EXTRACTING SURFACE FEATURES OF THE NUECES RIVER DELTA USING LIDAR POINTS

Lihong Su, Post-Doctoral Research Associate
James Gibeaut, Associate Research Professor
Harte Research Institute for Gulf of Mexico Studies
Texas A&M University - Corpus Christi
Corpus Christi, TX 78412
Li.Su@tamucc.edu
James.Gibeaut@tamucc.edu

ABSTRACT

Lidar has become one of the major techniques to collect topographic data. During February 2007, the Bureau of Economic Geology at The University of Texas at Austin acquired research-quality lidar data of the Nueces River Delta. The lidar points include reflections from the substrate, vegetation cover, water surface, buildings, and infrastructure. Further data processing of the lidar point cloud is required to generate a bare-earth DEM and to extract features from the landscape. In this paper, we present a new method to classify lidar data in water points and land points. Physical characteristics of laser shot interactions with water and land surfaces were considered in developing a new method, based on neighbor properties of lidar point clouds, for classifying lidar points as reflections from water or land. To illustrate the ability of the algorithm an example of Nueces river delta are presented. The results are promising and constitute a proof-of-concept for the proposed method.

Key words: Lidar, laser scanning, classification, filtering, water.

INTRODUCTION

Lidar has become one of the major techniques to obtain highly accurate digital elevation models (DEM) in coastal areas. Generally, a DEM is used as basic spatial information for applications such as morphologic change detection and hydrological modeling. It can then be derived from lidar three-dimensional point clouds. Lidar instruments optimized for land surfaces operate in the near infrared part of the spectrum and thus do not penetrate water. Lidar point clouds, therefore, consist of water surfaces and land points. To generate an accurate land surface DEM in bay and estuarine areas from lidar data, therefore, water points must be identified and exclude.

Water levels in coastal areas are typically affected by tides, wind, waves, and freshwater inflow. When lidar and multispectral data are simultaneously acquired. The multispectral imagery can be used to classify water (Lecki et al., 2005; Mundt et al., 2006). However, multispectral images are not always acquired during lidar data capture. For this reason, this paper works with pure lidar data.

Typically, lidar data providers deliver three-dimensional points (x, y, z) and intensity values of those points. On low-relief coastal deltas and estuarine margins, water features, such as ponds, lagoons, and tidal channels, may have varying water surface elevations. Furthermore, intertidal areas bordering water features typically have very low gradients and are only slightly higher than that the water surface. Thus, heights (z) alone cannot provide enough information to classify water and land points, and intensity must be included in the algorithm. Approaches to using the intensity of lidar points for classification were explored by Höfle and Pfeifer (2007). Their approach requires the correction of intensity to exclude all range-dependent influences. This is not practical, however, because many lidar datasets do not have readily available range information. This paper presents a new iterative algorithm for classifying lidar data into water and land points by using intensity and height properties. It does not require intensity to be corrected or calibrated. Through this approach water surfaces with different heights can be identified simultaneously.

In this paper, we first summarize important physical characteristics of lidar data and previous approaches, for classifying water points in lidar data. Then, the novel classification method is presented. To illustrate the ability of the algorithm, a case study of the Nueces river delta in Texas is presented.

STATE OF THE ART

Laser-surface interaction

The scattering characteristics of reflected laser pulses are the foundation of the presented method. Many airborne lidar instruments emit laser pulses in a scanning pattern oriented perpendicular to the flight path. Thus laser pulses illuminate surface targets at varying scan angles and when combined with Inertial Measuring Unit data, the angular orientation of each laser pulse is determined. The lidar instrument measures the time needed for each emitted pulse to reflect off a target and records the relative strength of energy returning to the sensor (intensity). The laser pulse flight time, orientation of the pulse, and position of the instrument as derived using GPS are used to derive three dimensional coordinates of the reflecting target. Atmospheric conditions and range to the target affect the intensity. But variation in intensity during a flight is largely determined by the target's Bidirectional Reflectance Distribution Function (BRDF) (Nicodemus et al., 1977).

The BRDF describes how objects appear when viewed from different angles and when illuminated from different directions. The BRDF depends on wavelength and is determined by the structural and optical properties of the object, such as shadow-casting, mutiple scattering, mutual shadowing, transmission, reflection, absorption by surface elements, orientation distribution, and density of surface elements. Because lidar receives the returning pulses at the emitting direction, lidar is a hot-spot observation according to definitions of BRDF studies. That is, no shadow-casting and mutual shadowing exists in lidar data. For lidar topographic mapping, the intensity is determined by illumination direction and the orientation and density of surface elements and their optical properties.

The optical properties of water at near infrared wavelengths results in significantly lower intensity reflections compared to land elements. Often a reflection from water can not be detected because the received energy is not distinguishable from background noise. This causes lower density of lidar point data on water surfaces compared to land surfaces. Additionally, smooth water surfaces result in specular reflections, and if the lidar incidence angle on the water surface is not normal to the surface, a small amount of the energy will be reflected back to the detector. On the other hand, a large amount of emitted energy may be reflected to the detector when the incidence angle is oriented normal to the water surface resulting in. intensity values significantly higher relative to land areas. Due to fluctuations of water surfaces created by waves, the roll and pitch of the aircraft, and the scanning laser, incidence angles normal to the water surface may occur off nadir as well as at nadir. This causes the neighborhood intensity values of lidar points from water surfaces to be generally noisier than from land. Additionally, the variance in Z values from the water surface of a given water body can be expected to be low during a given survey.

Classification of Water from Lidar Data

Brzank et al. (2005) developed an algorithm that separates water from non-water regions for lidar digital surface models of coastal areas. Their approach is to detect reliable water regions and expand those using height and intensity values. Local height minimums were considered potential seed zones of water areas. However, a limitation of this approach is that systematic changes of intensity depending on angle of incidence are not modeled. Brzank et al. (2008) proposed a supervised fuzzy classification to detect water surfaces from lidar measurements by using the features height, intensity, and 2D point density (Brzank et. al., 2008). This approach, however, requires much human input.

METHOD

On deltaic surfaces, water may reside in ponds with varying elevations making it difficult to map shorelines across a delta using elevation alone. Therefore, this algorithm collectively uses lidar point density, elevation and intensity. Based on the physical characteristics of lidar data, this novel approach is pure lidar, no additional information sources such as spectral images or vector GIS data, are needed. The general approach is first to identify those lidar points that we can classify with high confidence as being from water surfaces. Then an iterative calculation makes water and land points converge toward two ends so that water and land points can be accurately separated with a shoreline.

Generating an Initial Set of Water Cells

After a DEM with grid-node spacing of 1 m is formed using an Inverse Distance Weighted (IDW) algorithm on lidar point data, the following processing steps are used to generate an initial set of water cells.

1. The 1-m point density is scaled up to a 3-m grid using a 3x3-cell window. Because point density of lidar data within water areas is often significantly lower than within land areas, very low point densities, (e.g., less than 25% the number of lidar points in a 3x3 cell area of smooth water compared to land surface), indicates water cells with a high level of confidence. This is the first set of water cells.
2. Statistics of Z and intensity are obtained from the first set of water cells (i.e., average, average deviation and standard deviation).
3. A cell is classified as water if its intensity and Z match the statistics of the water surface cells determined above. The statistics pattern matching is based on the neighborhood of the cell, such as a surrounding 31x31-cell window. This is the second set of water cells.
4. The first and second set of water cells are merged and buffered by a 2-cell width, to generate the third set of water cells.
5. Using the third set of water cells, the variance of Z and intensity are computed for each 1x1 water cell using a 3x3 cell window.
6. Remaining cells of the DEM are then considered water cells if their intensities and Z variances match the statistics of previously defined water surface cells. This is the fourth set of water cells.
7. The first, second and fourth set of water cells are merged to form the initial set of water cells.

Generating a Final Water Classification

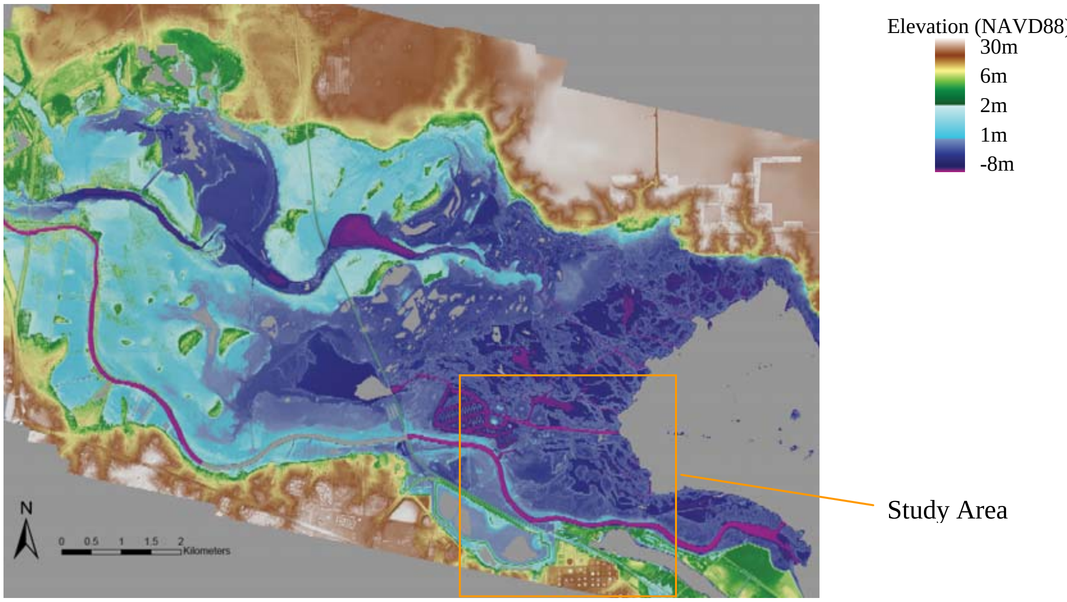
Water pixels defined by the previous steps are assigned an intensity value of zero. Non-water cells keep their original intensity. Next, cell intensity values are assigned the mean of intensity values of a surrounding 5x5-cell window. The 5x5-cell averaging is iterated 6 to 9 times. The mean value of intensity in areas with water decline much faster than areas without water allowing the delineation of the shoreline.

EXPERIMENT SITE AND DATA

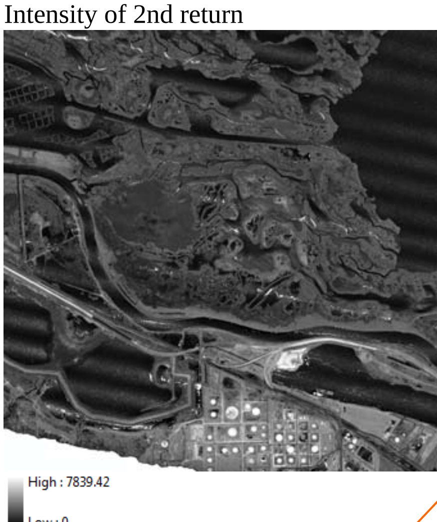
To show the capability of this approach a case study is presented. Lidar data from the Nueces River Delta, northwest of Corpus Christi, Texas were acquired and processed by the Bureau of Economic Geology, The University of Texas at Austin (Gibeaut et al., 2007). The flight altitude was 450-800m above ground level, and the ground speed was 80-105kts. The lidar data were collected between 4 February 2007 and 6 February 2007 using an Optech Inc. ALTM 1225 lidar instrument. Instrument parameters were set as follows: laser pulse rate: 25kHz, scanner rate: 26Hz, scan angle: +/-20deg; and beam divergence: narrow = 0.2 milliradian. The 0.2 milliradian divergence resulted in lidar footprints of about 0.09m for aircraft heights of 450m to 0.16m for aircraft heights of 800m. The ALTM 1225 records the range and backscatter intensity of the first and last laser reflection. The final lidar data have a horizontal accuracy of better than 1m, and a vertical accuracy, as measured on a road surface, of 0.041 m -0.063 m.

CONCLUSION

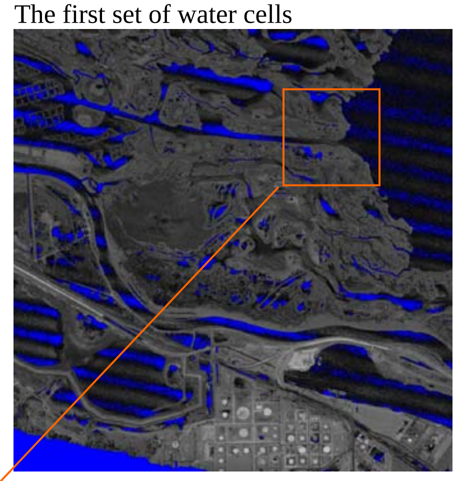
Qualitative assessment shows that this approach can successfully classify lidar points as water or land in estuary areas. The classification is based on an iterative algorithm. The case study of the Nueces rive delta illustrates the capability of this algorithm.

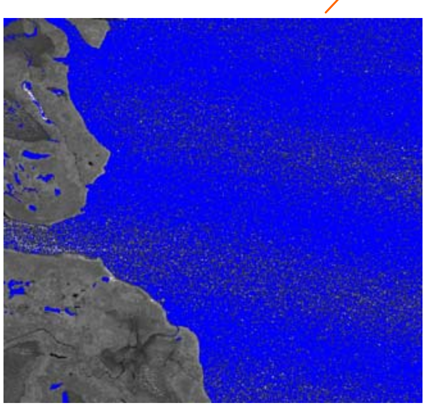


Intensity of 2nd return

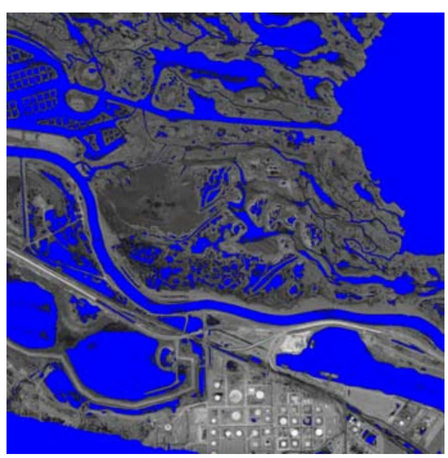


The first set of water cells





Intensity of sample area at finer scale



The final water and land classification

REFERENCES

Brzank, A., J. G¨opfert, and P. Lohmann, 2005. Aspects of lidar processing in coastal areas, *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, Vol.36 (Part 1/W3), on CD-ROM, pp6.

Brzank, A., H. Christian, J. Goepfert, and U. Soergel, 2008. Aspects of generating precise digital terrain models in the Wadden Sea from lidar–water classification and structure line extraction, *ISPRS Journal of Photogrammetry & Remote Sensing*, 63(5):510–528.

Gibeaut, J.C., T.Hepner, J. Andrews, and R. Smyth, 2007. Research-quality lidar survey of the Nueces River Delta, Corpus Christi, Texas, unpublished data set.

Höfle, B., and N. Pfeifer, 2007. Correction of laser scanning intensity data: data and model-driven approaches, *ISPRS Journal of Photogrammetry and Remote Sensing*, 62(6):415–33.

Leckie, D., E. Cloney, C. Jay, and D. Paradine, 2005. Automated mapping of stream features with high-resolution multispectral imagery: An example of the capabilities, *Photogrammetric Engineering & Remote Sensing*, 71(2):145-155.

Mundt, J.T., D.R. Streutker, and N.F. Glenn, 2006. Mapping sagebrush distribution using fusion of hyperspectral and lidar classifications, *Photogrammetric Engineering & Remote Sensing*, 72(1):47-54.

Nicodemus, F.E., J.C. Richmond, J.J. Hsia, J.W. Ginsberg, and T. Limperis, 1977. Geometrical considerations and nomenclature for reflectance, National Bureau of Standards (US), Tech. Note pp. 236–942.