LIDAR DATA REDUCTION FOR EFFICIENT AND HIGH QUALITY DEM GENERATION

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ABSTRACT:

Airborne Light Detection and Ranging (LiDAR) - also referred to as Airborne Laser Scanning (ALS), provides means for high density and high accuracy topographic data acquisition. LiDAR data have become a major source of digital terrain data and have been used in a wide of areas, such as building extraction and 3D urban modelling, hydrological modelling, glacier monitoring, landform or soil classification, river bank or coastal management, and forest management. However, terrain modelling has been the primary focus of most LiDAR collection missions. The use of LiDAR for terrain data collection is becoming a standard practice in spatial science community. 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 were developed. LiDAR data accuracy and density are such that reliable and high accuracy, high resolution DEM generation can be confidently contemplated. However, high density data lead to a significant increase in the data volume, imposing challenges with respect to data storage, processing and manipulation. Strategies for handling the large volume of terrain data without sacrificing accuracy are required. Through informed reduction in data (i.e. ration of the information content to the volume of the dataset), a more manageable and operationally sized terrain dataset for DEM generation is possible. This study aims to generate an efficient and high quality DEM using LiDAR data in a catchment region in Australia. It explored the effects of LiDAR data density on the accuracy of DEMs and examined to what extent a set of LiDAR data can be reduced yet still maintain adequate accuracy for DEM generation. LiDAR data reduction mitigates the data redundancy and improves data processing efficiency in terms of both storage and processing time.

1. INTRODUCTION

Airborne Light Detection and Ranging (LiDAR) - also referred to as Airborne Laser Scanning (ALS), provides means for high density and high accuracy topographic 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 have been used in a wide of areas, such as building extraction and 3D urban modelling, hydrological modelling, glacier monitoring, landform or soil classification, river bank or coastal management, and forest management. However, terrain modelling has been the primary focus of most LiDAR collection missions (Hodgson *et al.*, 2005). 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 spatial science community (Hodgson and Bresnahan, 2004). 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 were developed (Sithole and Vosselman, 2003). 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 kHz in 2001 to 250 kHz (Lemmens, 2007). LiDAR data accuracy and density are such that reliable and high accuracy, high resolution DEM generation can be confidently contemplated. However, high density data lead to a significant increase in the data volume, imposing challenges with respect to data storage, processing and manipulation.

Generally speaking, the denser the sampled terrain data are, the more accurate the derived DEM will be. However, because there is no scope to match data acquisition density by terrain type during a LiDAR data collection mission, some over-sampling is usually inevitable. As a result, the data storage requirement and processing times will be higher than necessary (Liu *et al.*, 2007a). Strategies for handling the large volume of terrain data without sacrificing accuracy are required. Through informed reduction in data (i.e. ration of the information content to the volume of the dataset), a more manageable and operationally sized terrain dataset for DEM generation is possible. The primary objective of data reduction is to achieve an optimum balance between density of sampling and volume of data, hence achieving a accurate and efficient DEM.

Some studies on terrain data reduction have been conducted based on the analysis of the effects of data reduction on the

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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). It was demonstrated that LiDAR datasets could withstand substantial data reductions yet maintain adequate accuracy for elevation predictions (Anderson *et al.*, 2005a).

Given that different data elements contribute differently to the accuracy of produced DEM, data reduction should be conducted in such a way that critical elements are kept while less important elements are removed (Chou *et al.*, 1999). This study aims to generate an efficient and high quality DEM using LiDAR data in a catchment management region, Australia. It explored the effects of LiDAR data density on the accuracy of DEMs and examined to what extent a set of LiDAR data can be reduced yet still maintain adequate accuracy for DEM generation. LiDAR data reduction mitigates the data redundancy and improves data processing efficiency in terms of both storage and processing time.

2. MATERIALS AND METHODS

2.1 Study Area

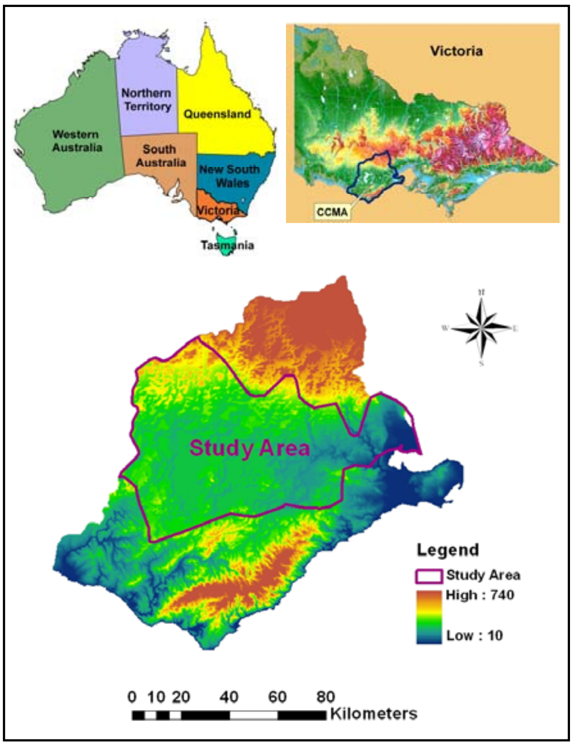

Figure 1. Study area

The study area is in the region of Corangamite Catchment Management Authority (CCMA) in south western Victoria, Australia. The CCMA was established in 1997 by the Victorian Government to ensure the protection and sustainable development of land, vegetation and water resources within a boundary stretching from Geelong to Ballarat and along the coast to Peterborough. The Corangamite region comprises 13,340 square kilometres and is home to a population of 333,000 people. The region as a whole is defined by the aggregation of its four river basins, plus the sea to three nautical miles off the shoreline. Agriculture dominates Corangamite's land use pattern, principally dairy and wool production. Other land use includes forestry, mining, manufacturing, urban expansion and tourism. The landscape in the region can be depicted to north and south highlands and a large Victoria Volcanic Plain (VVP) in the middle. The VVP is an extensive basaltic plain with numerous volcanic cones and eruption points. The VVP is dominated by Cainozoic volcanic deposits. It is characterized by vast open areas of grasslands, small patches of open woodland, stony rises denoting old lava flows, numerous volcanic cones and old eruption, and is dotted with shallow lakes both salt and freshwater. Terrain types vary between the comparatively treeless basins of internal drainage on Victoria Volcanic Plains (VVP) to dissected terrains north and south. The plains have high priority for a range of research and development projects pertaining to resource and environment management issues addressed in the catchment management strategy plan. In this study, LiDAR data cover an area of 6900 km², shown in Figure 1.

2.2 Data

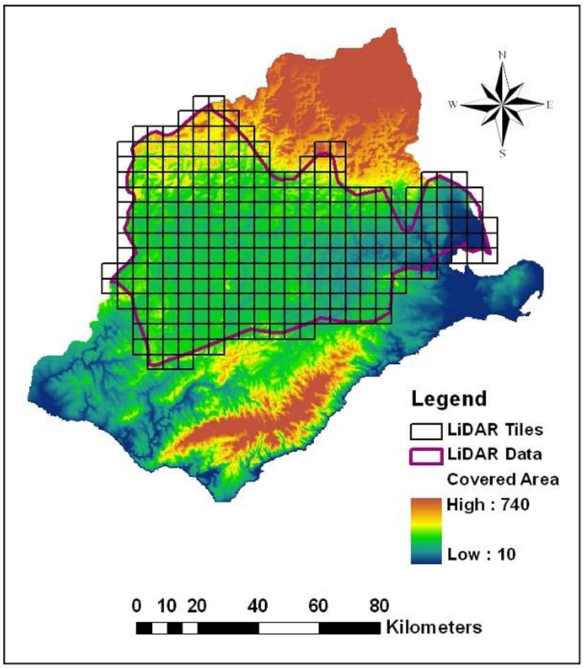

Figure 2. LiDAR data tiles and covered area

LiDAR data, covering most part of VVP in the CCMA region, were collected over the period of 19 July 2003 to 10 August 2003. The primary purpose of this LiDAR data collection was to facilitate more accurate terrain pattern representation for the implementation of a serious of environment related projects. The LiDAR data were delivered by AAMHatch Pty Ltd as tiles in ASCII files containing x, y, z coordinates and intensity values. The data have been classified into terrain and non-terrain points by using data filter algorithms across the project area. Manual checking and editing of the data led to further improvement in the quality of the classification. The resulting data products used for DEM generation are irregularly distributed ground 3D points, with an average spacing of 2.2 m. The accuracy of LiDAR data was estimated as 0.5 m vertically and 1.5 m horizontally (AAMHatch, 2003). The LiDAR data were delivered as tiles (5 km by 5 km) in ASCII files. Total number of 277 LiDAR tiles and covered area are illustrated in Figure 2.

2.3 Methods

Compared with the triangular irregular network (TIN), the grid DEM is simpler and more efficient approach in terms of storage and manipulation (El-Sheimy *et al.*, 2005). It is worth noting that the grid DEM 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. Kraus and Otepka (2005) showed the benefits of using a hybrid model for digital terrain modelling, which employed the TIN model for complex geomorphologic areas and grid model for simple terrain areas. However, this approach increases the model complexity. In practice, almost all the LiDAR-derived DEMs have been generated using grid model (Lohr, 1998; Wack and Wimmer, 2002; Lloyd and Atkinson, 2006; Liu *et al.*, 2007b). Therefore, the grid DEM was selected in this study for LiDAR DEM generation.

There many interpolation methods available for constructing a DEM from sample elevation points. 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). 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). It has been demonstrated that IDW (inverse distance weighted) method performs well if sampling data density is high (Ali, 2004; Blaschke *et al.*, 2004; Podobnikar, 2005). 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).

The choice of the adequate resolution of a DEM is constrained by terrain input data density. 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 a low resolution DEM from high density terrain data will devalue the accuracy of the original data. McCullagh (1988) suggested that the number of grid cells should be roughly equivalent to the number of terrain data points in covered area. In this study, the DEM with 2 m resolution was generated.

The high accuracy three dimensional terrain points prerequisite to very detailed high resolution DEMs generation offers exciting prospects to DEM builders. However, as mentioned before, because there is no sampling density selection for different area during a LiDAR data collection mission, some terrains may be over-sampled, thereby imposing increases in data storage requirements and processing time. Improved efficiency in these terms can accrue if redundant data can be identified and eliminated from the input data set. With a reduction in data, a more manageable and operationally sized terrain dataset for DEM generation is possible

A 113 km² sub-catchment area covered by LiDAR data was selected as the test site in order to explore the effects of LiDAR data density on the accuracy of DEMs and examined to what extent a set of LiDAR data can be reduced for improving storage and processing efficiency. Using the Geostatistical Analyst extension of ArcGIS 9.2, LiDAR data points were first randomly selected and separated to two datasets: 90% for training data and 10% for check points. Training datasets were used for subsequent reduction to produce a series of datasets with different data density, representing the 100%, 75%, 50%, 25%, 10%, 5%, 1% of the original training dataset. Reduced datasets were used to produce a series of DEMs.

This approach is similar to the method used by Anderson *et al.* (2005a) in that training dataset was used to produce a series of datasets representing a selected percentage of the training datasets, but here in our approach, 90% of the original LiDAR datasets were randomly selected for training data. The reason for separating training data as 90% and test data as 10% of the original dataset is to ensure the high density of the training dataset and provision of enough test dataset check points. In this case, the average density of training data is about 2.4 m (space interval), nearly same as the original dataset. In the test dataset, a total of 465,136 points can be used as check points to assess the accuracy of each of the range of DEMs produced (Liu *et al.*, 2007a). Independent elevation checking is conducted to assess the accuracy of DEMs generated from reduced LiDAR datasets. Elevation values of test data were compared with correspondent elevation values interpolated from the DEM were calculated for each generated DEM. Root mean squire errors (RMSEs) and standard deviation for each DEM were calculated to evaluate the overall accuracy of the DEM.

3. RESULTS

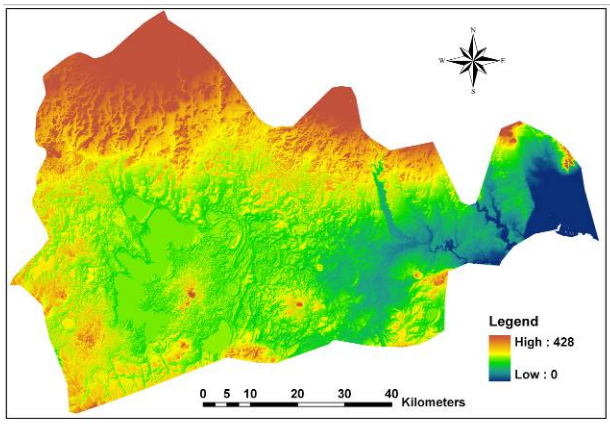

Figure 3. LiDAR-derived DEM in CCMA

With LiDAR data, a high-accuracy and high-resolution DEM, which covers an area of 6900 km² in the CCMA region was generated, shown in Figure 3. LiDAR-derived DEM has advantages over DEMs generated with traditional methods in terms of resolution and accuracy. In the past, a commonly used DEM in catchment management areas in Victoria, Australia, is *Vicmap Elevation*, a state wide 20 m resolution DEM. *Vicmap DEM* was produced using elevation data mainly derived from existing 1:25,000 contour maps and digital stereo capture. Estimated standard deviations are 5 and 10 m for vertical and horizontal accuracy respectively (DSE, 2002). Compared with *Vicmap DEM*, LiDAR-derived DEM has a significant improvement in both resolution and accuracy.

Data density reduction test shows that compared with the DEM produced from the total LiDAR training dataset, there is no significant decrease in accuracy for the DEM generated from the 50% training dataset. This can be seen from Figure 4 in terms of both RMSE (root mean square errors) and standard deviation. Processing time for generating the DEM is only the half of the time needed for generating the DEM using the total LiDAR training dataset (Liu *et al.*, 2007a). Therefore, for the test area and our used LiDAR dataset, the "efficient dataset" is the one with 50% of the original data density.

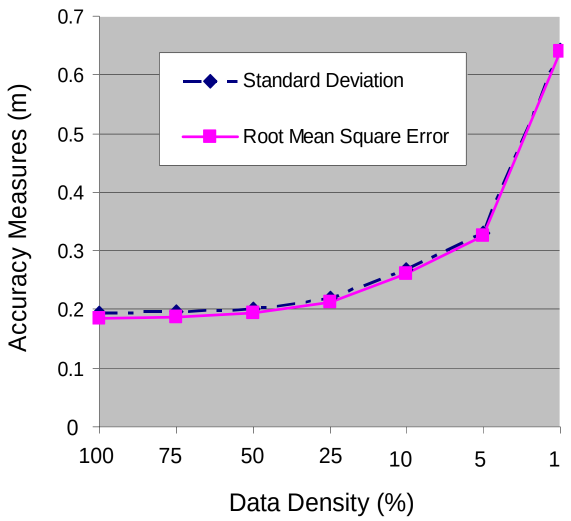

Figure 4. Data reduction and DEM accuracy

It is demonstrated that LiDAR dataset (density) reduction can increase the efficiency of DEM generation in terms of file size and processing time (Liu *et al.*, 2007a). However, to what extent a dataset can be reduced depends on the original data density, terrain characteristics, interpolation method for DEM generation, and target DEM resolution (grid size). In this study, the effects of LiDAR data reduction on the accuracy of DEM were evaluated for a terrain with a moderate complex relief attributes. Further comparison with different interpolation methods and DEM resolution needs to be implemented if comprehensive guidelines are to be assembled.

4. DISCUSSION AND FUTURE WORK

It should be noted that because not all data elements contribute optimally to the accuracy of produced DEM, the identification of feature-specific points (representing terrain features with more significant information content than other points) is important and should be kept in data volume reduction. Therefore, data reduction should be conducted in such a way that critical elements (feature specific elements) are kept while less important elements are removed (Chou *et al.*, 1999).

Of all the feature specific elements in DEM construction, breaklines (or known as structure lines or skeleton lines), such as ridge lines and valley lines, are the most important terrain features because 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, 2004b). 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).

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 valley lines connect the deepest points of valleys and ridge lines connect the highest points of ridges, they 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).

Once the breaklines are detected, they can be integrated to the generation of DEMs by using one of the two groups of methods. 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*) (Hutchinson, 1996; Hellweger, 1997; Hutchinson, 2006; Callow *et al.*, 2007). It is expected that the inclusion of breaklines into the generation of a DEM will decrease the number of data points while still maintaining high level of accuracy (Liu, 2008).

5. CONCLUSION

Airborne LiDAR is one of the most effective and reliable means of terrain data collection. The use LiDAR data for DEM generation is becoming a standard practice in spatial science community (Hodgson and Bresnahan, 2004). LiDAR-derived high quality DEM in the region of Corangamite Catchment Management Authority offers much more detailed description than previously used *Vicmap DEM*. It provides a reliable spatial data infrastructure to benefit a wide range of resource and environmental management in the region. It also provides a successful example of using LiDAR for high quality DEM generation at a catchment scale in Australia.

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 (Liu, 2008). 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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