ISPRS Journal of Photogrammetry and Remote Sensing 107 (2015) 38–49

Contents lists available at ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

journal homepage: www.elsevier.com/locate/isprsjprs

Street environment change detection from mobile laser scanning point clouds

Wen Xiao *, Bruno Vallet, Mathieu Brédif, Nicolas Paparoditis

Université Paris-Est, IGN, Lab MATIS, 73 Av. de Paris, 94160 Saint-Mandé, France

ARTICLE INFO

Article history:
Received 22 December 2014
Received in revised form 2 April 2015
Accepted 22 April 2015
Available online 11 May 2015

Keywords:
Change detection
Lidar
K-d tree
Occupancy grids
Point-to-triangle distance
Dempster–Shafer theory

ABSTRACT

Mobile laser scanning (MLS) has become a popular technique for road inventory, building modelling, infrastructure management, mobility assessment, etc. Meanwhile, due to the high mobility of MLS systems, it is easy to revisit interested areas. However, change detection using MLS data of street environment has seldom been studied. In this paper, an approach that combines occupancy grids and a distance-based method for change detection from MLS point clouds is proposed. Unlike conventional occupancy grids, our occupancy-based method models space based on scanning rays and local point distributions in 3D without voxelization. A local cylindrical reference frame is presented for the interpolation of occupancy between rays according to the scanning geometry. The Dempster–Shafer theory (DST) is utilized for both intra-data evidence fusion and inter-data consistency assessment. Occupancy of reference point cloud is fused at the location of target points and then the consistency is evaluated directly on the points. A point-to-triangle (PTT) distance-based method is combined to improve the occupancy-based method. Because it is robust to penetrable objects, e.g. vegetation, which cause self-conflicts when modelling occupancy. The combined method tackles irregular point density and occlusion problems, also eliminates false detections on penetrable objects.

1. Introduction

Change detection techniques have been applied in different fields such as environment monitoring (Tian et al., 2013), 3D city model updating (Taneja et al., 2013), street environment inventory (Pu et al., 2011), simultaneous localization and mapping (SLAM) (Wolf and Sukhatme, 2004; Moras et al., 2011), moving object tracking (Yin and Collins, 2007; Irani and Anandan, 1998; Lindstrom and Eklundh, 2001), surveillance systems (O'Callaghan and Haga, 2007) and so on. The spatial scale can be as large as a whole country, a forest, a city or as small as a street. Objects of interest vary from ground surfaces, vegetation, buildings, cars to pedestrians.

In remote sensing studies, large coverage images are usually used for large spatial scale change detection in forest or urban areas for land-cover and land-use monitoring (Hussain et al., 2013; Tian et al., 2013). Airborne laser scanning (ALS) data is also used for similar applications with high geometric precision due to accurate 3D acquisition (Xu et al., 2013; Hebel et al., 2013; Yu et al., 2004). In recent years, 3D maps and virtual city models have been under fast development, therefore many studies have focused on street environment monitoring and city model updating (Früh and Zakhor, 2004; Kang et al., 2013).

Mobile mapping systems (MMSs) can easily scan streets multiple times, therefore allow us to detect changes at street or even city-scale. A MMS is often a georeferenced vehicle mounted with image and/or laser sensor used for environment mapping. Laser scanning provides precise 3D geometric information on the environment, which is of great interest for 3D mapping, localization, scene perception, motion tracking and navigation purposes. Studies from computer vision mainly use imagery for city and street scene change detection (Pollard and Mundy, 2007; Sakurada et al., 2013; Košecka, 2013; Eden and Cooper, 2008; Taneja et al., 2011, 2013). However, lidar (**li**ght **d**etection **a**nd **r**anging) data (also referred to as laser scanning data, range data or lidar point clouds) have been proven to be an accurate data source for 3D urban reconstruction (Lafarge and Mallet, 2011; Chauve et al., 2010; Verma et al., 2006; Zhou and Neumann, 2010; Toshev et al., 2010; Banno et al., 2008; Poullis, 2013), infrastructure management and road inventory (Pu et al., 2011; Zhou and

* Corresponding author. Tel.: +33 143988000 + 7643.
E-mail addresses: wen.xiao@ign.fr (W. Xiao), bruno.vallet@ign.fr (B. Vallet), bruno.vallet@ign.fr (M. Brédif), nicolas.paparoditis@ign.fr (N. Paparoditis).
URL: http://recherche.ign.fr/labos/matis/~xiao (W. Xiao).

http://dx.doi.org/10.1016/j.isprsjprs.2015.04.011

Vosselman, 2012). Thus, mobile laser scanning (MLS) data is intensively studied nowadays (Weinmann et al., 2014; Demantké et al., 2011; Monnier et al., 2012; Yang and Dong, 2013; Aijazi et al., 2013; Serna and Marcotegui, 2014; Qin and Gruen, 2014).

Change detection methods specific to MLS point clouds have been seldom investigated, therefore the development of corresponding approaches becomes urgent. State-of-the-art distance-based methods, e.g. point-to-point, point-to-plane or point-set to point-set distances, may be used for this purpose (Girardeau-Montaut et al., 2005). However, irregular point density and occlusions still remain major challenges. In this paper, we aim to develop a street environment change detection method that is robust to point density variations and capable of distinguishing occlusions from real changes. First, related work and our contribution are discussed in Section 2. Then, the concept of occupancy-based change detection is explained in Section 3. Section 4 presents the PTT distance-based method and the combination with the occupancy-based one. Section 5 describes the experiments and the corresponding results. Quantitative evaluation is demonstrated in Section 6. Finally, conclusions are drawn and limitations are discussed in Section 7.

2. Related work

Change detection has been studied in different fields, e.g. remote sensing and photogrammetry, computer vision, robotics. Related work is presented based on different approaches.

2.1. Change detection from remote sensing and airborne lidar data

Remote sensing change detection approaches vary from pixel-based, region-based to object-based methods. Hussain et al. (2013) summarize approaches as pixel-based, e.g. image differencing, and object-based, e.g. classified object comparison, for remotely sensed images. Tian et al. (2013) use a region-based method for building and forest change detection, and claim that region-based methods perform generally better than pixel-based methods. Similarly, change detection using airborne laser scanning (ALS) data also starts from pixel-based method. Murakami et al. (1999) subtract digital surface models (DSMs) generated from ALS data at different times. Then a simple shrinking and expansion filter was utilized to remove edges of unchanged features. Changes are detected by simple image differencing at 2.5D. Many later studies follow the same strategy for both urban and forest environment change detection (Steinle and Bahr, 2003; Matikainen et al., 2003; Vögtle and Steinle, 2004; Yu et al., 2004; Champion et al., 2009; Choi et al., 2009; Rutzinger et al., 2010). Walter (2004) uses pixel-based and object-based classification of multispectral and lidar data for change detection in geographic information system (GIS) databases. Vosselman et al. (2004) classify ALS data as bare-earth, building and vegetation, and then compare with a topographical database for map updating. Xu et al. (2013) detect and classify changes in buildings after classification of ALS data into urban objects.

2.2. Change detection from terrestrial and mobile lidar data

Terrestrial laser scanning (TLS) and MLS data demand more accurate detection methods. Object-based change detection can be affected by the object recognition accuracy, thus point-based and region-based methods are often used. Girardeau-Montaut et al. (2005) propose a framework to detect changes from terrestrial lidar data semi-automatically. Point clouds are directly compared using three methods, i.e. average distance, best fitting plane orientation and the Hausdorff distance (the maximum distance among the points in one set to the closest point in another set). Results show that the Hausdorff distance performs best. A local model for distance calculation is suggested in order to avoid density variation issues. Kang et al. (2013) also use the Hausdorff distance to detect changes in buildings from TLS data. Point-to-point distance-based methods are practical for TLS and MLS data because changes can be detected directly in 3D. Nevertheless, point-to-point distance is very sensitive to point density. A local surface model can be helpful, since for example point-to-triangle distance (PTTD) or point-to-plane distance are more robust than single point-to-point distances. Zeibak and Filin (2007) treat 3D laser scans as range panoramas. Range images are compared from the sensor perspective, which avoids false detection on occluded parts. Qin and Gruen (2014) detect changes at street level using MLS point clouds and terrestrial images. After co-registration, points are projected onto each image. Then, stereo pairs of terrestrial images are compared with point clouds to find the geometrical consistency. Finally, initial changed areas are optimized by graph cut. Aijazi et al. (2013) firstly classify MLS data into permanent and temporary classes, and then construct similarity maps on the 3D voxels for multiple epoch data fusion to build a complete 3D urban map.

2.3. Change detection in computer vision

3D change detection has been applied to moving object detection and urban environment monitoring in computer vision. Yin and Collins (2007) detect moving objects by a Belief Propagation approach using a 3D Markov Random Field (MRF). A similar method has been presented by Košecka (2013) to detect changes from street scene images. Changes are differentiated as structural, appearance change or temporary dynamically moving objects. Sakurada et al. (2013) detected changes of 3D urban structures from a vehicle-mounted camera. The similarity of the local image patches is computed from multi-view images. The method is compared with Multi-View Stereo (MVS) based methods. Many investigations are based on voxelized space, which performs better than MVS models as compared by Taneja et al. (2011). Structural changes have been detected by voxelizing places of interest. Geometric consistencies between voxels are evaluated. Inconsistency indicates a change in the scene. They extend the work to city-scale in order to detect changes in cadastral 3D models for facilitating the model updating process (Taneja et al., 2013). Pollard and Mundy (2007) store probability distributions for surface occupancy and image appearance in 3D voxel grids. Then they are updated by new images based on Bayesian decision theory. The changes are detected by thresholding the probability to obtain a binary mask. The work has been extended to 4D by Ulusoy and Mundy (2014). 3D changes are detected on 3D models in a time series for model updating instead of rebuilding models at each time.

2.4. Change detection using occupancy grids from robotics

Pagac et al. (1996) use occupancy grids for constructing and maintaining a map of an autonomous vehicle's environment for navigation purposes. A sensor beam is projected on a rectangular grid assigned probabilities of cells being empty, full and ignorance outside the beam. Every cell is initialized, $m(empty) = m(full) = 0$ and $m(ignorance) = 1$, then the Dempster–Shafer Theory (DST) is used to fuse the sensor readings. The DST has proved to outperform the Bayesian method which needs to specify all conditional probabilities even if no *a priori* information exists. Wolf and Sukhatme (2004) also use an occupancy grid for SLAM in dynamic environments. The states of the occupancy grid are defined as *Free*, *Unknown* and *Occupied*. Two different grids are used to model