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Orchard mapping and mobile robot localisation using on-board camera and laser scanner data fusion – Part B: Mapping and localisation

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ABSTRACT

Accurate mobile robot localisation in orchards relies on precise orchard maps which help the mobile robot to efficiently estimate its position and orientation while moving between tree rows. This paper presents a new method for constructing a local orchard map based on tree trunk detection using camera and laser scanner data fusion. The final orchard map consists of the positions of the trees and non-tree objects (e.g. posts and tree supports) in the tree rows. The map of the individual trees is used as an *a priori* map to localise the mobile robot in the orchard. A data fusion algorithm based on an Extended Kalman Filter is used for position estimation. Experimental tests were conducted with a small robot platform in a real orchard environment to evaluate the performance of orchard mapping and mobile robot localisation. The mapping method successfully localised all the trees and non-tree objects of the tested tree rows in the orchard. The mapping results indicate that the constructed orchard map can be reliably used for mobile robot localisation and navigation. The localisation algorithm was evaluated against the logged RTK-GPS positions for different paths and headland turns. The average of the root mean square of the Euclidean distance between the ground truth and the estimated position for different paths was 0.103 m, whilst the average of the root mean square of the heading error was 3.32°.

1. Introduction

In recent years, the use of agricultural robots has increased significantly in many indoor and outdoor agricultural environments. Automated agricultural robots save labour costs, provide an alternative to people performing certain tedious, repetitive or high-risk operations, and increase productivity (Griepentrog et al., 2009). The rapid advancement in sensors and computing technologies has provided important progress in the field of agricultural autonomous robot systems.

The problem of feature selection and detection is more challenging in outdoor environments. In most typical semi-structured outdoor environments such as orchards and parks, tree trunks are relatively stable, regular and naturally occurring features that can provide very useful information for mobile robot localisation and navigation (Zhang et al., 2008).

The successful navigation of mobile robots in orchard environments consists of feature extraction, mapping, localisation, path planning and obstacle avoidance. A mobile robot with its on-board sensors can sense the surroundings and build a map of the orchard, and continuously update the map to incorporate, for example, fallen branches or other new obstacles. Precise orchard maps are essential for agricultural robots' path planning, localisation and navigation when detailed inspection (e.g. flowers, fruit, diseases) is to be undertaken. The integration of different sensors for feature extraction and orchard mapping can improve the robustness of the map (Shalal et al., 2013).

Localisation is the process of accurately determining the mobile robot's pose (position and orientation) relative to a given map of the environment using the data acquired from the mobile robot sensors (Auat Cheein and Carelli, 2013). The core of the localisation problem is the reliable acquisition or extraction of sensor information and the automatic correlation or correspondence of this information with the environment map (Zhang et al., 2008). Localisation is a critical issue in mobile robot navigation, and particularly so in an agricultural environment where, unlike a factory environment, a level ground surface cannot be presumed. The

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mobile robot cannot effectively plan its path, locate objects and navigate to the target unless it knows its position in the environment (Bloss, 2008).

In some orchards, GPS cannot be effectively used for localisation and navigation since the agricultural robots frequently move under the tree canopy blocking the satellite signals from the GPS receiver (Li et al., 2009). In addition, using precise GPS system such as Real Time Kinematic RTK-GPS is an expensive solution for position estimation. For these reasons, this study aims to develop localisation system for mobile robot in orchard without using GPS as the primary sensor for localisation. Furthermore, odometer is a very common sensor for position measurement that has been widely used due to its simplicity and low cost. However, this assumption is not always correct because of the wheel slippage on different surfaces which generate errors that accumulated over distance especially in outdoor environments. For this the mobile robot cannot rely only on the odometer to determine its position. All these challenges have motivated the development of a localisation system based on data fusion from different on-board sensors to provide accurate pose estimation of the mobile robot. The Extended Kalman Filter (EKF) provides a robust mathematical method for multi-sensor data fusion in real time. It has been adopted to solve the problem of position estimation of nonlinear mobile robot systems (Thrun et al., 2005).

The tree inspection and individual tree growth monitoring tasks require the mobile robot to have a map of the individual trees in the orchard. This facilitates the mobile robot to navigate to a specific tree to implement these tasks. Hence, this arises the need of constructing a local map of the individual trees in the orchard. The constructed map is essential for mobile robot localisation since the mobile robot need to know its position relative to these trees in the row. The mobile robot needs to execute different paths such as moving midway between tree rows, close to the row and between trees in the row to implement different tree inspection tasks. In addition, the movement of the mobile robot from one row to another requires executing either semi-circle turns or right angle turns. Therefore, the developed localisation algorithm is required to be capable of determining the mobile robot position for all these paths and turns.

This work presents a method for local-scale orchard mapping based on tree trunk detection using low cost vision and laser scanning technologies. Details of this tree trunk detection are presented in Shalal et al. (2015). The fusion of data from the sensors improves tree trunk detection because the laser scanner can provide accurate ranges, angles and widths of the tree trunks and objects, whilst the vision system can distinguish between tree trunks and other objects. The map obtained consists of the 2D position of the individual trees and non-tree objects in the orchard. In this study, trees are used as landmarks for localisation, together with the constructed map of the individual trees and the measurements from mobile robot on-board sensors (camera, laser scanner, odometer and IMU). The camera and the laser scanner are used to detect and measure the distances between the mobile robot and the trees which are necessary for the EKF algorithm to estimate the position and orientation of the mobile robot. The estimated positions were evaluated against the RTK-GPS position measurements to determine the position accuracy based on the root mean square (RMS) of the Euclidean distance between the RTK-GPS position measurements and the estimated positions.

This paper is organised as follows. Section 2 highlights some recent studies published in the field related to this work. Section 3 explains the proposed method for orchard map construction whilst Section 4 describes the localisation algorithm using EKF. Section 5 presents the experimental results and discussion. Finally, conclusions are presented in Section 6.

2. Related work

Studies in the literature have typically developed autonomous navigation systems for tractors or large agricultural vehicles (Barawid et al., 2007; Andersen et al., 2010; Hansen et al., 2011). In this present study, a small robot platform is used rather than traditional (manually-driven) agricultural vehicles. A robot of small size operating autonomously has the potential to meet the major requirements of routine orchard inspection tasks which are labour intensive, especially in large orchards. The small size and light weight are important as they imply easy accessibility of tree rows, lower power consumption, less soil compaction and less potential damage for trees and other objects in the orchard (such as irrigation infrastructure).

The literature offers several methods for the construction of a map of the orchard to be used later as an *a priori* map for mobile robot localisation and navigation. In some orchards, the trees are closely spaced in rows with branches spanning the area between the trees in the row or the tree trunks have small diameters with branches hanging low to the ground. Therefore, the best option is to estimate the position of the tree rows rather than the individual trees (Andersen et al., 2010). Hansen et al. (2011) and Andersen et al. (2010) developed a simple map of the orchard containing starting and ending points of the rows in the orchard. The map was formed in the Universal Transverse Mercator (UTM) coordinate system. From this map, straight line representation of the orchard rows can be obtained for localisation and navigation. According to the localisation algorithm developed by Andersen et al. (2010), the localisation error, laterally, when driving between rows has a standard deviation of 10.3 cm, and at the row ends a standard deviation of 16.7 cm longitudinally. In the work reported by Libby and Kantor (2011), an *a priori* map was developed which consists of line features formed by rows of trees in the orchard and point features consisting of reflective tape placed at the ends of the rows. This map was used for localisation by detecting both the row line and the row ends.

The literature demonstrates the effective use of EKF to estimate the pose (position and orientation) of the agricultural vehicles once appropriate models of the vehicle and the sensors are defined (Libby and Kantor, 2011; Subramanian et al., 2009). EKF provides a theoretical framework for multi-sensor data fusion. In the study presented by Libby and Kantor (2011), the EKF used two types of laser-based correction steps. The first used point features (ends of rows) while the second used line features (tree rows). To improve the performance of EKF, it is often combined with different optimisation techniques and control strategies. Subramanian et al. (2009) developed a fuzzy logic enhanced KF for sensor fusion for guiding an autonomous vehicle in the orchard. The guidance system was then tested in citrus grove alleyways, and average errors of 7.6 cm at 3.1 m/s speed and 9.1 cm at 1.8 m/s speed were observed. Mastrogiovanni et al. (2005) suggested a self-localisation of an autonomous mobile robot within a dynamic environment using EKF and 2D laser rangefinder for indoor environment. The robot managed to localise itself almost continuously in the lab with a maximum translational error of roughly 20 cm and a rotational one comparable to 5°.

Particle Filter (PF) is also used to solve the localisation problem. Unlike the EKF, the PF is not restricted to Gaussian processes and it has a better managing of non-linearities associated with the estimation process, but the real time implementation of the PF is still limited (Auat Cheein et al., 2011). González et al. (2009) developed a mobile robot localisation using Ultra-Wide-Band (UWB) range measurements and PF. The position of a mobile transceiver is determined from the distances to a set of fixed, well-localised beacons. The overall positioning errors (x, y) are of 0.2 m, while the