Computers and Electronics in Agriculture 145 (2018) 217–225

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

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

Original papers

Mapping forests using an unmanned ground vehicle with 3D LiDAR and graph-SLAM

Marek Pierzchała[a,*], Philippe Giguère[b], Rasmus Astrup[a]

[a] Norwegian Institute of Bioeconomy Research, PO Box 115, 1430 Aas, Norway
[b] Department of Computer Science and Software Engineering, Laval University, Québec, Canada

A R T I C L E I N F O

Keywords:
SLAM
LiDAR
Forest operations
Precision forestry
DBH

A B S T R A C T

Enabling automated 3D mapping in forests is an important component of the future development of forest technology, and has been garnering interest in the scientific community, as can be seen from the many recent publications. Accordingly, the authors of the present paper propose the use of a Simultaneous Localisation and Mapping algorithm, called graph-SLAM, to generate local maps of forests. In their study, the 3D data required for the mapping process were collected using a custom-made, mobile platform equipped with a number of sensors, including Velodyne VLP-16 LiDAR, a stereo camera, an IMU, and a GPS. The 3D map was generated solely from laser scans, first by relying on laser odometry and then by improving it with robust graph optimisation after loop closures, which is the core of the graph-SLAM algorithm. The resulting map, in the form of a 3D point cloud, was then evaluated in terms of its accuracy and precision. Specifically, the accuracy of the fitted diameter at breast height (DBH) and the relative distance between the trees were evaluated. The results show that the DBH estimates using the Pratt circle fit method could enable a mean estimation error of approximately 2 cm (7–12%) and an *RMSE* of 2.38 cm (9%), whereas for tree positioning accuracy, the mean error was 0.0476 m. The authors conclude that robust SLAM algorithms can support the development of forestry by providing cost-effective and acceptable quality methods for forest mapping. Moreover, such maps open up the possibility for precision localisation for forestry vehicles.

1. Introduction

Over the last two decades, technological developments in remote sensing and computing capabilities have altered the way information about forests is collected and processed. In Fennoscandia, airborne laser scanning (ALS), also known as LiDAR scanning, has been the main approach to developing estate-level forest inventories for over a decade (Næsset et al., 2004). Given improved sensors and improved image processing algorithms, both automatically generated photogrammetric point clouds obtained from aircraft (White et al., 2013; Rahlf et al., 2015) and unmanned aerial vehicles (UAVs) (Pierzchała et al., 2014; Puliti et al., 2015) are rapidly gaining widespread use and popularity in forestry. In general, image processing is carried out offline, either using robust computer vision algorithms to obtain highly precise and accurate 3D representation of surfaces, or using orthomosaics that are suitable for mapping (Turner et al., 2012). Additionally, ground-based sensors, especially terrestrial laser scanning (TLS), have received significant attention with respect to forest inventories (Liang et al., 2016) over the past decade. TLS has been used to obtain measurements of a wide array of forest attributes, including classic inventory variables (Liang et al., 2016), root systems (Smith et al., 2014), canopy and leaf attributes (Béland et al., 2011; Ducey et al., 2013), and wildlife habitats (Olsoy et al., 2014). In many cases, TLS has been shown to measure key variables such as stem diameter and volume with high accuracy (Liang et al., 2016) but in some cases there has been poor correlation between the TLS measurements and observed tree diameters (Ducey et al., 2013). Although ALS and photogrammetry are gaining widespread operational use, the application of TLS in forestry is still more popular in much of the research community than in operational management and inventorying. For operational use, TLS faces a number of challenges: is time and labour-intensive to carry, mount, and collect the data in the forest; it is both time and computationally demanding to process the data in the office; and there are significant challenges with non-detection of trees if multiple scans are not performed and stitched together (Astrup et al., 2014; Liang et al., 2016). Various promising attempts have been made to overcome these challenges, including correction for non-detection in single scans (Astrup et al., 2014), automatic stitching of multiple scans into a single point cloud (Liu et al.,

* Corresponding author.
E-mail address: Marek.Pierzchala@nibio.no (M. Pierzchała).

https://doi.org/10.1016/j.compag.2017.12.034
Received 2 February 2017; Received in revised form 20 December 2017; Accepted 24 December 2017

2017), and the use of TLS as a ground-truth for ALS applications (Hauglin et al., 2014). An alternative to traditional TLS applications is mobile laser scanning (MLS). MLS holds significant promise in forestry (Holopainen et al., 2014) but its application is still immature and only a few studies of MLS in forests have been conducted (Miettinen et al., 2007; Tang et al., 2015; Jaakkola et al., 2010; Rönnholm et al., 2016). MLS in forest environments faces a number of challenges, foremost among which is locating the position and movement of the scanner, given poor global navigation satellite system (GNSS) coverage under the canopy. Precise localisation under a forest canopy is a complex problem but, if the problem can be resolved, the method can open up numerous opportunities in forestry. For example, knowledge of the position of a forest harvester can allow for the precise geolocation of harvested trees. Another advantage of precise localisation is the ability to perform autonomous navigation in a forest (Hellström et al., 2006). One potential solution to the problem of localisation in forests is the use of simultaneous localisation and mapping (SLAM) algorithms (Siciliano and Khatib, 2008), which have been developed in the mobile robotics community.

Mapping and localisation are important components of advanced autonomous navigation systems for mobile robots. A map is required in order to perform any type of path planning algorithms, in order for a robot to navigate to its goal position. Maps are also required for localisation, with the latter usually defined with respect to the generated map frame of reference (as opposed to a global reference, such as with GNSS). The SLAM paradigm rests on Bayes filtering, a well-known probabilistic inference approach that tries to fuse different sources of information (odometry, measurements, and motion commands) in an optimal or near-optimal manner. Most importantly, the approach takes into account the various uncertainties (noise) from every source. A common type of sensor used to obtain such measurements is a camera. These rich sensors allow the extraction of robust natural visual landmarks, and the creation of maps consisting of their localisation (either within a single global frame of reference or with multiple frames of references). Computer vision algorithms, such as the Oriented FAST and Rotated BRIEF (ORB) descriptor, have been used to perform both landmark extraction and matching, culminating in the popular ORB-SLAM algorithm (Mur-Artal et al., 2015). However, vision algorithms suffer greatly from the fact that they require a strong matching of these visual landmarks between pose and have limited depth precision (for stereo) or none (for monocular systems, as they find geometry up to a scale factor). By contrast, range sensors such as LiDAR typically have good depth perception, and the newer models having somewhat higher bandwidths (over half a million points per second). They allow the creation of dense map representations, both in 2D and 3D; in other words, no landmarks are extracted, but rather most of the data are stored in the map. Such maps can be multilevel surface maps (Triebel et al., 2006), point clouds, and occupancy grids (Wurm et al., 2010). Dense maps are interesting not only for robot navigation but also because they provide more information about the environment, which makes it attractive to use them a posteriori. In the context of mapping forests, a prominent example is the use of such dense 3D maps for inventory purposes.

The use of SLAM has been explored previously in forest environments using 2D LiDAR combined with GPS (Miettinen et al., 2007) as well as small footprint LiDAR, IMU, and GPS for 2D SLAM (Tang et al., 2015). The goal of this paper was to test graph-SLAM for mapping of a forested environment using a 3D LiDAR-equipped UGV. The first sub-goal was to test the feasibility of creating a 3D point cloud representing the ground surface and lower stems based on data captured by the UGV. The second sub-goal was to quantify the accuracy of the extracted diameters and distances between stems together with development of support ratio as a function for determining the fraction of stem that is covered with laser points.

2. Theoretical background

In this section, we describe theoretical background of the SLAM paradigm, particularly the graph-SLAM concept. This includes the importance of its components such as odometry, loop closure and graph optimisation. We then present an overview of the technical aspects of our test, including the mapping platform and its elements as well as the field area used for testing. Thereafter, we describe the software architecture and process of map creation. We conclude by specifying the methods for data extraction which are used for quantifying the accuracy of our approach.

2.1. The SLAM concept

Generally speaking, the SLAM problem (in its full-SLAM variant) lies in estimating the posterior probability of the robot's complete trajectory $x_{1:T}$ and the map $\mathbf{m}$ of the traversed environment, given all the measurements $z_{1:T}$ and motion commands $u_{1:T}$, plus an initial position x_0 (Grisetti et al., 2010):

$$p(x_{1:T},\mathbf{m}|z_{1:T},u_{1:T},x_0). \quad (1)$$

For wheeled vehicles, wheel odometry is often used to compute a priori pose estimates in lieu of the true command u, before being corrected by exteroceptive sensor measurements z. However, due to the high probability of wheel slippage in forested environments (Ringdahl et al., 2012), several alternative strategies to pure odometry have been proposed. For instance, Nister has reported an extensive study of field testing of visual odometry in ground vehicle applications (Nistér et al., 2006).

2.1.1. Graph-SLAM approach

A number of SLAM solutions have been proposed. Earlier ones were based on Extended Kalman Filters (Bailey et al., 2006), where the state estimation included the map $\mathbf{m}$ of the position of all n landmarks. Due to the inherent computational complexity of $O(n^2)$ for these Kalman-based solutions, graph-SLAM approaches have reformulated the SLAM problem as a graph-related problem. In these approaches, a node represents a particular robot pose x_t, while edges encode either odometry or loop-closure constraints. For either edge, they represent a transformation matrix (rotation and translation) along with a covariance matrix encoding the uncertainties associated with these transformations. Once a graph representing the SLAM problem has been created, a global relaxation algorithm is used to optimise the trajectory $x_{1:T}$, in order to minimise the non-linear odometry and loop closure constraints and thus find the most likely map $\mathbf{m}$. Importantly, loop closures explicitly allow the correction of the accumulated errors during displacements. After optimisation, corrections are back-propagated along these loops, thus improving the map. An example of this effect on scan reassembly is shown in Fig. 1.

3. Material and methods

3.1. Hardware and software setup

To carry out the field tests, we built a dedicated mobile platform on top of a standard 4 wheeled rover 'Superdroid 4WD IG52 DB' (Fig. 3), which was controlled via a Spektrum DX5e remote controller for driving of the vehicle in the forest. An aluminium frame bolted on top of the Superdroid was used to carry the various sensors. At the highest point of the frame was our main sensor for mapping, a Velodyne VLP-16 LiDAR, used for acquisition of the 3D point clouds. The VLP-16 is a compact 3D scanner with 16 laser/detector pairs with a 360° horizontal field of view and a 30° vertical field of view. The laser beams have a divergence of 3 mrad. Full 360° scans of 300,000 points are acquired with frequencies of 2 Hz. According to the vendor manual, the scanner operates with a normal accuracy of ± 3 cm. The maximum range of the