Computers and Electronics in Agriculture 100 (2014) 41–50

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

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

Laser range finder model for autonomous navigation of a robot in a maize field using a particle filter

Santosh A. Hiremath [a], Gerie W.A.M. van der Heijden [a], Frits K. van Evert [b], Alfred Stein [c], Cajo J.F. ter Braak [a,*]

[a] Biometris, Wageningen UR, Wageningen, The Netherlands
[b] Plant Research International, Wageningen, The Netherlands
[c] Faculty of Geo Information Science and Earth Observation (ITC), University of Twente, Enschede, The Netherlands

ARTICLE INFO

Article history:
Received 18 January 2013
Received in revised form 12 September 2013
Accepted 12 October 2013

Keywords:
Probabilistic robotics
Autonomous navigation
Particle filter
Laser range finder

ABSTRACT

Autonomous navigation of robots in an agricultural environment is a difficult task due to the inherent uncertainty in the environment. Many existing agricultural robots use computer vision and other sensors to supplement Global Positioning System (GPS) data when navigating. Vision based methods are sensitive to ambient lighting conditions. This is a major disadvantage in an outdoor environment. The current study presents a novel probabilistic sensor model for a 2D range finder (LIDAR) from first principles. Using this sensor model, a particle filter based navigation algorithm (PF) for autonomous navigation in a maize field was developed. The algorithm was tested in various field conditions with varying plant sizes, different row patterns and at several scanning frequencies. Results showed that the Root Mean Squared Error of the robot heading and lateral deviation were equal to 2.4 degrees and 0.04 m, respectively. It was concluded that the performance of the proposed navigation method is robust in a semi-structured agricultural environment.

1. Introduction

Precision agriculture takes the variation within the field into account by observing and responding to this variation. It is considered vital for sustainable farming. Precision agriculture can be labour-intensive (Edan et al., 2009), therefore, there is great need for automation of various agricultural tasks like crop scouting, weed control, harvesting and tilling. In this vein, robotic solutions have been applied in various agricultural domains.

A basic component of automation in agriculture is autonomous navigation. Early navigation systems in agricultural domain used a camera as the sensor and were based on computer vision methods (Gerrish and Surbrook, 1984; Reid and Searcy, 1987). They were popular in agricultural robotics due to the availability of low cost cameras and the plethora of computer vision techniques that could be readily applied. For example, several methods based on the Hough transform were developed for row following (Hague and Tillett, 1996; Marchant and Brivot, 1995). Southall et al. (2002) developed a method for navigating a cabbage field in which plants were planted in a grid pattern. They used the knowledge of the environment to build a grid-based model of the local environment in the camera view to obtain the guidance information. There are also stereo based methods which try to extract depth information for robust navigation (Kise et al., 2005). Recent developments include the autonomous robots developed by Weiss et al. (2011) and Bergerman et al. (2012)

Vision based methods are sensitive to light conditions and atmospheric effects. Due to the large variation in ambient light in an outdoor environment, such as an agriculture field, most systems need frequent calibration to the specific operating conditions. Alternative methods to overcome this problems included those based on GPS technology (Heidman et al., 2002; Slaughter et al., 2008; Stoll and Kutzbach, 2001). However GPS technology has several critical drawbacks including insufficient accuracy for precision agriculture, interruptions in the signal and alterations in the environment which are not in the map but which need to be taken into account. This may lead to navigation failure.

Laser range finder(LIDAR) technology does not suffer from the effects of ambient lighting conditions and thus can be more reliable in an agricultural environment. Also the viewing range can be larger than that of a camera. Despite these advantages there is not much focus on LIDAR based navigation in agriculture mainly due to its high costs. Reducing costs in recent years has sparked renewed interest in this technology. Barawid et al. (2007) developed a real-time guidance system for navigating an autonomous vehicle in an orchard based on LIDAR. Hough Transform is used to extract plant rows for navigating the vehicle. They reported that the method is restricted to straight line recognition and thus have difficulty in curved rows. Another disadvantage of the method

* Corresponding author. Tel.: +31 317 480803.
E-mail address: cajo.terbraak@wur.nl (C.J.F. ter Braak).

0168-1699/$ - see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.compag.2013.10.005

occurs when the Hough transform fails to extract the correct plant rows causing the vehicle to lose track. LIDAR has also been used for obstacle detection and avoidance during navigation as in the case of Subramanian et al. (2006). More recently Weiss and Biber (2011) have developed a 3D LIDAR based navigation method where they used a statistical model for detection of the plant rows. The LIDAR acquires a 3D point cloud which is processed to remove the points corresponding to the ground. Then a statistical model identifies clusters of points that represents the plants. Though the results are promising, the method will not be easily scalable to other plants as the statistical model is specific to the maize plants. The statistical model depends on the cluster of 3D points which in turn depends on the shape and size of the plants. Moreover since the system is specifically designed for plant phenotyping, it imposes restrictions on the operating conditions like plant size and speed of the robot.

One of the main shortcomings in the aforementioned methods is the lack of robustness to uncertainties in the environment. Agricultural environments are dynamic and non-deterministic with several sources of uncertainty. For instance, there is noise due to uneven terrain and the varying shapes, sizes and colours of the plants. A robot operating in such an environment will suffer from wheel-slippage and sensor noise which is further compounded by controller and actuator noise. Therefore, designing a navigation method capable of managing multiple sources of variation is a challenging task. Probabilistic navigation methods proposed by Thrun et al. (2005) are most promising. They proposed a 2D LIDAR model that characterizes different types of noise in the environment. The sensor model is used within a particle filter for autonomous navigation of the robot in an indoor environment or in an outdoor urban environment.

This study aims to develop an autonomous navigation method for a robot equipped with a LIDAR for row following in a maize field. The navigation method is based on a particle filter algorithm (Thrun et al., 2005) which is used to estimate the robot-environment state of the system such as robot heading, lateral deviation, distance between the rows of plants and the end of the rows. These estimated values are in turn used to steer the robot. An important aspect of the particle filter is the measurement model. The study proposes a novel measurement model for the LIDAR where all the data obtained from the LIDAR is utilized to compute the likelihood of the particles. It is believed that this is the first (probabilistic) LIDAR model developed for robot navigation in a semi-structured environment like a maize field.

The paper is arranged as follows. Section 2 describes materials and methods along with the details of the LIDAR model. Section 3 reviews the performance and robustness of the new navigation algorithm. Whilst the limitations and extensions of the method and the scope for future research are covered in Section 4.

2. Materials and methods

2.1. Maize field

The robot navigates in a field that consists of rows of maize plants with a well defined headland. The rows may be either straight or curved. Additionally, there may be gaps within the rows. In general, the rows are approximately 0.75 m apart from each other which is the standard row width in commercial maize cultivation.

2.2. Robot architecture

The prototype robot used in this study consists of a chassis with three wheels, with overall dimensions 0.8 m × 0.45 m × 0.3 m. It has two rear wheels that do not pivot and a steering front wheel whose steering actuator is controlled via CAN-bus. All wheel units are equipped with incremental encoders to measure the rotational speed. In addition, the front wheel unit is equipped with an angle sensor to measure the steering angle. The driving speed of each wheel depends upon the target speed of the control point, the location of the wheel with respect to the control point and the turning radius. An electronic box between the rear wheels houses a mini-ITX computer with a 2.4 GHz Intel Core2 Duo processor running Windows XP operating system. The robot is controlled by a custom C# software which uses OpenCV library for image processing. Energy to the computer and the wheel units is provided by three 12 V NiMH racing packs: 1 for the front wheel unit, one for both rear wheel units, and one for the PC (see Fig. 1).

2.3. Laser range finder (LIDAR)

The robot is equipped with a LIDAR (LMS-111, Sick AG, Waldkirch, Germany) in the front at a height of 15 cm, through which it senses the world. The LIDAR operates on time-of-flight (TOF) principle. It emits pulsed laser beams using a laser diode. If a laser pulse is incident on an object, it is reflected. The reflection is detected using a photo diode. The distance to the object is calculated from the propagation time that the light requires from emission to reception of the reflection at the sensor. The emitted laser beams are deflected using a mirror at an angular resolution of 0.5 degrees and scan the surroundings in a circular manner with a maximum field of view of 270 degrees. The maximum range and scanning frequency of the LIDAR is 20 m and 50 Hz respectively.

Fig. 2(a) shows the top view of the mount. The axis of the LIDAR is aligned to the longitudinal axis of the robot. By convention, the starting and end angle of the scan are −135 and 135 degrees respectively, which are depicted by points A and C respectively in Fig. 2(a). A scan at any given time t consists of 541 observations $Z_t = (z^{(1)}, z^{(2)}, \ldots, z^{(541)})$ corresponding to the angles $\Phi = (\phi^{(1)}, \phi^{(2)}, \ldots, \phi^{(541)}) = (-135, -134.5, \ldots, 135)$, where $z^{(j)}$ is the range, that is, distance of an object (plant leaves or stem) measured by the beam j. Fig. 2(b) shows an example scan when the robot is between the rows. The data points $(\phi^{(j)}, z^{(j)})$ are represented in Cartesian coordinates for illustrative purpose. The blue circles indicate the position of the hit objects with respect to the LIDAR represented by the red circle.

2.4. Local world

A rectangular area around the centre of the robot is defined as the local world for the robot. If the robot is between the rows, the local world is approximated by two parallel rows of plants, one on either side of the robot. The rows have a finite width and are a finite distance apart. It is assumed that the row ends are usually not in view as shown in Fig. 3(a). When the robot enters into the headland, the ends of rows are in the field of view and the geometry is modelled as in Fig. 3(b). The geometry of the local world is characterized by four parameters, namely row width (rw), row distance (rd), end of left row (el) and end of right row (er). The central line halfway between the rows forms the reference axis with respect to which the robot position is determined. The robot is characterized by its main axis between the front wheel and the point halfway between the rear wheels. This point between the two rear wheels is the control point. The position of the robot in the local world is given by robot heading (h) and lateral deviation (l). The robot heading is the angle between the main axis and the reference axis measured in degrees. Lateral deviation is the signed distance between the robot's control point and the reference axis. Jointly, the parameters represent the robot-field state vector $X_t = (h, l, rw, rd, el, er)$ that characterizes the system