Computers and Electronics in Agriculture 151 (2018) 11–20

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

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

Original papers

Bounded memory probabilistic mapping of out-of-structure objects in fruit crops environments

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ARTICLE INFO

Keywords:
Probabilistic mapping
Precision agriculture
Dynamic object
Recursive subsampling
Kernel estimators

ABSTRACT

Spatial awareness and memory are key factors for a robot to evolve in semi-structured and dynamic environments as those found in agriculture, and particularly in fruit crops where the trees are regularly distributed. This paper proposes a probabilistic method for mapping out-of-structure objects (weeds, workers, machines, fallen branches, etc.) using a Kernel density estimator. The methodology has theoretical and practical advantages over the well-known occupancy grid map estimator such as optimization of storage resources, online update, high resolution, and straightforward adaptability to dynamic environments. An example application would be a control scheme through which a robot is able to perform cautious navigation in areas with high probability of finding obstacles. Simulations and experiments show that large extensions can be online mapped with few data and high spatial resolution.

1. Introduction

The United Nations proposed a 2030 agenda with 17 goals for sustainable development, placing food and agriculture as crucial pillars U. Nations. A profound change of the global food and agriculture system is needed to nourish today's 815 million hungry and the additional 2 billion people expected by 2050. One of the proposed objectives is to "Ensure sustainable consumption and production patterns", which points to do more and better with less. Precision agriculture is a modern farming practice that makes production more efficient by the proper application of inputs like water, fertilizer, pesticides, etc. at the correct time to the crop for increasing its productivity and maximizing its yields. Besides, precision agriculture provides farmers with a wealth of information to keep track of the farm, improve decision-making, ensure greater traceability, enhance marketing of farm products, improve lease arrangements and relationship with landlords, and enhance the inherent quality of farm products. A review of the motivations of implementing precision agriculture technologies is given in Pierpaoli et al. (2013).

In both developed and developing countries, the primary limiting factor in the development of agricultural industries is the manpower (Bechar and Vigneault, 2016), since it is the largest single cost-contributor in agriculture representing about 40% of the operational costs (Bechar and Eben-Chaime, 2014). The operational and socio-demographic factors that influence significantly in the adoption of precision agriculture technologies by German crop farmers are analyzed in Paustian and Theuvsen (2017). In the 20th century, technological progress in developed countries reduced the manpower for farming activities by a factor of 80 (Ceres et al., 1998). The transient nature of manpower in countries where wages are low reduces production capability and quality (Bechar and Vigneault, 2016). Furthermore, there are heavy manual tasks that cause injuries or chronic problems to workers (Perez-Ruiz et al., 2014). The enormous workforce force required for the different operations causes bottlenecks, downgrading productivity, reducing yield and increasing costs. Besides, problems such as aging of the workforce and shortage of rural workers contribute to the lack of manpower (Iida et al., 2013). This high manual labor requirement impedes cost reductions and increases the demand for robotics and automation (Bechar et al., 2007). Therefore, some human workers must be relocated to other sectors such as maintenance and programming of machines, supervision of tasks, or industrialization of primary agricultural goods (Autor, 2015). Statistics show that the agriculture labor is not lost but transformed (Employment Projections Program, 2017). A detailed analysis of the replacement of labor by machines is presented in Bechar and Vigneault (2016).

The use of robots enables the farmer to automate precision agriculture tasks (Yahya, 2018). There are already companies that offer robots that assist in agricultural tasks, such as Deepfield Robotics, Naïo Technologies, or Saga Robotics, to list some of them. The development of an agricultural robot must include the creation of sophisticated and intelligent algorithms for sensing, planning and controlling to cope with challenging, unstructured and dynamic agricultural environments

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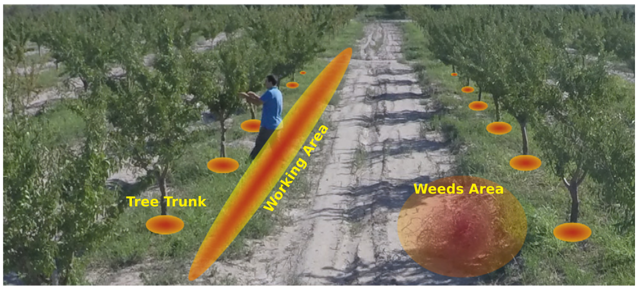
https://doi.org/10.1016/j.compag.2018.05.018
Received 3 November 2017; Received in revised form 11 May 2018; Accepted 14 May 2018



(a) Almond grove.

(b) Olive grove.

Fig. 1. Typical fruit grove environments with trees regularly located and workers performing a task. The working and weed areas are highlighted in order to identity regions of free movement and cautious navigation.

(Edan and Bechar, 1998). A review of recent research and developments in robotics for agricultural field applications and associated concepts, principles, gaps, and limitations can be found in Bechar and Vigneault (2016). One of the main limitations is the uncertainty accumulation during navigation, which can be reduced by including landmarks on the whole farm (such as QR codes in each tree) or by using prior information (such as an environment map or particular distributions of the trees), among others. For this reason, the mapping of partially structured agricultural environments is a valuable resource for precision agriculture. The regular geometry of the trees in an orchard (see Fig. 1) allows having prior precise information of their locations, which can be exploited by several automatic systems (Gimenez et al., 2015). Nevertheless, other objects, which are external to this regular structure, are also present in the agricultural environment. Among others, weeds, fallen branches, machinery, and rural workers are considered out-of-structure objects. These elements are also essential to be mapped because they can affect the robot navigation as well as the Human-Robot interaction (HRI) tasks. In such environments, the robot must be part of a more adaptive system, with the possibility to dynamically introduce new objects to the scene (Kaldestad et al., 2012).

Weeds and workers are part of any agricultural environment (see Fig. 1). Weeds affect the production by reducing crop yield and quality, delaying or interfering with harvesting, preventing water flow, etc. (Scursoni et al., 2011; Zimdahl, 2007). Tasks and other elements for weed control can be optimized by detecting and mapping the areas where weeds are more likely to grow (Torres-Sospedra and Nebot, 2014; Dammer, 2016; Panetta, 2015). On the other hand, the mapping of rural worker traffic allows generating appropriate control algorithms for HRI. Human capabilities of perception, thinking, and action are still unmatched in environments with anomalies and unforeseen events (Tervo and Koivo, 2014). Consequently, human and robot skills are complementary.

Dynamic environments are best represented with probabilistic maps in which areas with the highest probability of occupation are highlighted (see the working area in Fig. 1). This mapping procedure is often associated with the costly methods of occupancy grid maps in which the environment is regularly partitioned, and a probability is assigned to each grid cell (Thrun et al., 2005). In large-scale environments or when there is the need for high resolution, memory consumption of this methodology can become prohibitive, and even more if a 3D map is desired. The grid-based maps can be optimized using octrees, that allows to generate an original map with low resolution and refine each grid as their occupation probability increases (Hornung et al., 2013). The tree representation of the map reduces access times, memory consumption, and can also be used as a multi-resolution representation since it can be cut at any level to obtain a coarser subdivision (Hornung et al., 2013). However, these optimizations are not naturally designed to work in dynamic environments, and the incorporation of probabilities is not straightforward since it requires probabilistic models that are heuristically adjusted.

The main contribution of this paper is the development of a probabilistic method for mapping out-of-structure objects with the following properties: (i) It only requires storing the coordinates of an observation set detected outside the regular structure of the orchard; (ii) The observation set allows a nonparametric estimate of the unknown density function f of the out-of-structure objects through a Kernel estimator; (iii) It obtains a probabilistic map with high spatial resolution; (iv) It allows adapting the amount of stored information to the processing and storage capacities without compromising the map spatial resolution. The mapping procedure also allows incorporating new areas without increasing the required memory space. This is achieved by using a novel recursive subsampling methodology, which eliminates redundant non-informative data and reduces outliers. (v) The access times to the data can be optimized if a tree structure (like octrees) is generated, in which the observations are grouped according to the similarity of the decimal representations of their coordinates. (vi) It does not require constant updating of the probabilistic map, and the probability of observing an object at a specific point (and not the probability of finding an object within a grid cell) can be estimated online; (vii) It does not require: initialization, prior knowledge of the areas to be mapped, nor perform costly copy operations every time the map area is expanded; (viii) Free and unknown areas are not stored, and they are detected by the absence of points in spatial windows. (ix) It allows mapping dynamic environments by incorporating a forgetting factor. In this map, there are no regions without a significant probability of objects presence. (x) Kernel estimators are consistent and probabilistically optimal. Instead, the histogram estimator (or its generalization in grids) requires a cell size reduction (increasing the amount of storage memory required) to converge theoretically to f while increasing the sample size (Györfi et al., 2002). (xi) The estimates do not need the probabilistic modeling of the sensor, which generally contains heuristically adjusted parameters. (xii) It facilitates loop-closures in slam processes since original observations are stored instead of increasing data counters in each grill losing spatial information.

In addition, this paper presents an example application in which a robot uses this map to achieve cautious navigation by reducing its velocity in areas with high probability of finding rural workers. This navigation strategy includes an obstacle avoidance controller based on impedance. Fig. 1 presents two typical environments where the proposed system can be applied. In the first case, a worker performing a task on trees of the same line is observed. The points generated by these observations are incorporated into a database, which is kept bounded by using a recursive subsampling procedure. If the observation area is frequently occupied, then the algorithm marks it as a high traffic zone (working area in Fig. 1) and activates a cautious navigation mode. However, if the worker is never again observed in this region, the algorithm will forget these observations over time. Weeds are also detected and marked as areas with collision probability, but if they are removed, this area will be marked as a free area again. Fig. 1(b) presents a similar situation, in which a worker crosses the likely path of the robot. If this passage is commonly used for workers (or machines), the