Computers and Electronics in Agriculture 116 (2015) 88–100

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

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

Optimization methodology to fruit grove mapping in precision agriculture

Javier Gimenez *, Daniel Herrera, Santiago Tosetti, Ricardo Carelli

Instituto de Automática, Universidad Nacional de San Juan-CONICET, Argentina

ARTICLE INFO

Article history:
Received 30 March 2015
Received in revised form 27 May 2015
Accepted 14 June 2015
Available online 26 June 2015

Keywords:
Mapping
Agricultural environments
Optimization
Data filtering

ABSTRACT

The mapping of partially structured agricultural environments is a valuable resource for precision agriculture. In this paper, a technique for the mapping of a fruit grove by a mobile robot is proposed, which uses only front laser information of the environment and the exact position of the grove corners. This method is based on solving an optimization problem with nonlinear constraints, which reduces errors inherent to the measurement process, ensuring an efficient and precise map construction. The resulting algorithm was tested in a real orchard environment. For this, it is also developed a data filtering method capable to comply efficiently the observation-feature matching. The maximum average error obtained by the methodology in simulations was about 13 cm, and in real experimentation was about 36 cm.

1. Introduction

Robotics, a discipline considered within the automation area, is currently focusing their applications in partially structured or time varying scenarios, generating a significant and growing impact on the productive and service sectors. These applications require a high degree of operational autonomy, which should be designed for a specific task and take into account the environment conditions. An application scope of current interest with great potential impact in robotics is precision agriculture (Srinivasan, 2006). Within this, special robots, which have been called as service units (Auat Cheein and Carelli, 2013), are endowed with high degree of skill, autonomy and intelligence, allowing its application in the particular agricultural environment with variable weather conditions in terrains with irregular characteristics (Auat Cheein and Carelli, 2013).

Regarding map generation, there are many works (Ouellette and Hirasawa, 2008; Xiaogang and Xuetao, 2009; Lee et al., 2008) for indoor environments which give satisfactory results. However, there are still few proposals concerning the mapping in agricultural environments. When the map is available in this context, navigation errors decrease (Zhang et al., 2014). Moreover, this allows the vehicle to return to specific locations and perform tasks such as spraying in a suitable and precise manner, thus saving valuable resources (Libby and Kantor, 2011). From a cost perspective, the map should be built without expensive surveying equipment, and preferably using the same sensors used for vehicle guidance (Zhang et al., 2014). In Jin and Tang (2009), for example, a mapping strategy based on maize plants detection using a stereo camera is presented. In Zhang et al. (2014), Libby and Kantor (2011) it is reported navigation and mapping techniques on a commercial apple orchard, for which odometry and 3D LiDAR information is heavily used. Additionally, specific landmarks on the extremal trees were included to increase the probability of finding the next row and successfully enter in this, which also establish a loop closure indicator that facilitates odometry error corrections. In both articles, Zhang et al. (2014), Libby and Kantor (2011), the authors use landmarks in order to detect the extremal trees. Besides, these methods are based on a probalistic mapping approach. With exception of the filtering process, the mapping algorithm proposed in the present article is GPS and landmarks independent. It is also a non explicit probabilistic approach (such as Kalman Filter based mappings).

In recent years, many works have been made to solve the problem of simultaneous localization and mapping (SLAM) (Rovira-Mas, 2009; Bryson and Sukkarieh, 2008; Auat Cheein et al., 2011), in which a recursive process is generated in order to simultaneously minimize errors in vehicle location and environment mapping (Chatila and Laumond, 1985; Ayache and Faugeras, 1989). A concise introduction to the SLAM algorithm is offered in Durrant-Whyte and Bailey (2006,). Although SLAM is based on specific and precise methods such as the Kalman filter (Thrun et al., 2005), it involves high computational costs producing

* Corresponding author.
E-mail addresses: jgimenez@inaut.unsj.edu.ar (J. Gimenez), dherrera@inaut.unsj.edu.ar (D. Herrera), stosetti@inaut.unsj.edu.ar (S. Tosetti), rcarelli@inaut.unsj.edu.ar (R. Carelli).

http://dx.doi.org/10.1016/j.compag.2015.06.013
0168-1699/

List of symbols and acronyms

Symbols

$A_i^{\theta,\rho}$	homogeneous transformation matrix with a translation ρ_i and a rotation θ_i
$A_i^{-,\theta,\rho}$	matrix that results from eliminating the last row of $A_i^{\theta,\rho}$ when $i > 1$
$A_{k:m}^{\theta,\rho}$	product of the matrices $A_i^{\theta,\rho}$ with i from k to m
$a_n^{\gamma,\ell}$	$:= [-c_n^{\gamma}\widehat{\ell}_n, -s_n^{\gamma}\widehat{\ell}_n, 1]^T$
$a_1^{\varsigma,\delta,\gamma}$	$:= \widehat{\delta}_1[c_1^{\varsigma}, s_1^{\varsigma}]^T$
$a_n^{\varsigma,\delta,\gamma}$	$:= [-c_n^{\varsigma,\gamma}\widehat{\delta}_n, -s_n^{\varsigma,\gamma}\widehat{\delta}_n, 1]^T$ if $n > 1$
c_i^{θ}	$:= \cos(\widehat{\theta}_i)$
$c_n^{\varsigma,\gamma}$	$:= \cos(\varsigma_n + \gamma_{n-1})$
D_d	distance between the robot and the nearest right row of trees
D_i	distance between the robot and the nearest left row of trees
$d_1 = [d_{1,i}]$	vector with the average measurements of the left sides of the rectangles
$d_2 = [d_{2,i}]$	vector with the average measurements of the right sides of the rectangles
f'_{θ_i}	partial derivative of f with respect to $\Delta\theta_i$
f_n	function used to design the nth framing constraint
$\mathcal{F}$	$:= \{f, g, h, \phi\}$
g	function used to design the alignment constraint
h_n	function used to design the nth basic constraint
I_θ	set of all appropriate subscripts of θ
$\ell = [\ell_i]$	vector with the average measurements of the bases of the rectangles
M	maximum laser distance considered in the filtering process
$P_{i,1}$	exact position of the trees in the lower left corner of the plantation
$P_{i,2}$	exact position of the trees in the lower right corner of the plantation
$P_{f,1}$	exact position of the trees in the upper left corner of the plantation
$P_{f,2}$	exact position of the trees in the upper right corner of the plantation
p_n	exact position of the trees in the nearest left row
$\widehat{p}_n$	estimated position of the trees in the nearest left row
q_n	exact position of the trees in the nearest right row
$\widehat{q}_n$	estimated position of the trees in the nearest right row
R_i^{θ}	matrix that produces a rotation of θ_i grades
$R_{k:m}^{\theta,\rho}$	product of the matrices $R_i^{\theta,\rho}$ with i from k to m
s_i^{θ}	$:= \sin(\widehat{\theta}_i)$
$s_n^{\varsigma,\gamma}$	$:= \sin(\varsigma_n + \gamma_{n-1})$
v	control action of the linear velocity of the unicycle robot
$V[\theta_i]$	variance in the measurements corresponding to θ_i
w	control action of the angular velocity of the unicycle robot
$\tilde{x}$	position error of the vehicle in the corridor
X_i	points resulting from projecting the observations on a line with the estimated orientation of the tree rows
$\alpha = [\alpha_i]$	vector with average measures of the angles that define the locations of the nearest left row of trees
$\beta = [\beta_i]$	vector with average measures of the angles that define the locations of the nearest right row of trees
$\gamma = [\gamma_i]$	vector with average measures of the upper left angles of the rectangles
Γ	subset of $\Theta \cup \Lambda$ of independent variables, as small as possible, that allows writing the other variables as a function of them
$\delta = [\delta_i]$	vector with the average measurements of the diagonals of the rectangles
$\Delta^2(\Theta)$	objective function to be minimized for optimal corrections
$\Delta\theta_i$	correction to be made about θ_i in search of a compatible configuration
$\theta = [\theta_i]$	generic vector with some average measures of the rectangles
$\widehat{\theta}_i$	final estimation of θ_i
Θ	set of all vectors of averages measurements obtained
$\vartheta = [\vartheta_i]$	vector with average measures of the upper right angles of the rectangles
Λ	$:= \{\lambda_f, \lambda_g, \lambda_h, \lambda_\phi\}$ set of vectors containing the Lagrange multipliers arising in the optimization problem
μ	mode parameter of the density used in the filtering process
σ	distance between modes of the density used in the filtering process
$\varsigma = [\varsigma_i]$	vector with average measurements of the angles between the base and diagonal of the rectangles
Φ	Lagrangian function resulting in the optimization problem
ϕ_n	function used to design the nth rectification constraint
φ	orientation error of the vehicle in the corridor
φ_d	difference between the orientations of the robot and the nearest right row of trees
φ_i	difference between the orientations of the robot and the nearest left row of trees

Acronyms

LiDAR	Light Detection and Ranging
GPS	Global Positioning System
SLAM	Simultaneous Localization and Mapping
INTA	National Agricultural Technology Institute
ML	Maximum Likelihood

slow motions of the robot while mapping online. The matching problem between the observations and the map elements represents a weakness of the SLAM method (Adams et al., 2014). This drawback is drastically reduced if a draft map is previously obtained by exploiting the semi-structured nature of the working environment.

In this paper, a mapping algorithm for a grove of fruit trees is proposed. Thereby an autonomous robot may estimate the trees position faster without using self-localization devices as GPS, odometry or inertial measurement units, and without using-localization devices as GPS (which can fail due to occlusion by the orchard), among others, as is detailed in Section 2. The control system used for autonomous navigation of the robot is presented in Section 3. During navigation, the robot performs angular and linear measurements of the fruit grove as described in Section 4. Measurements include distance errors of the laser and angular errors caused by the discretization of the directions in which it measures. These errors lead to inconsistencies between the estimations, such as: sum of interior angles of the quadrilaterals other than 360° or improperly closed polygons. In Section 5, a measure adjustment procedure is developed in order to achieve the best consistent setting of the overdetermined measuring set. In Section 6, some simulations and an experience in a real olive grove show the proposed method benefits. Conclusions and future