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Large-scale classification of water areas using airborne topographic lidar data

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ABSTRACT

Accurate Digital Terrain Models (DTMs) are inevitable inputs for mapping and analyzing areas subject to natural hazards. Topographic airborne laser scanning has become an established technique to characterize the Earth's surface: lidar provides 3D point clouds allowing for a fine reconstruction of the topography while preserving high frequencies of the relief. For flood hazard modeling, the key step, before going onto terrain modeling, is the discrimination of land and water areas within the delivered point clouds. Therefore, instantaneous shorelines, river banks, and inland waters can be extracted as a basis for more reliable DTM generation. This paper presents an automatic, efficient, and versatile workflow for land/water classification of airborne topographic lidar points, effective at large scales (>300 km^2). For that purpose, the Support Vector Machine (SVM) method is used as a classification framework and it is embedded in a workflow designed for our specific goal. First, a restricted but carefully designed set of features, based only on 3D lidar point coordinates and flightline information, is defined as classifier input. Then, the SVM learning step is performed on small but well-targeted areas thanks to a semi-automatic region growing strategy. Finally, label probability output by SVM is merged with contextual knowledge during a probabilistic relaxation step in order to remove pixel-wise misclassification. Results show that a survey of hundreds of millions of points are labeled with high accuracy (>95% in most cases for coastal areas, and >90% for rivers) and that small natural and anthropic features of interest are still well classified even though we work at low point densities (0.5–4 pts/m^2). We also noticed that it may fail in water-logged areas. Nevertheless, our approach remains valid for regional and national mapping purposes, coasts and rivers, and provides a strong basis for further discrimination of land-cover classes and coastal habitats.

1. Introduction

1.1. Seashore and river monitoring

Global climate change is said to lead to an increase in the sea level in the forthcoming years. Coastal areas are particularly at risk, mainly because almost 50% of the Earth's population lives in such areas. Numerous thematic maps and Geographical Information Systems have been developed to meet management and forecasting needs on these areas subject to flooding. In addition, other legal requirements have emerged. For instance, the European Water and Flood Framework Directives (2000–2007) influenced strategies in Europe for establishing prevention and protection policies by imposing repeated nation-wide surveillance of all kinds of inland water reservoirs, rivers, and large catchment basins. Therefore, these issues are no longer considered merely at a local or a regional level. A local scale analysis may be sufficient for providing specific vulnerability documents or leading studies on chosen objects but not for assessing the socio-economic impact of natural hazards and in order to efficiently implement the appropriate policies. However, the accurate topography of areas with high human, economic or environmental stakes, and those subject to such hazards, has barely been described.

The characterization and quantification of coastal and river habitats have been improved over the last decades due to synergistic remote sensing techniques, that are able to deliver high-resolution spatio-temporal by-products (Yang, 2008). In addition, in order to provide some initial maps, remote sensing is also essential for monitoring and analyzing the evolution of the measured physical characteristics. Repetitive measuring is also crucial for areas undergoing most changes *i.e.*: flooding, erosion, accretion or retreating such as beaches, cliffs or unstable slopes (Addo, Walkden, & Mills, 2008; Miller et al., 2008; Revell, Komar, & Sallenger, 2002; White & Wang, 2003). Moreover, up-to-

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date information is necessary for building setback lines, estimating beach width (Rango et al., 2000), making an inventory of wetlands and agricultural land resources, and delineating flood and hurricane hazard areas, so as to estimate sediment transport volumes or alterations in intertidal habitat (Chust, Galparsoro, Borja, Franco, & Uriarte, 2008).

Using low or medium size resolution optical data or Synthetic Aperture Radar data allows for a quick and cost-effective way to obtain a landscape-level overview of coastline changes (Pardo-Pascual, Almonacid-Caballer, Ruiz, & Palomar-Vázquez, 2012; Ryu, Won, & Min, 2002; Yu & Acton, 2004), and helps to identify areas concerned that will require a more in-depth study. For this purpose, the small-footprint airborne lidar technology appears to be attractive because it provides fine scale seamless coastal Digital Terrain Models (DTMs) over a large coverage area. It allows to survey hundreds of kilometers of shoreline and rivers with a high spatial resolution within a few days only. Its very high vertical accuracy (<0.15 m) has opened up new possibilities of tackling very precise and specific problems, that were impossible to deal with before (Collin, Long, & Archambault, 2012; Hladik & Alber, 2012; Saye, van der Wal, & Pye, 2005; Young & Ashford, 2006), which is true even for country-based purposes (Mandlburger, Hauer, Hofle, Habersack, & Pfeifer, 2009), such as proper management of water defenses (Pe'eri & Long, 2011). In addition, lidar swath widths of a few hundred meters are ideal for coastal, river, and even tidal channel monitoring. The offshore ocean surface, subaerial beach areas and the backbeach, or river channels and their banks, can be mapped simultaneously (Irish & Lillycrop, 1999; Shrestha, Carter, Sartori, Luzum, & Slatton, 2005; Yates, Guza, Gutierrez, & Seymour, 2008). Moreover, repetitive lidar surveys allow to analyze coastal and dune development (Richter, Faust, & Maas, 2011; Thoma, Gupta, Bauer, & Kirchoff, 2005). In the specific case of shoreline mapping, lidar data only need to be acquired when the water level is below a specified level, which makes the method less stringent than airborne imagery (Parrish, 2012).

1.2. Motivation: towards automatic coastal lidar DTM generation

In France, in addition to the European Water and Flooding Directives, the National Institute of Geographic and Forest Information (IGN) and the Marine Hydrographic and Oceanographic Service of the Defence Ministry have initiated a national program, started in 2005, that aims to create a three-dimensional model of the French coastline. It is called Litto3D® (Pastol, 2011). Lidar is currently used to produce a continuous land–sea representation of the coast, allowing for accurate manual shoreline mapping.

Generating DTMs in coastal and river areas first requires to classify water areas in order to accurately extract the instantaneous shoreline[1]. Consequently, the aim of this paper is to propose a workflow for water/land classification in topographic lidar datasets that is efficient at large scales and is adaptive to various landscapes (rivers and seashores). Very high classification accuracies (>90%) are targeted since such coast delineation forms the basis of improving political decision-making in high-staked areas. In addition, this should allow for seashore delimitation with a horizontal accuracy less than 2 m, which is a significant improvement with respect to the existing historical coastline (HCL). HCL is available for the whole French territory, and is the geographical reference for sea and land delineation. HCL is a 2D polyline generated at a scale of 1:15,000, with a planimetric accuracy of 10 m, corresponding to the highest water mark for an astronomical tide of coefficient 120 in normal weather conditions.

[1] The term “shoreline” will be used here to refer to the land–water interface.

1.3. Related works on water detection from lidar data

We focus on airborne topographic lidar data that operates on the near-infrared channel (NIR, 1064 nm wavelength). Multi-spectral analysis coupling green and NIR wavelengths is excluded (Mallet & Bretar, 2009).

To the best of our knowledge, there is an abundant literature on shoreline extraction from Digital Terrain Models but only few papers exists about water detection in river and coastal areas from raw lidar topographic data. The simplest methods directly determine the water/land interface using either a Digital Surface Model (DSM) or a Triangular Irregular Network (TIN) computed from a 3D point cloud. Water areas are delineated as a junction of a given water level, water surface elevation or more simply by the 0 m line (Liu, Sherman, & Gu, 2007; Roberston, Whitman, Zhang, & Leatherman, 2004; White, Parrish, Calder, Pe'eri, & Rzhanov, 2011). Such a model-driven strategy is focused on land/water interface delimitation and is not adapted to inland waters, and can only be performed consecutively to a correct DTM generation step that efficiently deals with varying tidal conditions (Yates et al., 2008).

Water detection methods from lidar point clouds are divided into two main approaches. First, segmentation of water areas can be based on pattern recognition techniques. Features of interest can be breaklines (Brzank, Lohmann, & Heipke, 2005b), tidal channels (Lin, Yan, & Tong, 2008; Mason, Scott, & Wang, 2006) or gullies (Baruch & Filin, 2011). A scan line segmentation method is performed and water classification accuracies between 91 and 99% have been obtained, depending on the landscape. Nevertheless, the approach is based on the detection of vertical high frequencies of the relief. This means that planimetric lidar point distribution should be sufficiently regular and water areas are located in trenches and gullies. Such an assumption is efficient for specific habitats and areas but cannot be generalized to other kinds of landscapes. Conversely, Höfle, Vetter, Pfeifer, Mandlburger, and Stötter (2009) looked for atypically large triangles in a TIN, which are a strong hint about the presence of water. Indeed, the reflection properties of water surface for NIR lidar beams are characterized by either significant absorption or specular reflection resulting in numerous non-recorded laser echoes (unless there is excessive scatter due to water turbidity or close bottom features).

Secondly, more general classifiers can be adopted to discriminate water points from 3D lidar data. Since merely height information is insufficient, additional information was inserted, namely lidar intensity and point density. Brzank, Heipke, Goepfert, and Soergel (2008) used both features in a fuzzy logical classifier. The method performs well for water/mudflat discrimination (89–99%) for various lidar point densities but necessitates a preliminary object based analysis, based on the scan-line method developed by Brzank, Lohmann, and Heipke (2005a). The authors also noted that calibration/correction steps should be carried out to normalize the intensity feature. Even when such steps were performed, with a rule-based approach, Höfle et al. (2009) noted poor discrimination between asphalt and water surface. An overall accuracy of 95% was obtained but it requires the knowledge of the position of the sensor, GPS timestamps and scan angle to model lidar drop-outs. In addition, such an approach cannot be adopted since no procedure correcting the influence of soil moisture and water depth exists. To deal with such issues, the RGB channels of an orthoimage were inserted into an unsupervised Mean-Shift classifier (Lee, Wu, & Li, 2012). The approach is limited since the timing of optical data acquisition is critical and difficult to obtain over large scales. More advanced lidar geometrical features were proposed by Schmidt, Rottensteiner, and Soergel (2013), coupled with full-waveform attributes, which allowed to discard optical imagery. To cope with the local analysis of existing approaches, the authors adopted conditional random fields in order to introduce contextual knowledge and improve classification. In addition, other land categories (mudflat and mussel bed) were discriminated too (Schmidt, Rottensteiner, & Soergel, 2012). Very satisfactory water detection results were obtained (90–98%). Nevertheless, the approach is