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Review

Agricultural robots for field operations: Concepts and components

Avital Bechar [a,*], *Clément Vigneault* [b]

[a] *Institute of Agricultural Engineering, Agricultural Research Organization, The Volcani Center, Bet-Dagan, Israel*
[b] *Department of Bioresource Engineering, Macdonald Campus, McGill University, Sainte-Anne-de-Bellevue, Québec, Canada*

A R T I C L E I N F O

Article history:
Received 13 August 2015
Received in revised form
14 June 2016
Accepted 22 June 2016

Keywords:
Agricultural robots
Robotics
Field operations
Autonomous

This review investigates the research effort, developments and innovation in agricultural robots for field operations, and the associated concepts, principles, limitations and gaps. Robots are highly complex, consisting of different sub-systems that need to be integrated and correctly synchronised to perform tasks perfectly as a whole and successfully transfer the required information. Extensive research has been conducted on the application of robots and automation to a variety of field operations, and technical feasibility has been widely demonstrated. Agricultural robots for field operations must be able to operate in unstructured agricultural environments with the same quality of work achieved by current methods and means. To assimilate robotic systems, technologies must be developed to overcome continuously changing conditions and variability in produce and environments. Intelligent systems are needed for successful task performance in such environments. The robotic system must be cost-effective, while being inherently safe and reliable—human safety, and preservation of the environment, the crop and the machinery are mandatory. Despite much progress in recent years, in most cases the technology is not yet commercially available. Information-acquisition systems, including sensors, fusion algorithms and data analysis, need to be adjusted to the dynamic conditions of unstructured agricultural environments. Intensive research is needed on integrating human operators into the system control loop for increased system performance and reliability. System sizes should be reduced while improving the integration of all parts and components. For robots to perform in agricultural environments and execute agricultural tasks, research must focus on: fusing complementary sensors for adequate localisation and sensing abilities, developing simple manipulators for each agricultural task, developing path planning, navigation and guidance algorithms suited to environments besides open fields and known a-priori, and integrating human operators in this complex and highly dynamic situation.

* *Corresponding author*. Institute of Agricultural Engineering, Agricultural Research Organization, The Volcani Center, P.O. Box 6, Bet-Dagan 50250, Israel. Tel.: +972 3 9683753; fax: +972 3 9604704.
E-mail address: avital@volcani.agri.gov.il (A. Bechar).

http://dx.doi.org/10.1016/j.biosystemseng.2016.06.014

Nomenclature

ARS	Autonomous robot systems
CCD	Charge Coupled Device
CMOS	Complementary Metal Oxide Semiconductor
DGPS	Differential Global Positioning System
FOG	Fibre Optic Gyro
GPS	Global Positioning System
HO	Human Operator
HRS	Human Robot System
IR	Infrared
NIR	Near Infrared
LIDAR	Laser Scanner
PID	Proportional Integral Derivative
PLC	Programmable Logic Controller
RMSE	Root Mean Square Error
RTK	Real Time Kinematic
SF1	Starfire free access
SF2	StarFire paid subscription access
VLSI	Very Large Scale Integration

1. Introduction

Extensive research has been conducted on the application of robots and automation to a variety of field operations, and technical feasibility has been widely demonstrated. Recent research and developments in robotics for agricultural field applications and the associated concepts, principles, limitations and gaps are reviewed.

1.1. *Background*

Agricultural productivity has increased significantly over the years as a result of intensification, mechanisation and automation (Nof, 2009; Zhang, 2013). It is an important target for the application of various kinds of technology designed to increase both crop yield and quality while reducing agriculture costs. For example, precision seeding and planting increase average plant size and uniformity of plant maturity, precise fertigation consisting of adding water and plant nutrients required by the crop only at the optimal time and position decrease the ratio of agricultural inputs to crop production (Tremblay, Fallon, & Ziadi, 2011) and environmental impact (Tremblay, Bouroubi, et al., 2012): optimising in-season nitrogen application based on remote sensing and fuzzy inference system resulted in the same yield as that obtained with the recommended uniform application, which required 31% more nitrogen (Tremblay et al., 2010). In addition, recent studies indicate that the practise of robots or autonomous tractors in various agricultural tasks reduce the fuel consumption and air pollution (Gonzalez-de-Soto, Emmi, Benavides, Garcia, & Gonzalez-de-Santos, 2016; Gonzalez-de-Soto, Emmi, Garcia, & Gonzalez-de-Santos, 2015).

In the 20th century, technological progress in developed countries reduced the manpower that was traditionally available for farming activities by a factor of 80 (Ceres, Pons, Jimenez, Martin, & Calderon, 1998). Automation has considerably increased the productivity of agricultural machinery by increasing efficiency, reliability and precision, and reducing the need for human intervention (Schueller, 2006). However, agriculture is still suffering from an important lack of minimally trained workers, especially in the horticulture sector.

The problems generated by the absence of workers are amplified by the trends of increasing farm size, decreasing numbers of farmers and increasing environmental impact of food production, requiring even more efficient agricultural practices (Nagasaka, Umeda, Kanetai, Taniwaki, & Sasaki, 2004) and the productivity of conventional farming, in which the crop cultivation and management manually conducted by farmers, can be significantly improved by using intelligent machines (Xia, Wang, Chung, & Lee, 2015). Although robotics and automation require a more costly specialised workforce and equipment, they contribute to increased agricultural productivity because the required workforce, including skilled machine operators, generally declines enough to compensate for the higher initial cost. In addition to the reduced number of farms, the average age of the agricultural workforce is continuously increasing, indicating that this profession is not attractive enough for the younger generation (Iida et al., 2013; Noguchi, Will, Reid, & Zhang, 2004; Zhang, Noguchi, Ishii, Yang, & Zhang, 2013). However, despite the huge challenge of robotics and automation applications for farming operations, the reduction in tasks performed under harsh conditions and the increase in the farmer's quality of life should increase their attractiveness to the farming profession.

Unfortunately, unlike industrial applications which deal with relatively simple, repetitive, well-defined and predetermined tasks in stable and replicable environments, agricultural applications for automation and robotics require advanced technologies to deal with complex and highly variable environments and produce (Hiremath, Van der Heijden, Van Evert, Stein, & Ter Braak, 2014; Nof, 2009). Furthermore, agricultural production deals with live produce (fruit, vegetables, grains and flowers) which is highly sensitive to environmental and physical conditions (Eizicovits & Berman, 2014), such as temperature, humidity, gas, pressure, abrasion and acceleration. Live produce requires gentle, accurate and often complicated handling operations to maintain sufficient quality to travel the distance and time separating their production site from consumers. This characteristic makes the replacement of human ability by machines or automation extremely difficult. Therefore, most fruit, vegetable and flower growing and similar production tasks, e.g., trellising, harvesting, sorting and packaging, are still performed manually (Zion et al., 2014). This makes manual labour a major cost component in field operations (Eben-Chaime, Bechar, & Baron, 2011), reaching up to 40% of the total cost (Bechar & Eben-Chaime, 2014).

Most agricultural operations occur in unstructured environments characterised by rapid changes in time and space, such as military, underwater and space environments (Bechar & Edan, 2003). The terrain, vegetation landscape, visibility, illumination, and other atmospheric conditions are ill-defined, vary continuously, have inherent uncertainty, and generate unpredictable and dynamic situations (Bechar, 2010).

Fig. 1 – Images of pepper row in a greenhouse taken from a robotic platform at five different times of day along with the illumination data (Dar, Edan, & Bechar, 2011).

Figure 1 illustrates the influence of sun direction and illumination on the visibility of pepper rows in greenhouses.

Complexity increases when dealing with natural objects, such as fruits and leaves, because of high variability in shape, texture, colour, size, orientation and position which, in many cases, cannot be determined a-priori.

The robotic world can be divided into four groups according to the structural characteristics of the environments and objects: i) the environment and the objects are structured; ii) the environment is unstructured and the objects are structured; iii) the environment is structured and the objects are unstructured, and iv) the environment and the objects are unstructured. Each robotic domain, such as industry, medical, healthcare, mining, etc., can be associated with one of these groups (Table 1). This table highlights the differences between the domains, their complexity and difficulties. The agricultural domain is associated with the fourth group in which nothing is structured, making it a challenge in terms of commercialisation. Agricultural environments require that the robot be capable of movement, unlike most robots in factories or vehicles in car parks (Canning, Edwards, & Anderson, 2004). In such environments, there are many situations in which autonomous robots fail due to the many unexpected events (Steinfeld, 2004). This requirement for operating in unstructured environments complicates the robotics application and results in a system that is difficult and expensive to develop.

Robots are perceptive machines that can be programmed to perform specific tasks, make decisions, and act in real time. They are required in various fields that normally call for reductions in manpower and workload, and are best-suited for applications requiring repeatable accuracy and high yield under stable conditions (Holland & Nof, 2007). However, they lack the capability to respond to ill-defined, unknown, changing, and unpredictable events. The design of autonomous robotic systems frequently faces two important challenges. The first deals with the non-linear, real-time response requirements underlying sensor–motor control formulations. The second deals with how to model and use the human approach to address each different situation (Ng & Trivedi, 1998).

Research on autonomous vehicles in agriculture started in the early 1960s, focusing mainly on the development of automatic steering systems (Wilson, 2000). In the 1990s, the overwhelming majority of mechanical operations in field crop farming involved heavy, powerful and high-capacity machines, characterised by high-energy demands and high handling and operating costs. However, in the last decade, research at various universities and research institutions around the world has undergone a complete paradigm shift (Van Straten, 2004). The automation of agricultural robots is now considered essential for improving work efficiency and should include the potential for enhancing the quality of fresh produce, lowering production costs and reducing the drudgery of manual labour (Choi et al., 2015).

Table 1 – The four groups and associated robotics domains.

		Environment	
		Structured	Unstructured
Objects	Structured	Industrial domain	Military, space, underwater, mining domains
	Unstructured	Medical domain	Agricultural domain

1.2. Incentives for robots in field operations

Cultivation and production processes are complex, diverse, labour-intensive and usually unique to each crop. The process type and components are affected by many factors, including crop characteristics and requirements, the geographical/geometric/geological environment, the climatic and meteorological conditions (Tremblay et al., 2011), market demand and consumer preferences, and the farmer's capabilities and means. The technology, equipment and means required for executing an agricultural task involving any given crop and environment will not necessarily be applicable to another crop or a different environment. The wide variety of agricultural productions and their diversity worldwide make it difficult to generalise applications for automation and control (Schueller, 2006).

Labour is the largest single cost-contributor in agriculture (Bechar & Eben-Chaime, 2014). It is also the main limiting factor in the development of agricultural industries in both developed and developing countries. Labour force shortages damage farmer revenue, yield and durability. In countries where labour wages are low, their transient nature reduces production capability and quality. In addition, some of the manual work can cause musculoskeletal disorder risks and chronic health issues to workers (Perez-Ruiz, Slaughter, Fathallah, Gliever, & Miller, 2014). In a survey taken in the mid-1970s, bedding plant growers attributed about 25% of plant production costs to labour (Aldrich & Bartok, 1992). Nelson (1991) estimated the labour contribution to total production costs at 34.81%, including 5.58% depreciation and 2.5% interest. Labour is also considered a key factor in development and maintenance of the greenhouse production sector (Manzano-Agugliaro & Garcia-Cruz, 2009). In Southern Spain, the labour cost for greenhouse production of tomato, lettuce, pepper, melon, watermelon, squash, cucumber and bean amounts to 36–40% of the total cost (Manzano-Agugliaro & Canero-Leon, 2010; Montoya-Garcia, Callejon-Ferre, Perez-Alonso, & Sanchez-Hermosilla, 2013). Despite the differences and large variability in absolute magnitudes, labour contributes about 40% of the operational costs in all cases. The proportion increases in arable farming where maintenance and storage costs are much smaller. The enormous labour force required for the various operations causes bottlenecks, downgrading productivity, reducing yield and increasing costs and moreover, problems such as aging of workforce and shortage of farmers contribute to the lack of manpower (Iida et al., 2013). This high manual labour requirement impedes cost reductions and increases the demand for robotics and automation (Bechar, Yosef, Netanyahu, & Edan, 2007).

1.3. Conditions for robotic systems in agriculture

In the last three decades, there have been many research projects on agricultural robotics and intelligent automation that never reached the implementation stage. The main causes for these failures were excessive cost of the developed system, inability to execute the required agricultural task, low durability of the system, and its inability to successfully reproduce the same task in slightly different contexts or to satisfy mechanical, economic and/or industrial aspects. In addition, most approaches were adapted from an industrial point of view (Vidoni, Bietresato, Gasparetto, & Mazzetto, 2015). The usage of robotics in agriculture has to comply with the following rules:

i. The capricious requirements for manipulating specific produce must be considered first.
ii. The agricultural task and its components must be feasible using the existing technology and the required complexity.
iii. The cost of the agricultural robotics alternative must be lower than the expected revenue. However, it do not have to be the most profitable alternative.

In most cases, the implementation of robotics technology in agriculture is realisable if at least one of the following conditions is met:

i. The cost of utilising robots is lower than the cost of any concurrent methods.
ii. The use of robots enables increasing farm production capability, produce, profit and survivability under competitive market conditions.
iii. The use of robots improves the quality and uniformity of the produce.
iv. The use of robots minimises the uncertainty and variance in growing and production processes.
v. The use of robots enables the farmer to make decisions and act at higher resolution and/or increase the produce quality in comparison to the concurrent system to achieve optimisation in the growing and production stages.
vi. The robot is able to perform specific tasks that are defined as hazardous or that cannot be performed manually.

1.4. Limitations of robotic systems in agriculture

The technical feasibility of agricultural robots for a variety of agricultural tasks has been widely validated. Nevertheless, despite the tremendous amount of research, commercial applications of robots in complex agricultural environments are not yet available (Urrea & Munoz, 2015). Such applications of robotics in uncontrolled field environments are still in the developmental stages (Bac, Hemming, & Van Henten, 2013; Sivaraman & Burks, 2006). The main limiting factors lie in production inefficiencies and lack of economic justification. Development of an agricultural robot must include the creation of sophisticated, intelligent algorithms for sensing, planning and controlling to cope with the difficult, unstructured and dynamic agricultural environment (Edan & Bechar, 1998).

Agricultural robots require the development of advanced technologies to deal with complex and highly variable environments and produce (Nof, 2009). In addition, the seasonality of agriculture makes it difficult to achieve the high level of utilisation found in manufacturing. However, even if the technical and economic feasibility of most of the field robotics applications is not reached in the near future using the existing knowledge and technologies, partial autonomy will add value to the machine long before autonomous production robots are fully available. For many tasks, the Pareto principle applies. It claims that roughly 80% of a task is easy to adapt to robotics and/or automation, but the remaining 20% is difficult (Stentz, Dima, Wellington, Herman, & Stager, 2002). Therefore, by automating the easy parts of a task, one can reduce the required manual work by 80%. Furthermore, the development of partially autonomous robots is an excellent transitional path to developing and experimenting with software and hardware elements that will eventually be integrated into fully autonomous systems.

There has been a significant amount of research worldwide in this field in recent years (Conesa-Munoz, Gonzalez-de-Soto, Gonzalez-de-Santos, & Ribeiro, 2015) that demonstrated the technical feasibility of agricultural robots for a variety of crops, agricultural tasks and robotic abilities, as presented in Table 2. However, automation solutions have not yet been commercially implemented successfully for field operations and only few developments have been adopted and put into practice (Burks et al., 2005; Xiang, Jiang, & Ying, 2014).

Production inefficiencies are caused by limited autonomy and human–robot interactions, leading to long cycle times and delays, low detection rates (Zhao et al., 2016) and inability to perform agricultural tasks in unstructured environments. However, although limited in number, some robotics applications are now commercially available. These applications were implemented step by step, resulting in good performance of some dedicated tasks. Examples include milking robots (Halachmi, Adan, Van Der Wal, Van Beek, & Heesterbeek, 2003; Hansen, 2015; Kolbach, Kerrisk, Garcia, & Dhand, 2013) and autonomous combines or tractors (Bell, 2000; Schueller, 2006; Thuilot et al., 2002). The implementation process for the development of these first autonomous robots has indicated that the drawbacks and inefficiencies require solutions that uses the advantages of the human to enable the robot to react and cope with dynamic and complex conditions, thus, incorporate collaborative human–robot systems (HRS), at least for a while (van Henten, Bac, Hemming, & Edan, 2013b).

2. Concepts of robots for application in agriculture

2.1. *Human–robot concept*

Human capabilities of perception, thinking, and action are still unmatched in environments with anomalies and unforeseen events (Tervo & Koivo, 2014); as a result, human and robot skills are still complementary (Rodriguez & Weisbin, 2003). Human-robot research is a constant developing field, evolving from continuous human-controlled master–slave mechanisms to a broad range of robots incorporating artificial intelligence for many applications and under human supervisory control (Sheridan, 2016). Over the past two decades, research has investigated collaborations between a human operator (HO) and the system to create a HRS. Such research has addressed the levels of automation available for handling the various aspects of data acquisition, data and information analysis, decision-making, action selection and implementation appropriate for various task or sub-task goals and parameters. Various types and levels of automation have been evaluated by examining the associated human performance consequences, such as mental workload, situation awareness, complacency, and skill degradation (Guida & Lamperti, 2000). Sheridan (1992) described 10 levels of human–robot collaboration, ranging from fully autonomous without human intervention, to fully manual. It becomes necessary to shift from one collaboration level to another during task performance if the environment, crop, robot, or HO parameters change during the task operation. Mann et al. (2016) suggests two approaches of HRS, one is to combine human workers and robots synergistically, and the other, separating operations allow the strongest link - robot actuators, to operate independently from the weakest link – the sensing/HO. Intervention of a HO in the operation loop generally improves the performance of the global system by increasing guidance accuracy, enhancing target identification, shortening processing time, reducing system complexity, and handling unknown and unpredictable events that fully autonomous systems cannot deal with (Bechar, Meyer, & Edan, 2009). By taking advantage of human perception skills and the autonomous system's accuracy and consistency, the HRS is simplified, resulting in improved performance (Parasuraman, Sheridan, & Wickens, 2000) and reduced cost. In such systems, mapping the environment is important for the success of the interaction and for situation awareness by HOs (Nof et al., 2013).

Introducing a HO into the operation cycle—to interact with, instead of just supervising the system—is a relatively new trend in agricultural robotics research, which can help improve performance and reduce system complexity. In fact, some important progress has been made in the two last decades. According to Ceres et al. (1998), cooperation of an agricultural robot with a HO (a HRS) helps solve three difficult problems: i) driving the robot through the field, from tree to tree and/or from row to row; ii) detecting and localising the produce; iii) grasping and detaching selected produce. In their research, they successfully developed a HRS called "AGRIBOT" (Fig. 2) which solved these three problems. Nagasaka et al. (2004) developed a HRS in which the HO controls multiple semi-autonomous operating systems in paddy fields. Bechar and Edan (2003) reported that, on average, the HRS increased melon detection by 4% compared with manual detection, and by 14% compared with a fully autonomous system. This resulted in higher detection rates (average of 94% and up to 100%) and overcame the limitations of fully autonomous systems, in which detection success was, on average, lower (75–85%). In addition, the HRS detection times were 20% shorter than those achieved with manual detection. Bechar et al. (2009) developed an objective function to determine the best collaboration level subject to the HO, system, task and environmental properties. Oren, Bechar, and Edan (2012) provided tools to develop a HRS target-recognition system and classified the HRS into two types of systems, one focused on minimising false alarms and the second on detecting a target when one is present. Tkach, Bechar, and Edan (2011) developed a set of algorithms for real-time dynamic switching between collaboration levels in a HRS. The algorithms

Table 2 – Summary of technical feasibility of agricultural robots for crops, tasks and abilities. The research effort measured by the number of published articles in the past three decades using a Scopus (https://www.scopus.com/) search. Each article may contain one or several topics.

Category	Type (Research effort)	Sample references
CROP	Citrus (193)	(Brown, 2005; Edan & Miles, 1993; Hannan, Burks, & Bulanon, 2007; Harrell, Adsit, Munilla, & Slaughter, 1990; Mehta, MacKunis, & Burks, 2016; Muscato, Prestifilippo, Abbate, & Rizzuto, 2005)
	Apple (363)	(Baeten, Donné, Boedrij, Beckers, & Claesen, 2008; Bulanon, Kataoka, Ota, & Hiroma, 2002; D'Esnon, 1985; Nguyen, Kayacan, De Baedemaeker, & Saeys, 2013)
	Tomato (176)	(Huang, Yang, & He, 2012; Kondo, Monta, & Fujiura, 1996; Kondo et al., 2009; Zhao, Gong, Huang, & Liu, 2016)
	Pepper (73)	(Bac, Hemming, & Van Henten, 2014; Lehnert, Perez, & McCool, 2015; Mann, Zion, Shmulevich, & Rubinstein, 2016; Schor et al., 2016; Van Henten, Bac, Hemming, & Edan, 2013a; Vitzrabin & Edan, 2016)
	Cucumber (66)	(Ota et al., 2007; Van Henten et al., 2002; Van Henten, Schenk, van Willigenburg, Meuleman, & Barreiro, 2010; Van Henten, Van't Slot, Hol, & Van Willigenburg, 2009)
	Strawberry (51)	(Cui, Gejima, Kobayashi, Hiyoshi, & Nagata, 2013; Dimeas, Sako, Moulianitis, & Aspragathos, 2015; Guo, Cao, & Masateru, 2008; Hayashi et al., 2010; Xu, Imou, Kaizu, & Saga, 2013)
	Eggplant (31)	(Blanes, Ortiz, Mellado, & Beltrán, 2015; Hayashi, Ganno, Ishii, & Tanaka, 2002; Song, Sun, Zhang, Zhang, & Xu, 2007)
	Melon and Watermelon (46)	(Edan & Miles, 1993; Mann, Rubinstein, Shmulevich, Linker, & Zion, 2014; Mann et al., 2016; Sakai, Iida, Osuka, & Umeda, 2008; Umeda, Kubota, & Iida, 1999)
	Other vegetables (Asparagus, Cabbage, Radish, Cherry)	(Figliolini & Rea, 2006; Foglia & Reina, 2006; Irie, Taguchi, Horie, & Ishimatsu, 2009; Tanigaki, Fujiura, Akase, & Imagawa, 2008)
	Flowers (374)	(Abarna & Arockia Selvakumar, 2015; Rath & Kawollek, 2009; Van 't Ooster, Bontsema, Van Henten, & Hemming, 2013)
	Rice and paddy fields (186)	(Chen, Tojo, & Watanabe, 2003b; Choi et al., 2015; Tamaki, Nagasaka, & Kobayashi, 2009; Tamaki et al., 2013)
AGRICULTURAL TASK	Transplanting and seeding (255)	(Hu et al., 2014; Huang & Lee, 2008; Kutz, Miles, Hammer, & Krutz, 1987; Lin, Dong, Liu, & Yi, 2015; Mao, Han, Hu, & Kumi, 2014; Nagasaka, Mizushima, Noguchi, Saito, & Kubayashi, 2007; Nagasaka, Taniwaki, Otani, & Shigeta, 2002; Ruangurai, Ekpanyapong, Pruetong, & Watewai, 2015; Ryu, Kim, & Han, 2001)
	Plant protection and weed control (326)	(Astrand & Baerveldt, 2005; Bak & Jakobsen, 2004; Bakker, Van Asselt, Bontsema, & Van Henten, 2010; Byungho & Soohyun, 2013; Chen, Tojo, & Watanabe, 2003a; Choi et al., 2015; Hiremath, Van der Heijden, Van Evert, & Stein, 2012; Kim, Kim, Hong, Han, & Lee, 2012; Lamm, Slaughter, & Giles, 2002; Ogawa, Kondo, Monta, & Shibusawa, 2006; Perez-Ruiz et al., 2014; Ruckelshausen et al., 2006; Slaughter, Giles, & Downey, 2008; Tillett, Hague, Grundy, & Dedousis, 2008; Torres-Sospedra & Nebot, 2014; Van Evert et al., 2011)
	Harvesting (302)	(Ceres et al., 1998; Edan, Rogozin, Flash, & Miles, 2000; Foglia & Reina, 2006; Hayashi et al., 2010; Kondo et al., 1996; Mehta & Burks, 2014; Mehta et al., 2016; Muscato et al., 2005; Rath & Kawollek, 2009; Riyaz Ahammed, Sankar Reddy, Vennishmuthu, Hushein, & Gayathri, 2015; Scarfe, Flemmer, Bakker, & Flemmer, 2009; Tanigaki et al., 2008; Zhang et al., 2013; Zhao, Lv, Ji, Zhang, & Chen, 2011)
SUPPORTING TASKS	guidance and navigation (446)	(Astrand & Baerveldt, 2005; Bahadorian, Eaton, Hesketh, & Savkovic, 2014; Bakker, Van Asselt, Bontsema, Muller, & Van Straten, 2011; Bell, 2000; Bochtis, Sorensen, & Vougioukas, 2010; de Sousa, Tabile, Inamasu, & Porto, 2013; Dong, Heinemann, & Kasper, 2011; Galceran & Carreras, 2013; Hameed, la Cour-Harbo, & Osen, 2016; Khot, Tang, Blackmore, & Norremark, 2006; Morimoto, Suguri, & Umeda, 2005; Mousazadeh, 2013; Thuilot, Cariou, Martinet, & Berducat, 2002; Wilson, 2000)
	Mapping and Localisation (261)	(Bayar, Bergerman, Koku, & Konukseven, 2015; Eizicovits & Berman, 2014; Gimenez, Herrera, Tosetti, & Carelli, 2015; Griepentrog, Norremark, Nielsen, & Blackmore, 2005; Hansen et al., 2013; Ip & Rad, 2004; Qiao, Sasao, Shibusawa, Kondo, & Morimoto, 2005; Se, Lowe, & Little, 2005; Underwood, Jagbrant, Nieto, & Sukkarieh, 2015)

(continued on next page)

Table 2 – (continued)

Category	Type (Research effort)	Sample references
	Fruit and vegetable grasping (125)	(Chiu, Yang, & Chen, 2013; Dimeas et al., 2015; Eizicovits & Berman, 2014; Kondo et al., 2010; Kubota, McClure, Kokalis-Burelle, Bausher, & Rosskopf, 2008; Li, Li, Yang, & Wang, 2013; Monta, Kondo, & Ting, 1998)
	Multi-robot interaction (60)	(Bechar, Nof, & Wachs, 2015; Conesa-Munoz et al., 2015; Emmi, Paredes-Madrid, Ribeiro, Pajares, & Gonzalez-De-Santos, 2013; Garcia-Perez, Garcia-Alegre, Ribeiro, & Guinea, 2008; Li, Remeikas, Xu, Jayasuriya, & Ehsani, 2015; Tervo & Koivo, 2014; Zhang, Noguchi, & Yang, 2016)

were developed for a closed-loop controller to maximise system performance despite deviations in the parameter values of each component. These developments have enabled smooth real-time adaptation of the HRS to many possible changes in the environment, HO or robot performance. Stentz et al. (2002) investigated the context of a semi-autonomous system for agricultural spraying of groves, orchards, and row crops. Such tele-operation has been used to guide a hydrostatic transmission drive vehicle. A human programs a task by driving the relevant routes. The task is divided into sub-tasks and assigned to a tractor that drives portions of the routes. The tractor stops for obstacles until it receives advice from a supervisor over a wireless link. A complete system was tested in a Florida orange grove, where it drove 7 km autonomously. The major challenges were the time delay in communication and the need for full-time human attention (Subramanian, Burks, & Arroyo, 2006).

2.2. Fully autonomous robot concept

Autonomous robot systems (ARS) are developed to perform tasks, make decisions, and act in real time without human intervention. They are required in some domains which normally demand reductions in labour and workload, and are best suited for applications that require repeatable accuracy and high yield under stable conditions. In recent years, an increasing amount of robotics research has focused on mobile ARS in unstructured environments (indoors and outdoors).

Sensing and reasoning are the basic requirements for attaining a reasonable degree of autonomy. Thus, ARS must possess a high degree of flexibility to be involved in continuously changing environmental conditions as well as to process the information they have received from their own sensors. Two important challenges are frequently encountered when designing ARS. The first deals with the non-linear, real-time response requirements underlying the sensor–motor control formulation. The second deals with how to model and use the approach that a human would take to address the encountered problems (Ng & Trivedi, 1998).

The operation of ARS in real-world, dynamic, unstructured environments is difficult (Fletcher, Loy, Barnes, & Zelinsky, 2005), and still yields inadequate results involving inherent uncertainties, unknown operational settings and unpredictable environmental conditions. Inadequacies of sensor technologies further impair ARS capabilities. Therefore, the promise of an automatic and efficient ARS has fallen short of expectations in unstructured and complex environments (Kim & Shim, 2003; Xiang et al., 2014). In addition, the relevant agricultural produce is of relatively low commercial value; therefore, the utilisation cost of an ARS per produce unit should be very low to be economically justified. Similar to HRS, the seasonal nature of agriculture makes it difficult for

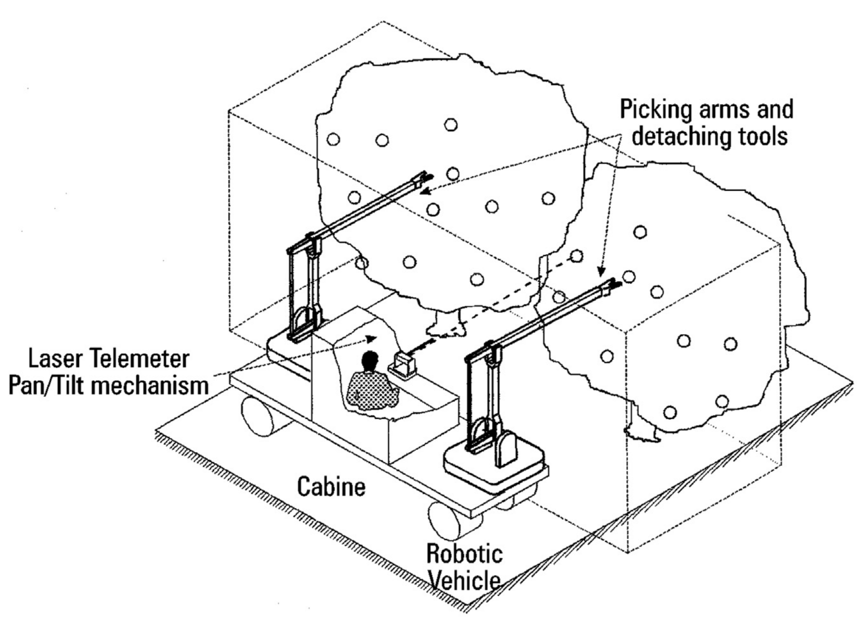

Fig. 2 – AGRIBOT (Ceres et al., 1998).

ARS to achieve a high utilisation level. Thus, the complex agricultural environment, combined with intensive production and a short production season require a robust ARS with short development time at low cost (Nof, 2009).

In the distant future, because of the increased data-processing required to cover a complete field at the individual plant level, it will be practicable to perform only certain operations by means of human intervention; therefore, various forms of automation will be needed, especially when dealing with high-value crops. However, in recent years, the development of autonomous vehicles in agriculture has garnered interest in seeking means to satisfy these requirements (Pedersen, Fountas, Have, & Blackmore, 2006). Even the ultimate goal of full autonomy for an agricultural robot is difficult to reach; partially autonomous vehicles or robotic systems can add value to the machine long before full autonomy is achieved, if its cost is low enough and its performance high enough to make it cost-effective. Furthermore, if the required human intervention is low enough, it may be possible for a single HO to supervise or collaborate with several machines (Stentz et al., 2002). In some cases, even if an ARS is available, some HRS could be developed to ensure safety.

3. Principles and components

3.1. *Principles and required abilities*

ARS used for crop production are composed of numerous sub-systems and devices that enable them to operate and perform their tasks. These sub-systems and devices deal with path planning, navigation or guidance abilities, mobility, steering and control, sensing, manipulators or similar functional devices, end effectors (produce contactors or tools), and above all, guidelines on how to manage individual or simultaneous unexpected events, and some level of autonomy (van Henten et al., 2013b). Agricultural robots are generally designed to execute a 'main task', which is usually a specific agricultural task such as planting, weeding, pruning, picking, harvesting, packing, handling, etc. To perform the 'main task', the ARS requires the ability to perform several 'supporting tasks', e.g., localisation and navigation, detection of the object to treat, the treatment or action to perform, etc. Information and commands are transferred between the 'supporting tasks' and between the 'supporting' and 'main tasks'. Each 'supporting task' controls one or several sub-systems and devices, and a sub-system or device may serve several 'supporting tasks' (Fig. 3). For instance, in developing a disease monitoring robot (Schor et al., 2016), the 'main task' is the disease monitoring, the ARS needs the ability to perform the 'supporting tasks' of self-localisation, trajectory planning, steering and navigating in the plot from its actual location to the new one, collaborating with HO or interacting with a human presence and other robots or unexpected objects in the pathway, and modifying its trajectory planning as necessary. Nguyen et al. (2013) developed and implemented a framework for motion and hierarchical task planning for apple harvesting robot and Ceres et al. (1998) developed and implemented a framework for human integrated citrus harvesting robot. A framework for agricultural and forestry robots was developed by Hellstrom and Ringdahl (2013).

3.2. *Mobility and steering*

The fundamental behaviour of a mobile ARS engaged in motion planning is regarded as a dynamic process involving interaction between the robot and its local environment. This process is modelled and controlled for motion-planning purposes (Jing, 2005). The mobility and steering sub-systems interact through soil contact, directing the vehicle in the desired orientation at the appropriate speed. According to Grimstad, Pham, Phan, and From (2015) several consideration need to be regarded in development of an agricultural robot, such as the need to operate during wet periods without getting stuck or damaging the soil structure, keeping the overall costs of the robot at a level which makes it economically viable and the robot frame/platform should be flexes, which reduces

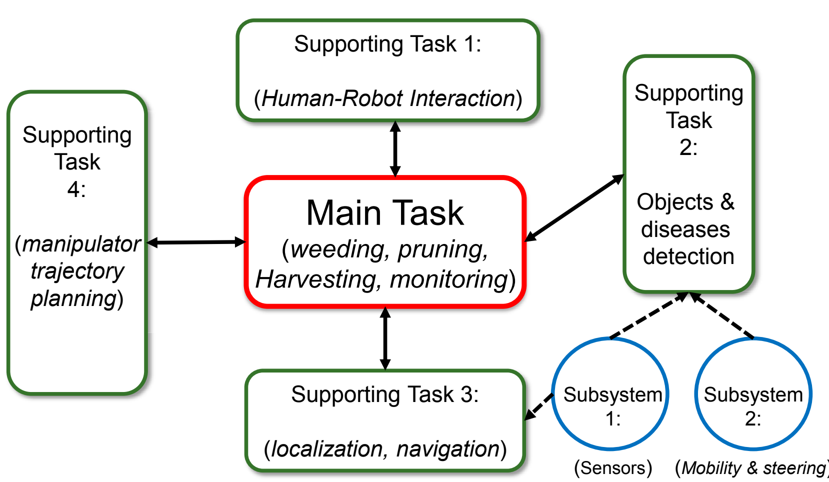

Fig. 3 – Structure of task sub-systems in an agricultural robot. Solid arrows represent commands, data and information transfer; dashed arrows represent conceptual connections. The writing in the parentheses are examples for agricultural robot 'main tasks', 'supporting tasks' and subsystems.

complexity but enables that all wheels are in contact with the ground. These platforms, commonly used in agriculture, comprise 4-wheel platforms with either 2 or 4-wheel drive and 2 or 4-wheel steering. Some platforms with 6-wheel drive or tracked platforms are also in use.

Lin et al. (2015) developed a 4-wheel drive/4-wheel steering robotic platform fits to the working environment and the agronomic requirements of a wheat precision seeding techniques (Fig. 4a). Rotation and steering of the wheels are controlled independently with four servomotors for propulsion and four step motors to steer. A central controller coordinated the eight motors. They used four identical wheel modules, each capable of steering and propulsion. The platform allows orienting the vehicle in any desired direction and modifying or maintaining the vehicle orientation independently of the vehicle displacement direction, even during the turning process. Field tests showed that the qualified rates of seeding exceed 93% in different sowing speed. A similar design was developed for weed detection (Bak & Jakobsen, 2004). The improved mobility and manoeuvrability of the platform allows parallel displacement of the vehicle to the rows during the turning process. The platform allows orienting the vehicle in any desired direction and modifying or maintaining the vehicle orientation independently of the vehicle displacement direction, even during the turning process. Evaluation tests indicated that this platform follows paths with standard deviations of up to 16 and 107 mm at speeds of 0.2 and 1.6 m s^{-1}, respectively.

The mobility and steering sub-systems are controlled by low-level control issuing steering and speed or throttle commands to the sub-systems based on the platform conditions as recorded by the sensors and the task plan. Gat, Gan-Mor, and Degani (2016) developed an autonomous vehicle steering control algorithm for manoeuvring in greenhouses using an overhead guide constructed in the greenhouse to mark the desired path of the vehicle and a rigid bar connected from the guide to the vehicle. Bergtold, Raper, and Schwab (2009) examined an automatic steering system for tillage and planting operations in cotton production. They conducted an economic analysis on improving the proximity and accuracy of the required operations. They demonstrated that as the distance between the planted row and tillage pass increases from 6 to 100 and then to 300 mm, seed cotton yields were reduced by 24–52% and net revenues from cotton production by 38–83%. This finding also indicated that auto-guidance systems with an accuracy of 25 mm or better could be highly profitable for larger farms, whereas systems with less accuracy (100 mm) and lower price provide a better economic alternative for smaller farms. Lipinski, Markowski, Lipinski, and Pyra (2016) examined three steering modes: one conventional when the tractor was operated manually and two automatic steering modes which relied on satellite navigation with free (SF1 (Starfire free access)) and paid subscription (SF2 (StarFire paid subscription access)) access to the correction signal. It was found that although the automatic steering modes were superior to the conventional there was no significant different between the performances using the SF1 or SF2 correction signal. Kodagoda, Wijesoma, and Teoh (2002) used a feed forward coupled with a fuzzy proportional derivative–proportional integral controller to guide a tractor through crop rows. Their designed controller out-performed the conventional proportional–integral–derivative (PID) schemes, which were shown to be insensitive to parametric uncertainty, load and parameter fluctuations, and it was suitable for real-time implementation. PID control was also used to guide a grain harvester by calculating the actuator command signal according to the heading offset (Benson, Reid, & Zhang, 2003). The performance of the controller was comparable to that of manual steering.

Although the mobility and steering abilities were extensively investigated and a variety of functioning semi-commercial systems were designed, information on comparisons between the different system types or their suitability for agricultural terrain is rarely available.

3.3. *Sensing and self-localisation*

Sensors are used for a wide variety of missions, such as mapping, localisation, navigation, guidance, plant detection, recognition, and measurement of environmental parameters (including soil, water, air and plants). They are used to support decision-making, operations, activation, execution of the task, and evaluation of the robot's performance. Sensors may be divided into categories according to the data they generate: i) motion measurement, i.e., odometry or inertial and artificial landmarks, laser positioning/radar or millimetre-wave radar; ii) local feature detection using sonar or machine vision (Hague, Marchant, & Tillett, 2000); iii) absolute positioning

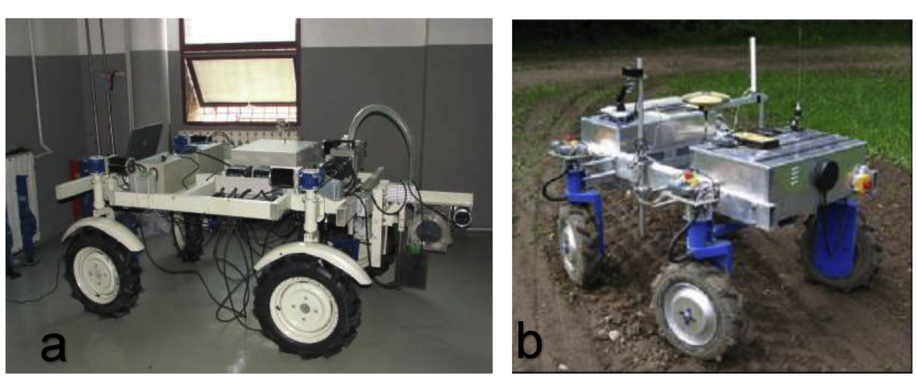

Fig. 4 – The 4-wheel steering/4-wheel drive robotic platforms for a) wheat precision seeding (Lin et al., 2015) and, b) weed detection (Bak & Jakobsen, 2004).

using a global positioning system (GPS); iv) environmental parameters using a wide variety of sensors, such as near-infrared (NIR) or infrared (IR), X-ray, fluorescence, acoustic, optic, 2-D and 3-D vision, strength gauge, etc (Li, Vigneault, & Wang, 2010; Tremblay, Wang, & Cerovic, 2012).

Sensor division may also be based on its position or the information it is measuring, i.e., internal and external sensors. Internal sensors measure the state of numerous different parts of the system, e.g., encoders reporting joint or wheel angles, accelerometers measuring linear accelerations or inertia, and gyroscopes measuring rotational accelerations. These sensors are generally used for dead reckoning. Inertial sensors have been used in a number of vehicle applications as an alternative to odometers for dead reckoning to avoid the difficulty of modelling odometer error. These sensors can also be encapsulated, resulting in a robust package (Hague et al., 2000). However, internal sensors tend to drift and accumulate errors due to temperature changes, gravity, wheel or track slip, and exposure to local magnetic fields or proximity to magnetic materials. When inertial sensor data are integrated to give position and orientation, these sources of error can rapidly lead to important positional drift.

The external sensors used in agricultural robots or automated systems collect environmental information regarding the state of the system relative to the position of the robot and the local positioning of its various components using GPS, IR, machine vision, laser radar (LIDAR), ultrasonic waves (Hague et al., 2000), hyperspectral (Zhao et al., 2016) and environmental parameters (ElMasry, Nassar, Wang, & Vigneault, 2008; ElMasry, Wang, Vigneault, Qiao, & ElSayed, 2008; Li, Wang, Vijaya Raghavan, & Vigneault, 2009). Among these external sensors, machine vision and GPS sensors have achieved the greatest commercial success (Slaughter et al., 2008).

GPS sensors, which provide absolute positioning of the system, are used for navigation and guidance. The advanced and high-accuracy GPS systems, i.e., real-time kinematic (RTK) GPS and differential GPS (DGPS), enable accurate real-time measurements. However, their high cost is one of the main factors increasing the cost of the robotic system (Pedersen et al., 2006) and they are too expensive to be widely used in farm machinery (Rovira-Más, Chatterjee, & Sáiz-Rubio, 2015). Nagasaka et al. (2004) demonstrated that RTK-GPS receivers give very accurate results during open field operation. Zhang et al. (2016) used a RTK-GPS for navigation of team robots. This high level of accuracy justifies their use as the primary sensor in agricultural vehicle navigation systems for steering control (Subramanian et al., 2006). However, in covered areas such as orchards, the GPS is not as accurate as in open fields since the receiver is frequently located under the tree canopy, which blocks the satellite signals or causes error accumulation from multiple reflections from the tree canopy (Subramanian et al., 2006). The greenhouse environment also generates positioning errors since its structure returns the GPS signal in multiple directions. Since the errors of GPS and dead-reckoning sensors are complementary in nature (Khot et al., 2006), the integration of a GPS with internal sensors for navigation reduces the errors accumulated by each, and acts as a reference. Gomez-Gil, Ruiz-Gonzalez, Alonso-Garcia, and Gomez-Gil (2013) developed a low-cost GPS receiver to provide geodetic positioning information. The aim of their work was to reduce the quantisation errors of some low-cost GPS receivers by using a Kalman filter (Rassameyoungtong & Srinonchat, 2012). Kinematic tractor model equations (Gomez-Gil, Alonso-Garcia, Gómez-Gil, & Stombaugh, 2011) were used to particularise the filter, which was tuned by applying Monte Carlo techniques (Brooks, 1998) on 18 straight trajectories, to select the covariance matrices that produce the lowest root mean square error (RMSE) in these trajectories. Filter performance was then tested by using straight tractor paths that were either simulated or acquired by a GPS receiver. The results showed that the filter reduces the quantisation distance error by approximately 43%, and the standard deviation of the heading by 75%, demonstrating the advantage of pre-processing the low-cost GPS receiver data when used in assisting guidance GPS systems for tractors. The filter can also smooth tractor GPS trajectories when moving over rough terrain.

Machine vision is a highly versatile sensor, often used for navigation, guidance and plant or object detection, but also for plant characteristic measurements associated with specific agricultural tasks. The sensor consists of a camera and a CCD (Charge Coupled Device) or a CMOS (complementary metal oxide semiconductor), usually operating in the IR, NIR or visible spectrums to extract both colour and depth information (Nissimov, Goldberger, & Alchanatis, 2015). It is a relatively inexpensive and powerful sensing tool. However, it must be combined with other sensors within the proper framework for use in guidance (Hague et al., 2000) or harvesting (Fernandez, Salinas, Montes, & Sarria, 2014). In some cases, multiple camera positions and viewing angles are taken simultaneously (i.e., stereo vision) or in time series due to the complex structure of the environment and the crop (Hemming, Ruizendaal, Hofstee, & van Henten, 2014).

LIDAR is used for distance measurements, mapping and obstacle detection and avoidance. Due to its ability to accurately measure a relative vectorial position (distance and direction), it is a promising tool for agricultural robot-guidance applications. Underwood et al. (2015) developed an algorithm for building detailed orchard maps for precision agriculture purposes using a 2D LIDAR sensor data (SICK LMS-291, SICK Ag, Reute, Germany) mounted on a moving ground platform and analysed using a hidden semi-Markov model. The results show an average matching performance of 86.8% and 98.2% of recognition and localization for data sets taken one full year apart. LIDAR technology can be also used to create a sort of stereoscopic vision when using a system composed by two LIDAR sensors aligned vertically, scanning the same targets (Bietresato, Carabin, Vidoni, Gasparetto, & Mazzetto, 2016). However, dust, fog and other similar conditions that block incoming light generally reduce LIDAR accuracy and performance (Subramanian et al., 2006).

Sensing and self-localisation abilities have been drastically improved in the last decade, mainly due to recent advances in sensor hardware, generating better accuracy, reliability and resolution, and to algorithm development that has improved real-time capabilities, reasoning and information extraction. For instance, Bayar et al. (2015) developed perception and navigation systems for autonomous orchard vehicles in modern planting environments, based on a 2-D laser scanner, wheel and steering encoders, and algorithms that process the sensor data and output the vehicle's location in the orchard. The navigation system includes an obstacle detection subsystem that prevents the vehicle from colliding with people, trees, and bins. Sensor fusion also investigated as a technique that allows to combine knowledge from various sources to maximize their usefulness (Jaroszek & Trojnacki, 2015) and it is a relative mature research field in other domains such as indoor and urban navigation, transportation, etc (Jo, Lee, & Sunwoo, 2016; Kim, Kim, Yoo, & Huh, 2016; Kim, Song, Lee, & Jang, 2015; Li, Chen, Li, Shaw, & Nüchter, 2014; Marín, Vallés, Soriano, Valera, & Albertos, 2013). Nevertheless, in different agricultural environments, more research needs to be conducted on multi-sensor fusion systems for generating, assembling and coordinating all of the required information to obtain a fully autonomous localisation system or the required sensing abilities for performing specific tasks, since many of the published studies focuses on a single sensor (e.g., GPS), which cannot reconstruct the full information required.

3.4. *Path planning and guidance*

Engineers and scientists have been trying to establish automatic guidance systems for agricultural vehicles for more than 50 years with little success (Yekutieli & Garbati-Pegna, 2002). On the other hand, crop-row guidance systems have recently achieved a high level of automation and some commercial success (Slaughter et al., 2008). Path planning is considered a sub-task of navigation, which in turn is one of the most common and required ‘supporting tasks’ of agricultural robots (Bochtis, Sorensen, & Busato, 2014). The basic path-planning problem involves finding a good-quality path from a source point to a destination point that avoids collision with obstacles (Bhattacharya & Gavrilova, 2008). Path planning was originally studied extensively in robotics application, but has gained more relevance in other areas, such as computer graphics, simulations, geographic information systems, very-large-scale integration (VLSI) design, and computer games. Path planning still presents one of the core problems for the development of ARS, autonomous vehicles and perceptive systems in modern robotics applications.

With respect to field production, many studies have been conducted and some developed systems have achieved acceptable path planning, reaching navigational capability in the field. Hameed et al. (2016) developed a side-to-side 3D field coverage approach which ensure 100% coverage regardless of the topographical nature of the field surface. Nagasaka et al. (2004) applied autonomous guidance for rice transplantation using fibre-optic gyro (FOG) sensors, GPS, and accelerometers to determine position and orientation, rotary encoders to determine steering angle, and proximity sensors to monitor the clutch and break positions of the vehicle. The system used outputs from an industrial programmable logic controller (PLC) as commands for the vehicle actuators to control the vehicle's orientation and speed. Bengochea-Guevara, Conesa-Muñoz, Andújar, and Ribeiro (2016) developed a small autonomous field inspection vehicle to minimise the impact of the scouting on the crop and soil compaction. Their system integrates a camera with a GPS receiver, a reflex camera positioned on the front of the robot for extracting the central crop row under uncontrolled lighting conditions in real time, two fuzzy controllers to achieve vision-guided navigation and a path planner algorithm regarding the field contour and the crop type to determine the best inspection route. Utstumo, Berge, and Gravdahl (2015) Developed a navigation controller for a mobile weeding robot that follows the established wheel tracks in the plot in order to minimise soil compaction.

Bhattacharya and Gavrilova (2008) developed a computational geometric data structure to solve the problem of generating an optimal path between the source and destination points in the presence of simple disjoint polygonal obstacles. Canning et al. (2004) developed a forest-navigating robot using encoders, ultrasonic sensors and a fuzzy-logic control to improve the safety of forest operations by removing the HO from the vehicle and reducing costs by automating these operations (Fig. 5). In another study, a path tracking controller for an articulated service unit was developed based on an algebraic approach and implemented to a hierarchical navigation controller (Auat Cheein et al., 2016).

Additional investigated methods for navigation and path planning include probabilistic road mapping and artificial potential-field-based methods. In the latter, the mobile robot is regarded as a charged particle moving through repulsion potentials presented by obstacles and attractive potentials associated with the goals. The potential force provides the most appropriate heading for the robot to take. Other methods, such as behaviour-based methods, genetic algorithms, neural networks, fuzzy logic, reinforcement learning, and many combinations of these methods have been used for the development of path planning and navigation systems (Jing, 2005).

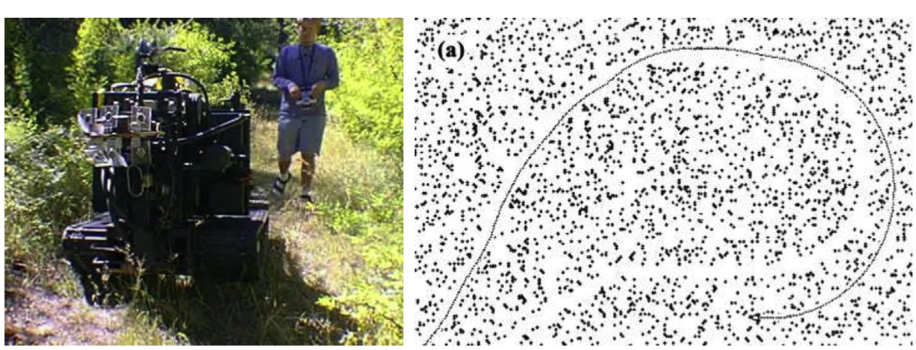

Fig. 5 – Forest-navigating robot using encoders, ultrasonic sensors and a fuzzy-logic control (Canning et al., 2004).

3.5. Manipulators and end effectors

In robotics, a manipulator is generally an arm-type electro-mechanical device that is able to move in a confined space, and ends in a tool or end effector. The manipulators are classified according to their degree of freedom, type of joint, link length, and offset length (Kondo & Ting, 1998). The principal task of a manipulator is to move its end effector to a position where it can interact with the task object, and to orient the end effector to enable it to perform the required mission. Each manipulator and end effector is usually designed for a specific task and environment. However, a special-purpose manipulator can be used to perform various other tasks as well by using different end effectors.

Robots are widely used in the industrial domain. However, despite the universality of industrial robots and their capacity to be fitted to many agricultural tasks, their heavy weight, high power consumption, and high costs make them inappropriate for agricultural purposes (Bloch, Bechar, & Degani, 2016). In robotics and automated systems for most field crop-production tasks, such as weed control, tillage, harvesting and transportation, the manipulator, if it exists, will be simple and basic, and the end effector will not necessarily be in physical contact with the object. In most cases, the end effector is a sensor or an applicator such as a camera or a spray nozzle, respectively. Due to these facts, most of the simpler manipulators for agricultural tasks must be specifically designed instead of adapted from those for industrial purposes (Belforte, Deboli, Gay, Piccarolo, & Ricauda Aimonino, 2006; Gao, Feng, Yang, & Li, 2016; Liu, Li, & Mao, 2015; Sakai et al., 2008; Scarfe et al., 2009).

The choice of mechanism for any given end effector depends on the specific task, or operation to be performed (measurement, destruction, harvesting), the environment (sub-soil, soil, water, air), and the object to be manipulated (data, soil, plant, fruit). Most of the objects handled in plant production systems are, at least to some degree, of various sizes and shapes, even if they are of the same type (apple) or even variety (e.g. McIntosh or Empire). They are also normally much softer than the materials covering the contacting part of the end effector, and are usually easily damaged. Therefore, when physical contact is required, the end effector should be accompanied by sensors measuring the direction and force applied on the object to avoid injuring it and grasp-pose maps (Eizicovits & Berman, 2014) need to be constructed for gripper design and online grasp planning. These measurements are even more important when specific movements must be executed to accomplish the task. A typical example is apple harvesting, which does not consist of simply pulling the fruit from the tree in random directions until the tree releases the fruit. The harvesting movements are specific for each fruit and depend on the fruit position and orientation in relation to the tree structure, branch position and orientation, and other nearby fruit. In recent years, several multi-arm systems have been developed for applications in agriculture (Zion et al., 2014). Dual-arm mobile robotic manipulators have been employed in many agricultural activities including the manipulation of delicate and deformable products, spraying and harvesting (Korayem, Shafei, & Seidi, 2014). However, agricultural manipulators still do not perform field tasks commercially (Bechar, 2010) and there is no methodology for task description to design a robotic arm.

4. Conclusions

Robots or intelligent automation systems are generally highly complex since they consist of several different sub-systems that need to be integrated and correctly synchronised to perform tasks perfectly as a whole, and to successfully transfer the required information. This integration needs to take into account time delays, cycle times, and the characteristics of communication among all sub-systems.

Robotic systems for crop production are even more sophisticated since they must operate under unstructured agricultural environments without reducing productivity and work quality relative to concurrent methods. In that area, there has been considerable progress in the few last decades.

To assimilate robotic systems into agricultural processes, several issues need to be addressed. Firstly, technologies must be developed to overcome difficult problems such as the continuously changing conditions, the variability of the produce and environment, and hostile environmental conditions such as vibration, dust, extreme temperature, and humidity. Secondly, development of intelligent systems is necessary to achieve successful operation in such environments. Even though much effort has been invested in developing obstacle detection and avoidance algorithms and systems, this is still in the research stage. Possible solutions to overcoming this problem might be agronomical modifications of plants, or human-integration domains. Thirdly, the specific economic aspects of the agricultural production system must be addressed to realise the practical use of various kinds of robots. The costs of robotic systems must be sufficiently low to economically justify their use, since the agricultural produce being dealt with is of relatively low value. However, the recent cost reductions in electronics, computers and robotics should enable such systems to penetrate more widely into agriculture. Fourthly, agricultural robotic systems could be assimilated only in areas and processes where other solutions, such as mechanics or automation, cannot exist or where robotics has a diminishing marginal utility upon them. Fifthly, inherent safety and reliability form one of the most important aspects; safeguarding people, the environment, the crop and the machines is mandatory and until this can be ensured, autonomous systems will not be allowed to operate in open fields.

For robots to satisfactorily perform in agricultural environments and execute agricultural tasks, research must focus on the fusion of several complementary sensors to reach adequate localisation and sensing abilities, the development of simple manipulators to perform the specified agricultural task, the development of path-planning, navigation and guidance algorithms suited to environments other than open fields and known a-priori, and, integration of HO in this complex and highly dynamic situation.

It is inevitable that machines will become smart enough to be fully autonomous; it is only a matter of time (Blackmore, Griepentrog, Fountas, & Gemtos, 2007). However, to achieve these developments, and reap the associated benefits, it is mandatory to clearly determine how intelligent these machines need to be, and define their appropriate behaviours. Increases in labour costs and the demand for high-quality produce on one hand, and decreases in the cost of progressively more powerful computers, electronics and sensors on the other, will promote the economic feasibility of the agricultural robot.

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