spatial related areas. However, the effective processing of the raw LiDAR data and the generation of an efficient and high-quality DEM remain big challenges. This paper reviews the recent advances of airborne LiDAR systems and the use of LiDAR data for DEM generation, with special focus on LiDAR data filters, interpolation methods, DEM resolution, and LiDAR data reduction. Separating LiDAR points into ground and non-ground is the most critical and difficult step for DEM generation from LiDAR data. Commonly used and most recently developed LiDAR filtering methods are presented. Interpolation methods and choices of suitable interpolator and DEM resolution for LiDAR DEM generation are discussed in detail. In order to reduce the data redundancy and increase the efficiency in terms of storage and manipulation, LiDAR data reduction is required in the process of DEM generation. Feature specific elements such as breaklines contribute significantly to DEM quality. Therefore, data reduction should be conducted in such a way that

critical elements are kept while less important elements are removed. Given the high-density characteristic of LiDAR data, breaklines can be directly extracted from LiDAR data. Extraction of breaklines and integration of the breaklines into DEM generation are presented.

Key words: airborne LiDAR, DEM, filter, resolution, data reduction, breakline

I Introduction

Digital Elevation Models (DEMs) play an important role in terrain-related applications. Researches on terrain data collection and DEM generation have received great attention. Traditional methods such as field surveying and photogrammetry can yield high-accuracy terrain data, but they are time consuming and labour-intensive. Moreover, in some situations, for example, in forested areas, it is impossible to use these methods for collecting elevation data. Airborne Light Detection and Ranging (LiDAR) - also referred to as Airborne Laser Scanning (ALS), provides an alternative for high-density and high-accuracy three-dimensional terrain point data acquisition. One of the appealing features in the LiDAR output is the direct availability of three dimensional coordinates of points in object space (Habib *et al.*, 2005). LiDAR data have become a major source of digital terrain information (Raber *et al.*, 2007) and has been used in a wide of areas, such as building extraction and 3D urban modeling, hydrological modeling, glacier monitoring, landform or soil classification, river bank or coastal management, and forest management. However, terrain modeling has been the primary focus of most LiDAR collection missions (Hodgson *et al.*, 2005). Actually, the use of LiDAR for terrain data collection and DEM generation is the most effective way (Forlani and Nardinocchi, 2007) and is becoming a standard practice in the spatial science community (Hodgson and Bresnahan, 2004).

LiDAR has been studied since the 1960s (Flood, 2001). Researches and design on Airborne LiDAR for topographic data collection started from the 1980s (Krabill *et al.*, 1984; Bufton *et al.*, 1991). Commercial Airborne LiDAR systems have been operational since the mid-1990s (Pfeifer and Briese, 2007), and it continues to be an active area of research and development (Flood, 2001). There has been a significant increase in the use of LiDAR data for DEM generation over the last decade as more reliable and accurate LiDAR systems are developed (Sithole and Vosselman, 2003). Lohr (1998) and Kraus and Pfeifer (1998) are pioneers who demonstrated the suitability of using airborne LiDAR for the generation of DEM. Since then DEM generation from LiDAR data under various conditions has been documented by many authors (Lloyd and Atkinson, 2002; Wack and Wimmer, 2002; Lee, 2004; Gonçalves-Seco *et al.*, 2006; Lloyd and Atkinson, 2006; Kobler *et al.*, 2007). With LiDAR data, high density and high accuracy DEM can be generated. Compared with photogrammetry, one of the main competing technologies with airborne LiDAR in terms of accuracy, due to LiDAR's capability of canopy penetration, DEM generation from LiDAR data overcomes the limitations of photogrammetry for DEM generation in forested areas. Kraus and Pfeifer (1998) demonstrated that the accuracy of LiDAR-derived DEM in forested areas is equivalent to that of photogrammetry-derived DEM in open areas. As an active remote sensing technology, airborne LiDAR data are free of shadow. As such, LiDAR has advantage over photogrammetry for DEM generation in urban areas as well. However, raw LiDAR data can contain return signals from no matter what target the laser beam happens to strike, including human-made objects (e.g., buildings, telephone poles, and power lines), vegetation, or even birds (Barber and Shortrudge, 2004; Stoker *et al.*, 2006). The desired target for DEM generation is the bare earth points. Therefore, it is crucial to filter or extract bare earth points from LiDAR data. Various filter methods have been developed to classify or separate raw LiDAR data into ground and non-ground data. However, none of automated filter processes is 100% accurate so far (Romano, 2004). Manual editing of the filtering results is still needed (Chen, 2007). Efforts are still needed to improve the performance of filter algorithms.

Airborne LiDAR technology is still developing rapidly in both sensor and data processing. The competition between LiDAR sensor manufactures is mostly focused on increasing laser pulse repetition rates to collect more data points. The pulse repetition rate has increased from less than 50 kH in 2001 (Flood, 2001) to 250 kH now (Lemmens, 2007). High density data make it possible to represent terrain in much detail. However, high density data lead to a significant increase in the data volume, imposing challenges with respect to data storage, processing and manipulation (Sangster, 2002). Although LiDAR data has become more affordable for users due to the gradually dropping of the costs of LiDAR data collection, how to effectively process the raw LiDAR data and extract useful information remains a big challenge (Chen, 2007). Furthermore, because of the specific characteristics of LiDAR data, issues such as the choices of modeling methods, interpolation algorithm, grid size, and data reduction are challenging study topics for the generation of a high quality DEM from LiDAR data. This paper reviews the recent advance of using LiDAR data for DEM generation, with special focus on LiDAR data filters, interpolation methods, and LiDAR data reduction. The following section gives an introduction of airborne LiDAR system, highlighting some recent developments of airborne LiDAR systems. Section 3 reviews the development of algorithms for filtering LiDAR data. Issues regarding terrain model and interpolation methods are discussed in section 4. Section 5 presents approaches to LiDAR data reduction for efficient DEM generation. The final section concludes the discussion.

II Airborne LiDAR systems

Airborne LiDAR is an active remote sensing technology. It actively transmits pulses of light toward an object of interest, and receives the light that is scattered and reflected by the objects. An airborne LiDAR system is typically composed of three main components: a laser scanner unit, a Global Positioning System (GPS) receiver, and an Inertial Measurement Unit (IMU) (Habib *et al.*, 2005; Hollaus *et al.*, 2005; Reutebuch *et al.*, 2005; Webster and Dias, 2006; Pfeifer and Briese, 2007). The laser scanner unit consists of a pulse generator of Nd:YAN laser with a wavelength in the range of 0.8 μm to 1.6 μm (typically, with 1.064 μm or 1.500 μm) and a receiver to get the signal of scattered and reflected pulses from targets (Wehr and Lohr, 1999; Mukai *et al.*, 2006; Pfeifer and Briese, 2007). The laser pulses are typically 4 to 15 ns in duration and have peak energy of several millijoules (Wehr and Lohr, 1999; Acharya *et al.*, 2004; Lemmens, 2007). Laser pulses are emitted at a rate of up to 250 kHz to the Earth surface (Lemmens, 2007). The distance (range) between the LiDAR sensor and the object can be calculated by multiplying the speed of light by the time it takes for the light to transmit from and return to the sensor (Watkins, 2005; Weitkamp, 2005). With recently developed LiDAR sensors, range precision can reach 2-3 cm

(Lemmens, 2007). The GPS receiver is used to record the aircraft trajectory and the IMU unit measures the attitude of the aircraft (roll, pitch, and yaw or heading) (Webster and Dias, 2006). The calculated range between the scanner and the target and the position and orientation information obtained from the GPS and IMU to determine target location with high accuracy in three dimensional spaces (Liu *et al.*, 2007b). The accuracy of LiDAR points is related to the accuracy of GPS and IMU. Airborne GPS is able to yield results in 5 cm horizontally and 10 cm vertically, while IMU can generate attitude with accuracy within a couple of centimetres. LiDAR data can get an accuracy of 15 cm root mean square error (RMSE) in vertical and 20 cm RMSE in horizontal (BC-CARMS, 2006).

The three dimensional LiDAR points are initially represented with latitude, longitude, and ellipsoidal height based on the WGS84 reference ellipsoid. They can be transformed to a national or regional coordinate system. At the same time, elevations are converted from ellipsoidal heights to ortho-metric heights based on a national or regional height datum by using a local geoid model (Webster and Dias, 2006; Liu *et al.*, 2007b). Currently, LiDAR data are typically delivered as tiles in ASCII files containing x, y, z coordinates, and (as clients demand) with LiDAR intensity values (Liu *et al.*, 2007b).

Airborne LiDAR systems are also capable of detecting multiple return signals for a single transmitted pulse (Wehr and Lohr, 1999; Charaniya *et al.*, 2004; Reutebuch *et al.*, 2005). Most LiDAR systems typically record first and last returns, but some are able to record up to six returns for a single pulse (Wagner *et al.*, 2004; Lim *et al.*, 2003). Multiple returns occur when a laser pulse strike a target that does not completely block the path of the pulse and the remaining portion the pulse continues on to a lower object. This situation frequently occurs in forested areas where there are some gaps between branches and foliage (Reutebuch *et al.*, 2005). Recording multiple returns is quite useful for the topographic mapping in forested area or for the description of forest stand and structure (Sheng *et al.*, 2003).

In addition to the three dimensional coordinates, most LiDAR systems also have the capability of capturing the intensity of the backscattered laser pulse. The backscattered laser signal is a function of many variables such as the transmitted laser power, laser beamwidth, range, atmospheric transmission, and effective target cross section (the effective area for collision of the laser beam and the target). The target cross section is strongly dependent on the target reflectance at the laser wavelength, the target area, and the target orientation with respect to the incoming laser beam (Jelalian, 1992; Wagner *et al.*, 2004; Coren *et al.*, 2005; Parrish *et al.*, 2005). The optical signal received by the sensor is converted to an electrical signal by a photodetector (typically an avalanche photodiode). The generated photocurrent or voltage is then quantized to a digital number (usually expressed in percent value, representing the ratio of strength of reflected light to that of emitted light (Song *et al.*, 2002)) which is referred to as the LiDAR intensity value for the particular return (Jelalian, 1992; Barbarella *et al.*, 2004; Coren *et al.*, 2005). The LiDAR intensity data then can be interpolated to a geo-referenced intensity image with orthogonal geometry. This intensity image assists surface classification and therefore is of potential to improve the generation of DEMs (Höfle and Pfeifer, 2007).

The aforementioned airborne LiDAR is so called discrete return system. Currently, commercial full-waveform airborne LiDAR is available (Pfeifer and Briese, 2007). While discrete return systems typically allow for one or multiple (up to six) returns to be recorded for each laser pulse (Lim *et al.*, 2003), full-waveform systems digitize and record the entire backscattered signal of each emitted pulse (typically with an interval of 1 ns) (Wagner *et al.*, 2006; Chauve *et al.*, 2007; Mandlburger *et al.*, 2007). In post processing, the waveform is decomposed into a sum of components or echoes, so as to characterise the different targets along the path of the laser beam (Chauve *et al.*, 2007). For each returning echo of single laser pulse, the echo width and the amplitude for all the small individual scatterers contributing to one echo is determined. If the echo width is small, a rather flat surface element was illuminated (Doneus and Briese, 2006a). Doneus and Briese (2006b) investigated the possibility for DEM generation using full-waveform LiDAR data. With the help of a pre-filter step that eliminates echoes with a higher echo width, a significant improvement of the DEM could be achieved (Pfeifer and Briese, 2007).

Currently, most airborne LiDAR systems are only able to record the reflections of one laser pulse before the next is emitted. In order to increase the data coverage rate by an increase in the flying height, pulse repetition rate and maximum range, the so-called multi-pulse technology was introduced. This technology allows to detect the returns of multi laser pulses simultaneously (Mandlburger *et al.*, 2007; Pfeifer and Briese, 2007). Moreover, multiple scanners can be boarded on one airborne platform for increasing side-looking or for forward and backward looking (Mandlburger *et al.*, 2007).

Other important developments of airborne LiDAR systems include the integration of a high resolution digital camera or a digital video camera with a LiDAR system (Ackermann, 1999; Ahlberg *et al.*, 2004). For each collected digital image, the position and orientation of the camera can be obtained by using the GPS and IMU data. Exterior orientation parameters for each frame of imagery are directly provided by these position and orientation data. Therefore, no stereo overlapping images and/or ground control points are needed. Orthorectification can be completely automatic by using the digital images and a LiDAR-derived DEM (Ahlberg *et al.*, 2004). Currently, the commercial system integrating a passive RGB (true colour) and CIR (colour infrared) line scanner with airborne LiDAR is available (BC-CARMS, 2006). It is expected that the LiDAR system can be combined with multispectral or hyperspectral imaging systems, which will result in highly versatile systems and extended LiDAR application potential (Ackermann, 1999). For details of some commercial airborne LiDAR systems, readers are referred to Lemmens (2007), Petrie (2006) and Jenkins (2006).

III Filtering of LiDAR data

One of the critical steps for DEM generation from LiDAR data is to separate the LiDAR points into ground (terrain) and non-ground (non-terrain) points. Automatically separating ground and non-ground points from LiDAR point clouds has proven to be surprisingly difficult, especially for large areas of varied terrain characteristics. Therefore, developing efficient and effective methods for filtering LiDAR points is currently an active research topic (Silván-Cárdenas and Wang, 2006).

Over the past years, several filter algorithms have been developed for automatically extracting ground points from LiDAR point clouds (Sithole and Vosselman, 2004; Silván-Cárdenas and Wang, 2006; Kobler *et al.*, 2007), among which interpolation-based (Kraus and Pfeifer, 1998), slope-based (Vosselman, 2000; Roggero, 2001; Sithole, 2001; Shan and Sampath, 2005), and morphological (Zhang *et al.*, 2003; Zakšek and Pfeifer, 2006; Chen *et al.*, 2007) are the most popular approaches (Silván-Cárdenas and Wang, 2006).

1 Interpolation-based filter

Interpolation-based filter, or called linear prediction, was first proposed by Kraus and Pfeifer (1998). It iteratively approximates the terrain surface using weighted linear least squares interpolation (Chen *et al.*, 2007). A rough approximation of the terrain surface is calculated first with equal weights for all points. This estimated surface is an averaging surface between terrain points and non-terrain points. The residuals, i.e. the oriented distances from the surface to the points are then calculated (Pfeifer *et al.*, 2001). Terrain points usually have negative residuals, while non-terrain points have positive residuals (Chen *et al.*, 2007). Each point is then assigned a weight according to its residual (Kraus and Pfeifer, 1998; Pfeifer *et al.*, 2001). Points with negative residuals are assigned high weights (Chen *et al.*, 2007) which are considered to be on the terrain surface, while points with low weights are assumed to be non-terrain points (Lee and Younan, 2003). The process is iterated so that the surface gets closer and closer to the ground (Crosilla *et al.*, 2004).

This filter method was originally developed for filtering LiDAR data and terrain modelling in forested areas, and later extended to use in urban areas (Pfeifer *et al.*, 2001). However, this filter method is not applicable to a terrain with steep slopes and large variability (Lee and Younan, 2003). To overcome this problem, Lee and Younan (2003) developed a combined modified linear prediction and an adaptive processing method. The modified linear prediction is an extension to the previous work presented by Kraus (1997), Kraus and Pfeifer (1998), Pfeifer *et al.* (1998), and Pfeifer *et al.* (1999). The ground points obtained from the linear prediction filtering are compared with the original points, and only those points with the same x and y coordinates as the original points are extracted for refinement purpose. Spurious peaks are eliminated by using adaptive filtering in which the normalized least square is used to replace the least square algorithm used in Kraus and Pfeiger's method (Lee and Younan, 2003). It was shown that better results can be achieved in the area with steep slopes and large variability. However, the implementation of this method requires a priori knowledge of a number of parameters such as the delay factor, the adaptation parameter, and the filter order (Lee and Younan, 2003; Chen *et al.*, 2007). The performance of the adaptive algorithm depends on appropriately selecting these parameters (Lee and Younan, 2003). Mandlburger *et al.* (2007) used full-waveform information to determine a-priori weights of the LiDAR points. These a-priori weights allow to combine the additional knowledge of the echo attributes with the geometric criteria within surface estimation so that improve the ground surface approximation.

2 Slope-based filter

The slope-based filter developed by Vosselman (2000) assumes that the gradient of the natural slope of the terrain is distinctly different from the slope of non-terrain objects such as buildings and trees (Sithole, 2001). Slopes between a LiDAR data and its neighbours are compared. If the slope between this LiDAR point and any other point within a given circle exceeds a predefined threshold, the LiDAR point is assumed to be a non-terrain point. The success of using this method is dependent on threshold definition and terrain type. It is a critical step to determine an optimum threshold in slope based filtering methods (Zhang *et al.*, 2003). Obviously, the lower the threshold, the more points will be classified to bare earth. The definition of a reasonable threshold should incorporate the knowledge about terrain in the study area (Vosselman, 2000; Zhang *et al.*, 2003). Good thresholds may be obtained from training datasets. However, it is impractical for the training datasets to include all types of ground measurements in a study area (Zhang *et al.*, 2003). Slope-based filters work well in fairly flat terrain, but become more difficult as the slope of the terrain increases (Sithole and Vosselman, 2004), especially in a steep forested landscape. To overcome this limitation, Sithole (2001) proposed a modified approach in which the threshold varies with the slope of the terrain. It was demonstrated that modified method improved filtering results, especially in steep terrain area.

3 Morphological filter

Morphological filter for LiDAR data processing is based on the idea of mathematical morphology (Kilian *et al.*, 1996; Lohmann *et al.*, 2000), which has been used to identify objects in a greyscale image by using morphological operations such as opening and closing (Harlick and Shapiro, 1992). The elevations of non-terrain objects such as trees and buildings are usually higher than those of surrounding ground points. If LiDAR points are converted to a greyscale image in terms of elevation, the non-terrain objects can be identified by the difference of grey tone (Zhang *et al.*, 2003). A point with the lowest elevation within a given window size is first detected by performing an opening operation on the LiDAR data. The points in this window that fall within a band above the lowest elevation are then selected as ground points. The determination of band width is dependent on the accuracy of the LiDAR data, which is normally 20 to 30 cm. All LiDAR points are filtered by moving the filtering window over the entire LiDAR covered area (Zhang *et al.*, 2003). It is critical to select an optimal window size for using this morphological filter (Kilian *et al.*, 1996). If a small window size is used, only small non-ground objects such as trees and cars can be effectively removed, but the points corresponding to the tops of large building complexes in urban areas can not be removed. On the other hand, the filter will treat some ground points as non-ground points if using a large window size (Zhang *et al.*, 2003). To solve this problem, Kilian *et al.*, (1996) applied the operations several times with different window sizes to the LiDAR data starting with the smallest size. Each point was then assigned a weight related to the window size if it is classified as a ground point. The larger the window size of an operation is, the higher the weight of a point. Points which are likely on ground have high weights while non-ground points have low weights. Finally, the terrain surface is estimated by using all the LiDAR points with assigned weights (Kilian *et al.*, 1996).

Zhang *et al.*, (2003) described a progressive morphological filter to remove non-ground points while preserving ground points by gradually increasing the window size and using elevation difference thresholds. An initial filtered surface is derived by applying an opening operation with a window size to the raw LiDAR data. An opening operation is then performed on the initial surface to derive a second surface. The elevation difference of a cell between surfaces is compared to a threshold to determine if the point in this cell is non-ground point. In the next iteration, the window size is increased, and another opening operation is applied to the filtered surface. These steps are repeated until the size of the filtering window is larger than the pre-defined largest size of non-ground objects. The threshold is determined by the elevation difference and terrain slope (Zhang and Whitman, 2005). Zakšek and Pfeifer (2006) proposed an improved morphological filter by incorporating trend surfaces extracted from raw LiDAR data to the morphological operation to improve the filtering results in steep forested area. Chen *et al.*, (2007) presented a method that is similar to (Zhang *et al.*, 2003)'s method, but does not require the assumption of a constant slope. The method is based on the assumption that non-ground objects such as buildings usually have abrupt elevation changes along boundaries while the change of natural terrain elevation is gradual and continuous.

4 Other filters and future development

All the above described filters are based on such measures as height difference and slope. As local properties are scale-dependent, it is necessary to integrated measurements at different scale. Silván-Cárdenas and Wang (2006) proposed a multi-scale Hermite transform method, employing the scale-space theory to represent the grided elevation values in the filtering LiDAR data. A scale component was also added to the method presented by Evans and Hudak (2007), called to as multiscale curvature algorithm. This method is base on curvature filter (Haugerud and Harding, 2001), but iteratively classifies LiDAR data as ground and non-ground points at multiple scales.

For segmentation-based filters, raw LiDAR data are first interpolated to grid image, and then segmentation is performed by aggregation of pixels in connected sets by region growing algorithm. Segmentation approaches vary with the measurements of the similarity between regions (Rabbania *et al.*, 2006). Height difference is the commonly used measurement. Segmented regions are separated by a step edge from the adjacent ones. Finally, the classification is conducted based on the geometric characteristic of each region and their topological relationships (Nardinocchi *et al.*, 2003). Other research work on segmentation-based filter can be found in (Jacobsen and Lohmann, 2003; Sithole, 2005; Sithole and Vosselman, 2005; Tóvári and Pfeifer, 2005).

A wavelet-based filter was proposed by Vu and Tokunaga (2001). In this method, K-mean clustering method was applied to grided LiDAR data to label pixels to ground and non-ground. Multi-resolution clustering was further used with the wavelet-based method to improve the filtering results. For other studies regarding wavelet-based filter for LiDAR data, readers are referred to Amgaa (2003), and Bartels and Wei (2006).

New filtering methods continue to be proposed and published in some journals at time of writing of this paper. For example, Kobler *et al.* (2007) proposed a repetitive interpolation method, attempting to filter LiDAR data for terrain modelling in steep forested area. Zheng *et al* (2007) described a facet-based filtering method which is based on the zero, second, and third orders of orthogonal polynomials, using the simple, quadratic, and cubic faced models to approximate ground surface. Forlani and Nardinocchi (2007) presented a three stage LiDAR data classification algorithm. It includes the steps of interpolation of LiDAR data to a gird image, segmentation from region growing based on geometric characteristics and topological relationships, and approximation of the terrain surface and point filtering by examining the distance from the surface.

To assess the performance of various filters developed, the ISPRS (International Society of Photogrammetry and Remote Sensing) Working Group III/3 "3D Reconstruction from Airborne Laser Scanner and InSAR Data" initiated a study in 2002 for experimental comparison of the strength and weaknesses of the different filtering approaches. The primary aim of the study was to: (1) determine the comparative performance of existing filters; (2) determine the sensitivity of filtering algorithms under varying point densities; and (3) identify future research issues in the filtering of point clouds (Sithole and Vosselman, 2004). It has been found that most filters performed well in landscape of low complexity. However, complex landscapes, especially in the urban areas still pose big challenges for future researches for effective LiDAR data filter development (Sithole and Vosselman, 2003).

Most of filtering algorithms developed so far require the raw LiDAR data to be interpolated into grid images first. Filtering on grid image runs faster. Existing raster image classification and feature extraction methods can be used for filtering operation. However, interpolation of the raw LiDAR data to an image causes a significant loss of information and introduces errors to the results. When elevation values are interpolated between ground points and non-ground points, the elevation differences in the interpolated data will be reduced. This will cause difficulty to correctly identify and remove non-ground points (Vosselman, 2000). Therefore, the filtering algorithm should work on raw LiDAR point data instead of interpolated grid image (Sithole and Vosselman, 2005; Zhang and Cui, 2007).

Currently, all the filtering algorithms are dependent only on geometric characteristics of LiDAR point data. There is increasing awareness of using additional information such as intensity and derivatives from full-waveform in order to increase the accuracy and reliability in the filtering process (Lohmann *et al.*, 2000; Mandlburger *et al.*, 2007). Vosselman (2002) suggested using the intensity of the laser beam response in order to estimate and improve the position of the edge in between areas with different reflectance properties. Doneus and Briese (2006b) used full-waveform information to eliminate echoes with a significantly higher echo width which are correspondent to non-ground points. Mandlburger *et al.* (2007) used echo width to determine weights for LiDAR points in the interpolation-based filtering process.

IV Model, interpolation and resolution for DEM generation

1 Model selection

Different digital elevation models have been developed to represent the terrain surface. The regular grid (usually square grid) digital elevation model (DEM), the triangular irregular network (TIN), and the contour line model are the most commonly used digital elevation models (Ramirez, 2006). The grid DEM uses a matrix structure that implicitly record topological relations between data points (El-Sheimy *et al.*, 2005). Each grid cell has a constant elevation value for the whole cell (Ramirez, 2006). This constant elevation value is usually obtained by interpolation between adjacent sample points. Of the three digital elevation models, the grid DEM is the simplest and the most efficient approach in terms of storage and manipulation since this data structure is similar to the array storage structure in computer (El-Sheimy *et al.*, 2005; Ramirez, 2006; Ziadat, 2007). However, this approach is liable to introduce errors because of its discontinuous representation of the terrain surface. It is evident that the bigger the grid size, the more general the approximation of the terrain surface representation (Ramirez, 2006). LiDAR data have high density, and will overcome this kind of limitation of grid DEM. Furthermore, large volume of LiDAR data needs such a model for efficient storage and manipulation. Therefore, almost all the LiDAR-derived DEMs have been generated using grids (Lohr, 1998; Wack and Wimmer, 2002; Lloyd and Atkinson, 2006; Liu *et al.*, 2007b). Kraus and Otepka (2005) showed the benefits of using a hybrid model for digital terrain modelling. This approach employed TIN model for complex geomorphologic areas and grid model for simple areas.

2 DEM interpolation method

Interpolation is an approximation procedure in mathematics and an estimation issue in statistics (Li *et al.*, 2005). It is the process of predicting the values of a certain variable of interest of unsampled locations based on measured values at points within the area of interest (Burrough and McDonnell, 1998). Interpolation in digital terrain modelling is used to determine the terrain height value of a point by using the known heights of neighbouring points. Two implicit assumptions here are: the terrain surface is continuous and smooth; and there is a high correlation between the neighbouring data points. Interpolation is one of the core techniques in digital terrain modelling (Li *et al.*, 2005).

Interpolation methods available for constructing a DEM from sample elevation points can be classified into: deterministic methods such as inverse distance weighted (IDW) (assumes that each input point has a local influence that diminishes with distance) and spline-based methods that fit a minimum-curvature surface through the sample points; and geostatistical methods such as Kriging that takes into account both the distance and the degree of autocorrelation (the statistical relationship among the sample points). Deterministic methods create surfaces from sample points but do not take into account a model of the spatial processes within the data (Anderson *et al.*, 2005a). Geostatistical methods utilize the spatial correlation properties to the sample data (Anderson *et al.*, 2005a).

IDW assumes the closer a sample point is to the prediction location, the more influence it has on the predicted value. It estimates a point value using a linear-weighted combination set of sample points. The weights assigned depend only on the distances between the data locations and the particular location to be estimated, but the relative locations between sampling data are not considered (Myers, 1994). Points closer to the predicted location exert bigger weights than those farther away (Anderson *et al.*, 2005a). The IDW works well for dense and evenly-distributed sample points (Childs, 2004). However, if the sample points are sparse or uneven, the results may not sufficiently represent the desired surface. Moreover, because the IDW is a weighted average method, it can not make estimates that are outside the range of minimum and maximum sample point values. As a result, some important topographical features such as ridges and valleys can not be generated unless they have been adequately sampled (Lee, 2004).

Spline interpolation method estimates values using a mathematical function that minimizes overall surface curvature. This results in a smooth surface that passes exactly through the sample points (Podobnikar, 2005). It is like bending a sheet of ruber so that it passes through all the sample points while minimizing the total curvature of the surface (Childs, 2004). Unlike the IDW method, the spline method can estimate values that are below the minimum or above the maximum values in the sample data. This makes the spine method good for predicting ridges and valleys where they are not included in the sample data (Childs, 2004).

Kriging were originally developed to estimate the spatial concentrations of minerals for the mining industry, and now has been widely used in geography and spatial data analysis (Lee, 2004; Tang, 2005). Kriging assumes that the distance or direction between sample points reflects a spatial correlation that can be used to explain variation in the surface (Childs, 2004). Kriging takes into account both the distance and the degree of variation between sampling data. The extent to which this assumption is true can be examined in computed variogram (Chaplot *et al.*, 2006). Kriging is essentially a weighted average technique, but its weights depend not only on the distances between sample points and estimation locations but also on the mutual distances among sample points (Cressie, 1993; Desmet, 1997; Anderson *et al.*, 2005a).

The variety of available interpolation methods has led to questions about which is most appropriate in different contexts and has stimulated several comparative studies of relative accuracy (Zimmerman *et al.*, 1999). To evaluate the performance of some commonly-used interpolation methods, a variety of empirical work has been conducted to assess the effects of different methods of interpolation on DEM accuracy (Zimmerman *et al.*, 1999; Ali, 2004; Blaschke *et al.*, 2004; Mardikis *et al.*, 2005; Chaplot *et al.*, 2006; Kyriakidis and Goodchild, 2006; Lloyd and Atkinson, 2006). There seems to be no single interpolation method that is the most accurate for the interpolation of terrain data (Fisher and Tate, 2006). None of the interpolation methods is universal for all kinds of data sources, terrain patterns, or purposes. Zimmerman *et al*. (1999) showed that kriging yielded better estimations of elevation than IDW did, especially when sampling points become sparse (Lloyd and Atkinson, 2006). The result is probably due to the ability of kriging to take into account the spatial structure of data (Chaplot *et al.*, 2006). However, If the sampling density is high, there is no significant differences between IDW and kriging methods (Chaplot *et al.*, 2006). Furthermore, Ali (2004), Blaschke (2004) and Podobnikar (2005) pointed out that the IDW method performs well if sampling data density is high, even for complex terrain. LiDAR data have high sampling density, and so the IDW approach is a suitable interpolator for DEM generation from LiDAR data (Liu *et al.*, 2007b). Spline-based methods are easy to use and produce smooth surface (Podobnikar, 2005; Smith *et al.*, 2005) but with less recognisable characteristic features like peaks, ridges and valleys (Podobnikar, 2005). New or modified interpolation methods are still being developed, attempting to improve the interpolation of terrain surface (Almansa *et al.*, 2002; Shi and Tian, 2006).

3 DEM resolution

Resolution initially refers to the level of detail or smallest object that can be recognized on an aerial photograph (Way, 1978). For a grid DEM, it refers to the grid size of the DEM, expressed as ground distance. The smaller the grid size the higher the resolution, representing terrain surface in more detail. Determination of a DEM grid size is the central problem for DEM generation and spatial analysis. The general idea is get an adequate description of terrain surface with a minimum amount of DEM data or with grid size as big as possible while still meeting a defined accuracy to serve the specific purpose (Gao, 1997). A very high resolution DEM may result in representation of a terrain surface that is much more detailed than is relevant for the process being modelled (Ziadat, 2007), imposing unnecessary computation burden. The optimal grid size for a DEM is therefore a compromise between the accuracy of terrain representation and cost effectiveness (Hengl *et al.*, 2003). An appropriate grid size is dependent on source data density (McCullagh, 1988; Hu, 2003), terrain complexity (Gao, 1997; Chou *et al.*, 1999; Hengl *et al.*, 2003; Hengl, 2006), and applications (Barber and Shortrudge, 2004; Kienzle, 2004; Ziadat, 2007).

It is inappropriate to generate a high resolution DEM with very sparse terrain data: any surface so generated is more likely to represent the shape of the specific interpolator used than that of the target terrain because interpolation artefacts will abound (Florinsky, 2002; Albani *et al.*, 2004). The source data density constrains the resolution of DEM (Florinsky, 1998). On the other hand, generating of a low resolution DEM from high density terrain data will devalue the accuracy of the original data.

Clearly, the choice of the adequate resolution of a DEM is constrained by terrain input data density. McCullagh (1988) suggested that the number of grids should be roughly equivalent to the number of terrain data points in covered area. The grid size of a DEM can be estimated by:

$$S = \sqrt{\frac{A}{n}}$$

where n is the number of terrain points and A is the covered area (Hu, 2003). This means that the DEM resolution should match the sampling density of the original terrain points.

The optimized grid size for a DEM is the one that reflects the variability of the terrain surface and is able to represent the majority of terrain features (Kienzle, 2004; Hengl, 2006). If terrain is treated as a signal, its frequency can be determined by the density of inflection points. Hengl (2006) gave an idea of determining the grid size based on the terrain complexity that the grid size should be at least half the average spacing between the inflection points:

$$S = \frac{L}{2 \cdot N_p}$$

where L is the length of a transect and N_p is the number of inflection points observed. For example, if there are 20 inflection points and average spacing between them is 0.8m, a grid resolution of at least 0.4m is recommended.

Selection of a suitable resolution for a DEM is also highly dependent on different applications. High resolution DEMs may significantly improve the predictive ability of terrain attributes (Lassueur *et al.*, 2006). However, the choice of input DEM data resolution for terrain based environmental modelling depends on the output of interest (Chaubey *et al.*, 2005). The general idea is to select a resolution that produces best predictive properties. Many researches have investigated the effects of different resolutions on the accuracy of specific application models (Hengl, 2006). Instead of analysing elevation differences data directly, terrain attributes and hydrological or other environmental parameters derived from different resolution DEMs are compared for selecting a suitable resolution for the DEM that corresponds to the content of the source data (Kienzle, 2004). The relevant researches can be seen in (Garbrech and Martz, 1994; Zhang and Montgomery, 1994; Florinsky and Kuryakova, 2000; Kienzle, 2004).

The grid DEM is commonly over-sampled in low relief areas and under-sampled in high relief areas (Hengl *et al.*, 2003). Furthermore, the size of regular grids can not be adapted to the complexity of the relief. Feature specific points such as peaks and pits may be missed (El-Sheimy *et al.*, 2005), and linear features such as breaklines are not well represented. One way to increase the details of the terrain representation is to increase the sample point density and decrease the grid size. This will lead to the redundancy of sample point and the increase of data size.

V LiDAR data reduction

1 Why LiDAR data reduction

The primary objective of data reduction is to achieve an optimum balance between density of sampling and volume of data, hence optimizing cost of data collection (Robinson, 1994). Under optimal interpolation, very detailed high resolution DEMs with high accuracy can be generated from high density LiDAR data. However, because there is no scope to match data acquisition density by terrain type during a LiDAR data collection mission, some oversampling is usually inevitable. As a result, the data storage requirement and processing times will be higher than otherwise. Strategies for handling the large volumes of terrain data without sacrificing accuracy are required (Kidner and Smith, 2003) if efficiency is to be considered (Bjørke and Nilsen, 2002; Pradhan *et al.*, 2005). Via data reduction (i.e. ratio of the information content to the volume of the dataset) (Chou *et al.*, 1999), a more manageably and operationally sized terrain dataset for DEM generation is possible (Anderson *et al.*, 2005a).

Some studies on terrain data reduction have been conducted based on the analysis of the effects of data reduction on the accuracy of DEMs and derived terrain attributes.

For example, Anderson *et al.* (2005b) evaluated the effects of LiDAR data density on DEM production at a range of resolutions. They produced a series of DEMs at different horizontal resolutions along a LiDAR point density gradient, and then compared each DEM produced with different LiDAR data density at a given horizontal resolution, to a reference DEM produced from the original LiDAR data (the highest available density). Their results show that higher resolution DEMs are more sensitive to data density than lower resolution DEMs. It was demonstrated that LiDAR datasets could withstand substantial data reductions yet maintain adequate accuracy for elevation predictions (Anderson *et al.*, 2005a). Liu *et al.* (2007a) examined the relationship between data density, data file size, and processing time.

It has been demonstrated that the effects of data density and DEM resolution on the accuracy of DEM and derived terrain attributes are related to terrain complexity (Chou *et al.*, 1999; Kyriakidis and Goodchild, 2006). Different complex terrains require different data density and resolution to produce DEMs to represent terrain surfaces at a certain accuracy level. Furthermore, different data elements contribute differently to the accuracy of produced DEM. The inclusion of critical terrain elements such as breaklines into the construction of a DEM will decrease the number of data points while still maintaining high level of accuracy (Hsia and Newton, 1999). Therefore, Data reduction should be conducted in such a way that critical elements are kept while less important elements are removed (Chou *et al.*, 1999).

2 Breakline extraction

Breaklines (or called as structure lines or skeleton lines), such as ridge lines and valley lines, are important terrain features as they describe changes in terrain surface (Lichtenstein and Doytsher, 2004). Breaklines not only provide the elevation information, but also implicitly represent terrain information about their surroundings. They describe terrain surface with more significant information than other points (Li *et al.*, 2005). Their preservation and integration in the generation of DEM significantly contribute to obtaining a reliable, morphological correct, and hydrologically enhanced DEM (Brügelmann, 2000; Lichtenstein and Doytsher, 2004). Moreover, breaklines play an important role in the process of data reduction of the DEM (Briese, 2004a). With breaklines involved in the creation of DEMs, the number of points needed to represent the terrain can then be reduced (Little and Shi, 2001).

Traditionally, breaklines were derived either by manually digitizing existing maps (Briese, 2004a) or by photogrammetric processing (Brügelmann, 2000). Both approaches are time consuming. Given the high density characteristic of LiDAR data, much attention has been paid to the direct derivation of breaklines from LiDAR data. Developed methods work either on irregular LiDAR points or on LiDAR-derived range image - raster representation of the surface (Briese, 2004a). As breaklines are discontinuities in the terrain surface, Weidner (1994) proposed an algorithm for parameter free information-preserving surface restoration. The signal and noise properties of data are extracted simultaneously by applying variance component estimation and are used to filter data. This way, discontinuities in the data are preserved. A similar method was used by Wild *et al.* (1996) for the automatic DEM generation and breakline detection. The method proposed by Gomes Pereira and Wicherson (1999) calculated first derivatives from digital surface. Cells are then labeled as slope cells where the slope changes abruptly. Breaklines are connections of border cells between slope and flat areas (Brügelmann, 2000). Gomes Pereira and Janssen (1999) applied the Laplacian operator to LiDAR range image for breakline detection. Förstner (1998) used the principle of edge detection in intensity images to extract breaklines by means of hypothesis testing. Based on Förstner's method, Brügelmann (2000) presented a procedure by using second derivatives and hypothesis test after performing a smoothing operation on range image.

All the above approaches work on grid image derived from LiDAR elevation data rather than on LiDAR point clouds. This implies a decrease of accuracy due to the necessary interpolation process (Brzank *et al.*, 2005). An approach to 3D breakline extraction directly from LiDAR points was presented by Kraus and Pfeifer (2001) and Briese (Briese, 2004a). This method estimates the 3D position of a breakline through the intersection line of continuously overlapping surface patch pairs along the breakline (Briese, 2004b). The construction of surfaces requires the appropriate position of searched breakline (Brzank *et al.*, 2005). 3D breakline growing (Briese, 2004a) and edge detection (Brzank *et al.*, 2005) approaches were proposed to obtain this approximation.

Valley lines connecting the deepest points of valleys and ridge lines connecting the highest points of ridges are the typical breaklines, and are of essential importance for the description of terrain surfaces (Aumann *et al.*, 1991; Gülgen and Gökgöz, 2004). Since a stream occurs along the bottom of a valley (Underwood and Crystal, 2002), the determination of streams in a DEM provides a good way to detect valley lines (Dorninger *et al.*, 2004). Most approaches to extracting drainage networks from DEM employed the well-known water flow accumulation model. This method, designated D8 algorithm (eight flow directions), was introduced by O'Callaghan and Mark (1984) and has been widely used. Ridge lines can also be detected this way by inverting a DEM (Dorninger *et al.*, 2004).

3 Integration of breaklines to the generation of DEM

A number of algorithms have been developed for integrating breaklines to the generation of a DEM. They can be classified to two groups. The first is based on TIN model, in which breaklines are integrated into triangulated network and are physically preserved (Lichtenstein and Doytsher, 2004). The second is applied to grid DEMs and based on the ideal of constructing hydrologically correct DEMs. Examples include stream burning and surface reconditioning (e.g. *Agree* or *ANUDEM*). Stream burning was developed to improve the replication of stream positions by modifying the elevation value of stream cells within a DEM to trench known hydrological patterns into a DEM at a user specified depth (Callow *et al.*, 2007). The Agree method, developed by Hellweger (1997), is a DEM reconditioning process, modifying elevation values within DEMs by imposing breaklines such as ridge or stream lines to DEMs. The modifications work on both breakline cells and the surrounding cells within a user defined horizontal buffer distance (Callow *et al.*, 2007). The *ANUDEM* method can alter the entire DEM via an iterative drainage enforcement algorithm to eliminate abrupt jumps between the stream and non stream cell (Hutchinson, 1996; Callow *et al.*, 2007). The drainage enforcement algorithm is one of the principal innovations of ANUDEM. It ensures good shape and drainage structure in the calculated DEMs by imposing a drainage enforcement condition on the fitted grid values directly from input streamline data (Hutchinson, 2006).

VI Conclusion

Advances in airborne LiDAR systems make it possible to acquire high quality terrain data in terms of accuracy and density. Using LiDAR data for DEM generation is becoming a standard practice in spatial related areas. Separating LiDAR points into ground and non-ground is the most critical and difficult step for DEM generation from LiDAR data. Although different filtering algorithms have been developed, further efforts are needed to improve the filtering results. Almost all the algorithms are dependent only on geometric characteristics of LiDAR point data. Using additional information such as intensity and derivatives from full-waveform has a potential for increasing the accuracy and reliability in the filtering process. Although DEM generation from LiDAR data has been documented in several papers, due to the specific characteristics of LiDAR data, extensive attention should be paid to issues such as choices of modelling methods, interpolation algorithms, and DEM resolution. For high density LiDAR data, IDW is a suitable interpolator. The optimized DEM resolution must match the density of LiDAR data, and be able to reflect the variability of the terrain surface and represent the majority of terrain features. Furthermore, in order to reduce the data redundancy and increase the efficiency in terms of storage and manipulation, LiDAR data reduction is required in the process of DEM generation. Different data elements have different effects to the DEM accuracy.

Therefore, data reduction should be conducted in such a way that critical elements are kept while less important elements are removed. Extraction and inclusion of critical terrain elements such as breaklines into the generation of a DEM will decrease the number of data points while still maintaining high level of accuracy.

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