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Research Paper

Agricultural robots for field operations. Part 2: Operations and systems

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This part of our review of the research, developments and innovation in agricultural robots for field operations, focuses on characteristics, performance measures, agricultural tasks and operations. The application of robots to a variety of field operations has been widely demonstrated. A key feature of agricultural robots is that they must operate in unstructured environments without impairing the quality of work currently achieved. Designs, developments and evaluations of agricultural robots are diverse in terms of objectives, structures, methods, techniques, and sensors. Standardisation of terms, system-performance measures and methodologies, and adequacy of technological requirements are vital for comparing robot performance and technical progress. Factors limiting commercialisation and assimilation of agricultural autonomous robot systems are unique to each system and to each task. However, some common gaps need to be filled to suit unstructured, dynamic environments; e.g. poor detection performance, inappropriate decision-making and low action success rate. Research and development of versatile and adaptive algorithms, integrated into multi-sensor platforms, is required. Cycle time must be reduced and production rate increased to justify economic use. Improved wholeness or integration of all sub-systems will enable sustainable performance and complete task operation. Research must focus on each of these gaps and factors that limit commercialisation of agricultural robotics. Research needs to focus on the field use of autonomous or human–robot systems, the latter being a reasonable step toward fully autonomous robots. More robust, reliable information-acquisition systems, including sensor-fusion algorithms and data analysis, should be suited to the dynamic conditions of unstructured agricultural environments.

1. Introduction

Although agricultural field operations are complex, diverse, labour-intensive, and crop-directed, agricultural productivity has significantly and continuously increased over the centuries as a result of mechanisation, intensification, and more recently, with the introduction of automation (Nof, 2009). Important targets for the application of the various technologies designed to improve crop yields, are reduced costs and

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Nomenclature

ADM	appropriate decision-making, %
ARS	autonomous robot systems
ASR	action success ratio, %
CART	classification and regression tree
CCD	charge-coupled device
CORT	capability to operate under real-time conditions
CT	cycle time, s
DC	detection capability
DOF	degrees of freedom
DP	detection performance, %
EKF	extended Kalman filter
FF, FT	false/false, false/true
FOG	fibre optic gyroscopic
GPS	global positioning system
HO	human operator
HRI	human–robot interface
HRS	human–robot systems
IR	infra-red
LIDAR	laser radar
LPS	local positioning system
MSS	master–slave system
NIR	near infra-red
OT	operation time under real-time conditions, s
OV	operation velocity under real-time conditions, m s^{-1}
PE_a	position error average, mm or °, etc.
PE_{sd}	position error standard deviation, mm or °, etc.
PID	proportional–integral–derivative
PM	powdery mildew
PR	production rate, kg h^{-1} or ha h^{-1} or number of actions h^{-1}, etc.
PRRRP or P3RP	manipulator assembled from a series of prismatic (P) and rotation (R) joints. PRRRP or P3RP begins with a prismatic joint, followed by three rotation joints and end with one prismatic joint. A P6R manipulator would begin with a prismatic joint follow by six rotation joints
RGB	red, green and blue
R-G-NIR	red–green–near Infrared
RHEA	robot fleets for highly effective agriculture and forestry management
RTK	real time kinematic
TF, TT	rue/false, true/true
TSWV	tomato spotted wilt virus

reduced environmental impact. The advent of agricultural robots has the potential to raise the quality of fresh produce, lower production costs, reduce the drudgery of manual labour, and, in some parts of the world, to compensate for the lack of workers in some agricultural sectors (Bechar, 2010).

Robots are perceptive programmable machines that perform a variety of agricultural tasks, such as cultivation, transplanting, spraying, and selective harvesting. However, agricultural robots operating in dynamic and unstructured environments often still produce inadequate results due to the inherent uncertainties, unknown operational settings and the unpredictability of events and environmental conditions. Inadequacies of sensor technologies further impair the capabilities of autonomous robot systems (ARS).

The unstructured environment of agricultural production is characterised by frequent changes in time and space generating stochastic task requirements, features which are very different from the stable requirements encountered in industrial robotic lines. The topography, soil structure and composition, vegetation landscape, visibility, illumination and atmospheric conditions change at rates varying from seconds to months and on scales from millimetres to kilometres. In addition, the natural components and the objects found in the environment vary widely in shape and size. These unstructured environments are therefore subject to inherent uncertainty, heterogeneity, and unpredictable situations, resulting in lack of information (Bechar & Vigneault, 2016; Oberti & Shapiro, 2016) and very complex modelling requirements.

Extensive research has focused on the application of robots and intelligent automation systems to a large variety of field operations, and their technical feasibility has been widely demonstrated (Bac, van Henten, Hemming, & Edan, 2014; Bechar & Vigneault, 2016). Nevertheless, and in spite of the tremendous amount of robotic applications in the industry, very few robots are operation in agricultural production (Xiang, Jiang, & Ying, 2014). Complexity increases when dealing with natural objects, such as fruits and leaves. This is due to the high variability of many of the parameters that affect robot behaviour, many of which cannot be determined a-priori. In addition, agricultural robots work with live and fragile produce making the tasks and features of agricultural applications quite different from industrial applications which work with inanimate products. The main limiting factors lie in production inefficiencies and the lack of economic justification due to the very short period of potential utilisation each year (Bechar & Vigneault, 2016). Development of a feasible 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), or integrate a human operator (HO) into the system. Because of the nature of the agricultural terrains, the guidance and navigation of agricultural robots has been likened to driving a cross-country vehicle across a rough terrain rather than steering a high-speed vehicle along a motorway (Khadraoui et al., 1998). Such tasks and systems therefore still require the support of a HO for solving the problems associated with operating robots in rough terrain (Ceres, Pons, Jimenez, Martin, & Calderon, 1998) particularly since safety issues can be handled by HOs as a preliminary stage towards full autonomy. However, recent technical reports (Anonimous, 2014; Loughran, 2016; Tobe, 2014) and scientific papers (Abdelmotaleb, Hegazy, Imara, & El-Din Rezk, 2015; Thanpattranon, Ahamed, & Takigawa, 2016) have presented many types of autonomous robots capable to operate in uniform and/or structured agricultural large-scale surfaces such horticultural crops, orchards and plantations.

Contradictory opinions are often expressed about the capacity, level of improvement, and performance of robots operating under agricultural conditions. Diverging opinions are due to a lack of uniformity in the methods and parameters used to evaluate the performance of the devices tested, and sometimes due to the vague descriptions of the methods used. The first step of this study was to identify general parameters that can easily measure the performance and characteristics of agricultural robots (Section 2). These parameters were then used to compare robot performance and technological progress through different tasks and operations (Section 3).

2. Characteristics and performance measures of field robots

2.1. *Characteristics of field robotic applications*

The next generation of in-field and greenhouse robots must be able to recognise and understand the physical properties of each specific object encountered, and also be able to work under both varying field and controlled environment conditions. Therefore, their sensing systems, specialised manipulators and end effectors must be able to work under different and unstable environmental conditions (Eizicovits & Berman, 2014; Eizicovits, van Tuijl, Berman, & Edan, 2016). Such conditions may occasionally be severe enough with regard to high humidity, dust, temperature and rain to cause major concerns for electric circuits and problems with material corrosion. These conditions must be taken into account when designing or selecting plant-production robotic systems (Kondo & Ting, 1998).

The classical operation process of agricultural robots consists of four general stages. First, the robot senses and acquires raw data from and about the environment, task and/or its state using various sensors. Secondly, the robot processes and analyses the data received from its sensors to generate reasoning and a perception of the environment, the task or its state to some level of situation awareness. Thirdly, the robot generates an operational plan based on its perception of the environment and state, or the task objectives. Fourthly, the robot executes the required actions included in the operational plan.

In performing an agricultural task in an unstructured environment, the robot must repeat these four steps continuously since its state, the task status and the environment are changing constantly. In fact, the limited ability of robotic systems to reason and plan in such environments results in poor global performance (Bechar, Meyer, & Edan, 2009), which make this process appear ineffective.

To improve the robot's performance, several more recent approaches have been developed. These include behaviour-based robotics (Brooks, 1991; Proetzsch, Luksch, & Berns, 2010; Woolley, Peterson, & Kresge, 2011), which link the sensing (first stage) to the action (fourth stage), resulting in a reactive type of behaviour, or integrating a HO in the reasoning (second) and planning (third) stages (Bechar & Edan, 2003; Oren, Bechar, & Edan, 2012; Tkach, Bechar, & Edan, 2011). In both approaches, the different operation-process stages require the execution of sub-tasks. With the behaviour-based approach, only the robot controls these sub-tasks. With the HO-integration approach, either the robot or the operator controls these sub-tasks. This is presented in a case study for a selective tree-pruning task (Table 1).

Agricultural field robots that are operating in unstructured environments require two categories of abilities. The first deals with the robot functionalities, such as obstacle avoidance (Belkhouche & Belkhouche, 2005; Bergerman et al., 2015; Gonzalez-de-Soto, Emmi, Perez-Ruiz, Aguera, & Gonzalez-de-Santos, 2016), self-localisation and map building (Bayar, Bergerman, Koku, & Konukseven, 2015; Gimenez, Herrera, Tosetti, & Carelli, 2015; Gomez-Gil, Ruiz-Gonzalez, Alonso-Garcia, & Gomez-Gil, 2013; Lepej & Rakun, 2016; Underwood, Jagbrant, Nieto, & Sukkarieh, 2015), and navigation and path planning (Bodur, Kiani, & Hacisevki, 2012; Hameed, Bochtis, & Sorensen, 2013; Hameed, la Cour-Harbo, & Osen, 2016; Kraus et al., 2013; Vroegindeweij, van Willigenburg, Groot Koerkamp, & van Henten, 2014). The second deals with the specific applications, such as vehicle dispatching for transportation (Benyahia & Potvin, 1998; Lacomme, Prins, & Ramdane-Chérif, 2005), security, reconnaissance, exploration (Baron Sam, Balaji, Anthuvan Jerald Majella, & Ashokkumar, 2015; Birk & Kenn, 2002; Flann, Moore, & Ma, 2002; Matthies et al., 2002; Thrun et al., 2004), planting, harvesting, sorting and handling (Abarna & Arockia Selvakumar, 2015; Ashraf, Kondo, & Shiigi, 2011; Auat Cheein et al., 2016; Ceres et al., 1998; Hayashi et al., 2010; Huang & Lee, 2008; Mehta & Burks, 2014; Muscato, Prestifilippo, Abbate, & Rizzuto, 2005; Nagasaka, Mizushima, Noguchi, Saito, & Kubayashi, 2007; Qiang, Cai, Bin, Lie, & Zhang, 2014; Tanigaki, Fujiura, Akase, & Imagawa, 2008; Van Henten, Van't Slot, Hol, & Van Willigenburg, 2009; Zhao, Lv, Ji, Zhang, & Chen, 2011).

2.2. *Engineering performance measures and technological requirements*

In the design, development and evaluation of agricultural robots for field operations, several performance measures and technological requirements need to be addressed before commercial application can be envisaged. Overall, the performance measures are the same, but the relative importance of each measure and their effects on the design of the required sensor systems are specific to each agricultural task, type of produce, environment, etc. Performance measurement and adequacy of the technology are also required to compare robots and evaluate technical progress. Unfortunately, there are no standard methods and parameters used to evaluate the performance of the different system tested. This lack of standardised parameters makes it difficult to compare the different devices or technologies, or even measure the progress of single systems. While trying to compare the different systems, devices and technologies, some parameters were identified (Table 2) as potentially the most useful ones. These parameters were used throughout the present study to determine and facilitate comparisons of robot performance and technical progress when the necessary information was available in the literature.

Table 1 – Operation-process stages of a selective tree-pruning task (Bechar et al., 2014).

Stage	Sub-task	Control
Sensing	Image acquisition	Robot
Reasoning	Cutting point and orientation detection	HO and robot
Planning	Trajectory planning	Robot
Action	Manipulator reaching and branch pruning	Robot

3. Robotic tasks and operations

This section reviews the research into, and development of agricultural robotics in recent years. It is divided according to application type (common agricultural tasks and operation abilities to perform the required agricultural tasks): navigation and guidance, including transportation and autonomous tractors (3.1); transplantation and seedling systems (3.2); pruning and thinning (3.3); weed control and disease monitoring (3.4); harvesting (3.5); traceability and geo-positioning (3.6); and multi-robot interactions to perform a common agricultural task (3.7). Each section is arranged according to the technology evolution, technological gaps that were defined or detected and the 'readiness level' of different systems.

3.1. *Navigation and guidance*

A basic component of automation in agriculture is autonomous navigation. Early navigation systems in agricultural domains used a camera as the sensor and were based on computer vision techniques (Hiremath, Van der Heijden, Van

Table 2 – Performance measures, technological requirements, descriptions and standard units of measurement used for comparing robots and determining technical progress.

Measure or requirement	Description
CT: Cycle Time (s)	Average time required to complete one specific action cycle in a task (e.g., handling one individual object, harvesting a fruit, pruning a branch)
OT: Operation Time under real-time conditions (s)	Average time required to accomplish a mission or complete a specific task under real-time, dynamic agricultural conditions
OV: Operation Velocity under real-time conditions ($m\ s^{-1}$)	Average velocity measured during a mission or task under real-time, dynamic agricultural conditions
PR: Production Rate ($kg\ h^{-1}$, $ha\ h^{-1}$, number of actions h^{-1}, etc.)	Amount of produce, area or successful actions (e.g., number of weeds sprayed or trees pruned) treated per time unit
CORT: Capability to Operate under Real-Time conditions ($CORT^{+}$ or $CORT^{-}$)	Ability to operate under real-time conditions; presented as binary result: either capable to operate under real-time conditions, $CORT^{+}$; not capable to operate under real-time conditions, $CORT^{-}$
DC: Detection Capability (DC^{+} or DC^{-})	Ability to measure, evaluate or detect objects, borders, colour, or physical, chemical or optical characteristics that a robotic system needs to perform for a specific task or mission; presented as binary result: either capable to perform the specific detection, DC^{+}; not capable to perform this detection, DC^{-}
DP: Detection Performance (%)	Performance of robotic systems requiring detection ability. Detection results are of four types: TT[a], TF, FT, FF. DP is the ratio of the number of appropriate detections (TT + FF) over the sum of all detection attempts made by the robotic system during the performance of a specific task or mission under real-time, dynamic agricultural conditions
ADM: Appropriate Decision-Making (%)	Ratio of the number of appropriate decisions over all decisions of the same type made during the execution a specific task or mission under real-time and dynamic agricultural conditions; the type of decision may vary considerably among the task such as turning to the right direction, harvesting appropriate produce, applying a specific treatment on a specific surface, beginning or ending a task at the appropriate position and etc.
ASR: Action Success Ratio (%)	Ratio of actions (fruit picking, branch pruning, etc.) resulting in success according to the agricultural task description and without jeopardising the crop, over total number of attempts
PE_a: Position Error Average and PE_{sd}: Position Error Standard Deviation (mm, °, etc.)	The average and standard deviation of positioning error, which is the difference in terms of distance and angle between the estimated location and orientation, and the real position of the object (tree, fruit, row, field limit, etc.)
Safety	System safety to humans, infrastructures, plants, as defined by the nature of the task and the closed or open agricultural environment should be also evaluated although this aspect is rarely covered and difficult to compare
Wholeness	Ability of the robotic system to provide a full solution to execute and complete an agricultural task, integrate the solution, and coordinate the communication of each required piece of information to and from all sub-systems

[a] T = true, F = false.

Evert, Stein, & Ter Braak, 2014). Navigation, guidance and transportation include three levels of autonomy: conventional steering, an operator-assisted or automatic system (supervised by HO), and a fully autonomous system. Navigation and guidance can be the system's main task, e.g., transporting the crop from the field to the packing house, or be a supporting task enabling the system to perform its main task, e.g., a supporting task for spraying, or transporting a robot from tree to tree during its harvesting process.

Automatic guidance has been the most active research area throughout the history of automation of agricultural machinery (Nof, 2009). The available systems stem from two main approaches. In the first, a predetermined path, primarily based on input from either local positioning system (LPS) stations or global positioning system (GPS) satellites (Lipinski, Markowski, Lipinski, & Pyra, 2016), guides the tractor. This approach is technically simple, but it suffers from an inability to respond to unexpected changes or events in the field (Stentz, Dima, Wellington, Herman, & Stager, 2002). In the second approach, the tractor operates with reference to a crop line, such as along a row of plants, or a limit between ploughed and unploughed soil or between cut and standing forage, by using a sensing system, generally machine vision (Astrand & Baerveldt, 2005; Bak & Jakobsen, 2004; Bakker et al., 2008; Bietresato, Carabin, Vidoni, Gasparetto, & Mazzetto, 2016; Choi et al., 2015; Ortiz & Olivares, 2006). This approach enables the machine to tailor its operation to individual plants as they change over time, but it is generally considered to be more technically difficult to identify a crop line than to follow a determined path (Stentz et al., 2002). Developing an ARS that can navigate autonomously in changing and dynamic outdoor agricultural environments is a challenging and difficult task, but it is a crucial operation for any intelligent farm vehicle (Hagras, Colley, Callaghan, & Carr-West, 2002).

Automatic steering systems for tractors, with LPS- or GPS-based guidance, offer farmers the opportunity to reduce operation costs and increase crop production and profitability (Rovira-Más, Chatterjee, & Sáiz-Rubio, 2015). The economic benefits include: reduction in overlaps or skipped areas in fertiliser and pesticide applications, improvement of operation timeliness by allowing a 24-h operation schedule and guidance under restricted visibility, increasing accuracy of water and fertiliser application based on plant-requirement measurements and mapping, and better implementation of precision agricultural practices (Bergtold, Raper, & Schwab, 2009).

For navigation and guidance tasks, researchers at Stanford University developed automatic steering for a medium-size John Deere 7800 tractor by incorporating a RTK-GPS (Bell, 2000). The typical positioning error average (PE_a) of this control system under full engine load was almost zero, while manually steered operation generally resulted in PE_a between 40 and 60 mm from the optimal trajectory. Thuilot, Cariou, Martinet, and Berducat (2002) developed an automatic guidance system relying on a single RTK-GPS (Nagasaka, Umeda, Kanetai, Taniwaki, & Sasaki, 2004) to guide a tractor along pre-recorded paths. The tractor heading was derived according to a Kalman state reconstruction (Welch & Bishop, 2006), and a non-linear velocity-independent control law was designed. Although current navigation systems for agricultural vehicles rely on GPS as the primary sensor for steering control, an alternative method is still required in cases such as orchards, where the tree canopy blocks the satellite signals from the GPS receiver, or when the accuracy is insufficient to generate acceptable PE_a and standard deviation (PE_{sd}) and/or action success ratio (ASR) (Subramanian, Burks, & Arroyo, 2006). Bakker, Van Asselt, Bontsema, Muller, and Van Straten (2011) developed an RTK-GPS based autonomous field navigation system including automated headland turns to provide a method for crop row mapping combining machine vision, and to evaluate the benefits of a behaviour based reactive layer in a hybrid deliberate systems architecture. The system PE_a, PE_{sd}, of the robot while following a straight path on the field at OV of 0.3 m s^{-1} were 1 and 16 mm respectively.

For open-field tasks, Debain, Chateau, Berducat, Martinet, and Bonton (2000) developed a guidance-assistance system for agricultural machines. They used an analysis based on image processing for recognising the vehicle's environment to deduce a control law in the image space. Their results confirmed the application's feasibility and demonstrated the need to know the reliability of the image-processing results to ensure the viability of a complete system.

For in-row tasks, Astrand and Baerveldt (2005) developed a row-following navigation system for agricultural field machinery. They applied a Hough transform to near-infrared (NIR) images to recognise the plant-row line. The PE of the navigation system was evaluated on a mobile robot coupled with a row cultivator working in sugar beet and rape fields, and resulted in $PE_a < 12$ and PE_{sd} of ± 27 mm. Ortiz and Olivares (2006) presented a new approach for solving the autonomous navigation problem in an agricultural environment. Their system relied on a vision system that retrieves the mapping of the plantation rows within which the robot navigates. Bakker et al. (2008) presented a row-recognition system based on the application of a grey-scale Hough transform to intelligently merged images and reducing image-processing time. The system found the row at various plant-growth stages (detection capability, DC^+); the PE_a between the estimated and real crop row ranged from 5 to 198 mm, and the PE_a for crop-row detection was 22 mm at an operation velocity (OV) ranging from 0.5 to 1 m s^{-1}. The largest errors were mainly due to limited numbers and sizes of the crop plants, overexposure of the camera, and the presence of green algae under greenhouse growing conditions. Dar, Edan, and Bechar (2011) developed an adaptive vision algorithm to detect and follow the path between two pepper rows. The algorithm used a classification and regression tree (CART)—a decision tree to classify images from a RGB camera and create an adaptive-unique feature (detection algorithms) for the current conditions in the greenhouse. The algorithm was tested on different plots and under different conditions, and achieved a detection performance (DP) of 92%.

For orchards or forests, Subramanian et al. (2006) developed a guidance system based on machine vision and laser range detection (LIDAR) to overcome poor GPS signals, and to enable a John Deere 6410 tractor to navigate between the rows of a citrus grove with an OV $\leq$ 4.4 m s^{-1} and PE_a < 60 mm. Machine vision and LIDAR were used separately for guidance, a rotary encoder provided the feedback of the steering angle, and a proportional–integral–derivative (PID) controller minimised the path error. Khot, Tang, Blackmore, and Norremark (2006) developed a navigation technique based on sensor fusion for tree nurseries. A RTK-GPS and dynamic measurement sensors determined the position and orientation of the robot, and a LIDAR located the tree positions within a selected range (DC^+). The RTK-GPS error was calculated using a second-order autoregressive model, and the error states were incorporated into an extended Kalman filter (EKF) design (Welch & Bishop, 2006), resulting in lower PE_a and PE_{sd}, with reductions from 40.5 to 22.1 mm and ±82.7 to ±18.9 mm, respectively. Geo-referenced tree positions along the navigational paths were recovered using a K-means-clustering algorithm (Kanungo et al., 2002), for a PE_a of 44 mm for tree position. Yekutieli and Garbati-Pegna (2002) used a mechanical sensor to develop an automatic guidance system for a tractor in a vineyard. A spring continuously pushed the sensor arm toward a guidance line and the deviation of the arm angle controlled the steering. The guidance line was a wire stretched along posts positioned in every second row. At the end of a row, the tractor would turn according to dead reckoning. Yekutieli and Garbati-Pegna (2002) demonstrated that with only a two-stage control (ON/OFF) and a simple curved sensor arm or a sensor arm consisting of two hinged parts, it was possible (DC^+) to guide a crawler tractor automatically in a vineyard, using the vines as the guidance line. Canning, Edwards, and Anderson (2004) described an application of fuzzy logic to control an ARS for forest environment purposes. The robot used an ultrasonic sensor, encoder sensors and two fuzzy logic controller modules, each capable of providing heading recommendations, and directed the robot along a path in a forest environment resulting in a capability to operate in real time ($CORT^+$). One module used dead-reckoning calculations based on data provided by shaft encoders attached to the wheels of the robot. The other module used data provided by three ultrasonic ranging transducers. The test vehicle was able to consistently navigate 152 m down a forest path. A new data fusion algorithm was proposed for navigation, that optimally fused the localisation data from various sensors in vineyard (Zaidner & Shapiro, 2016). Each sensor was pre-filtered according to its noise distribution. The localisation algorithm was validated using simulation of the robotic platform and using visual odometry based on real field video data.

For transportation operations, Morimoto, Suguri, and Umeda (2005) developed a vision-based navigation system for ARS vehicles carrying goods between the field and warehouse (Fig. 1). The system was mounted on a commercial crawler-type transporter, followed a path and turned at intersections. The navigation system was comprised of RTK-GPS, rotary encoders and a CCD camera. The path intersections were designated with special marks. The vehicle was tested at an OV of 0.8 m s^{-1} resulting in a $CORT^+$ with a maximum offset from the desired path of ≤330 mm and ≤450 mm for straight-line travel and for turning at an intersection, respectively. In the open field, the autonomous navigation system reached good performance with relative high ASR, PE_a and PE_{sd}. In orchards and obstacle-saturated environments, the overall performance success rate was low, resulting in a $CORT^-$ due to insufficient DP and appropriate decision-making (ADM), and a high PE resulting from the GPS errors.

More recently, technical and scientific literature presented many types of autonomous robots capable to operate in uniform and/or structured agricultural large-scale surface such as horticultural crop (Abdelmotaleb et al., 2015), orchard or plantation (Thanpattranon et al., 2016). For example, the results of manual and autonomous robot sprayer performance were compared for the five PE_a aspects such as straight path, curved path, sine wave path, offset discontinuity, and angle discontinuity; and presented similar overall PE_a with only a 0.9 mm average difference, and a PE_{sd} of 18 mm (Abdelmotaleb et al., 2015). Comparing specific aspects, the robot PE_a was 12 times more precise then the HO during straight path treatment, but 4 and 2.7 time less precise during curved and sine wave path treatments, respectively. These results confirmed the robot's capability to operate under real-time conditions ($CORT^+$) in uniform and structured agricultural conditions; but still required improvements for obstacle-saturated or unstructured environments for autonomous and safe navigation.

3.2. *Transplanting and seedling*

Transplanting is a preliminary stage of growing and production operations, and may be used for many types of crop growth and plots. Automating transplantation is feasible in several situations, mainly when the operations are repeated every few weeks in the same plot, as is the case with leafy vegetables or herbs. When the transplantation involves large areas, intensive human labour, and/or when high accuracy is mandatory, automated transplanting devices offer many advantages but they are generally complex and expensive. They also require high levels of plant quality and uniformity (Parish, 2005).

Mao, Han, Hu, and Kumi (2014) developed a new pincette-type pick-up device for automatic transplanting of seedlings in greenhouse. The robotic mechanism consisting of a manipulator, an end effector and two conveyors. At a transplanting rate of 22 seedlings min^{-1}, the ASR for picking up seedlings was 90.14%. A high-speed plug seedling transplanting robot was designed for greenhouses by making use of a 2-DOF parallel translation mechanism with a pneumatic manipulator (Hu et al., 2014). Based on simulation test the CT of such a system will be 1.08 s.

Nagasaka, Taniwaki, Otani, and Shigeta (2002) and Nagasaka et al. (2009) developed an automated six-row rice-transplanter (Fig. 2) using RTK-GPS to determine the system location, and fibre optic gyro (FOG) and gyroscopic sensors to measure the direction and inclination of the vehicle. The purpose of the FOG was to correct RTK-GPS reading errors caused by the influence of vehicle roll and pitch on the GPS antenna when the transplanter was moving along a straight path, resulting in $PE_a < 100$ mm. Based on their previous work, Nagasaka et al. (2007) modified the ARS transplanter to carry long mat-type hydroponic rice seedlings and attached an herbicide-dripping machine, resulting in a fully automated rice transplantation system. The transplanter was able to drive in straight lines along the plot and perform U-turns at each end. The PE_a and maximum deviations from the planned

Fig. 1 – Robot-transporter using a vision-based and RTK-GPS navigation system (Morimoto et al., 2005).

path were 30 and 110 mm, respectively. Chen, Tojo, and Watanabe (2003) also developed a guidance system for a six-row automatic rice transplanter based on machine vision analysing images of field borders and seedling rows. This automated transplanter was tested with more than 3000 concrete bank, soil bank, or rice seedling images, resulting in image processing cycle times (CT) of 3.27, 3.03, and 4.34 s, and DP of 99.2, 98.6, and 98.9%, respectively.

Huang and Lee (2008) developed an image-processing algorithm to determine the grasping location on the roots of *Phalaenopsis* plantlets, as part of an automatic transplanting operation. They demonstrated that a DP of 99.9% is achievable, given appropriate choices of colour and shape features. Their proposed classifier also achieved a DP of 94.9% in identifying suitable grasping points on complete plantlets.

Ryu, Kim, and Han (2001) developed a robotic transplanter for bedding plants equipped with a Cartesian manipulator with two linear electric motors, an end effector, plug-tray conveyors, and a vision system. The end effector, which was comprised of two pneumatic cylinders and fingers, picked up seedlings one by one from a high-density plug tray and moved them to a low-density growing tray. The conveyors that moved the plug trays to the desired position were driven by servomotors. The vision system was able to identify empty cells (DC^+), and the end effector reached a PE_a of 1 mm. The system identified empty cells in 72-cell and 128-cell trays with DP of 99 and 95%, respectively. The end effector gripped the seedlings from 72- and 128-cell plug trays with an ASR of 96 and 98%, respectively. The overall ASR values of transplanting were 97.8, 97.7 and 98.2% for 16-day cucumber, 13-day cucumber and 26-day tomato seedlings, respectively.

An automatic rolling system for rice seedlings, designed to roll up the seedling mat from a 300 × 600 mm tray into a cylindrical shape ready for transportation, was developed by Chiu and Fon (2000). The system was moved by a pneumatic mechanism and controlled by a programming-logic

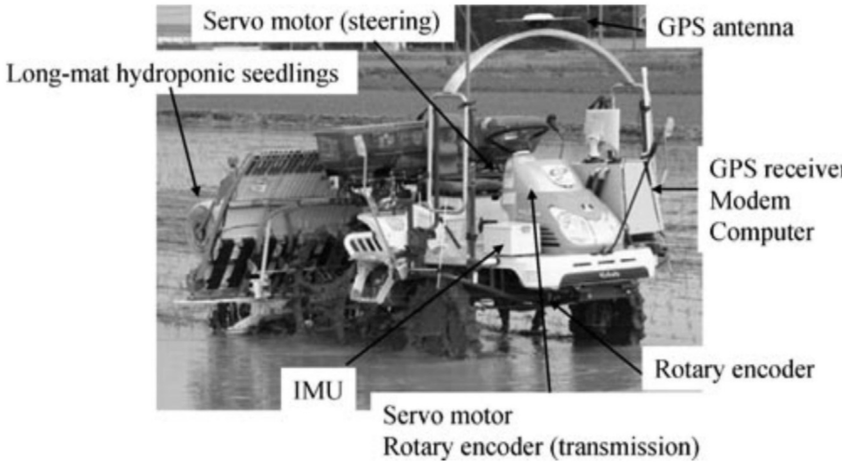

Fig. 2 – An automated rice-transplanting system mounted on a six-row rice transplanter (Nagasaka et al., 2009).

controller. Their system production rate (PR) reached 362 trays h^{-1} with a rolling ASR >95% of the seedling mats, achieving a seedling quality that was not significantly different from that in manually rolled mats.

3.3. *Pruning and thinning*

Tree pruning is a labour-intensive task, with labour making up more than 25% of the total costs. The main objectives of this task are to increase exposure to sunlight, control tree shape and remove protruding branches. In most orchards, this task is conducted once a year and up to 20% of the branches are selectively removed.

Although no ARS or automated systems for fruit thinning or tree pruning have been reported in the literature, there are several ongoing projects involving the development of systems for mechanising and automating these processes.

An electro-mechanical arm shaker for fruit thinning in nectarine, peach and prune orchards was developed to reduce manual labour and costs (Rosa et al., 2008). The system deals with individual branches and includes a special mechanism to prevent the clamping of bunches. A system was developed for vineyards enabling the mechanisation of dormant and summer pruning, leaf removal, shoot and fruit thinning, canopy management, and harvesting, while maintaining or enhancing fruit quality (Morris, 2007). In a comparison with the standard manual processes, yield and quality characteristics of grapes harvested by the respective methods were not statistically different. Nor did an objective analysis of the vine components show any practical commercial differences. Use of the complete vineyard mechanisation system would reduce the required manual labour by 45–62% compared with the trellising method.

In ongoing research, selective tree pruning by human–robot systems (HRS) is being developed (Bechar et al., 2014; Linker & Neer, 2014), and a visual servoing methodology and HRS for selective tree pruning have been tested. The system consists of: a manipulator, a colour camera, a single-beam laser distance sensor, a human–robot interface (HRI), and a cutting tool based on a circular saw specifically developed for this task. The cutting tool, the camera and the laser sensor are mounted on the manipulator‘s end effector, aligned parallel to each other (Fig. 3). The system works in two phases. Firstly, the camera transfers a 2D image of the tree to a HO, who marks the branches to be removed on a display. Secondly, the system works in autonomous mode. The manipulator manoeuvres the laser sensor to measure the branch distance and calculates a trajectory to the cutting point on the screen. Then, it follows the trajectory to perform the cut. Two types of motion planning are conducted between the tool's initial location and the cutting point: linear motion in global Cartesian coordinates, and in the robot joint space. The system is in the testing phase.

3.4. *Weed control and disease monitoring*

Different abiotic and biotic stresses affect the potential yield of crops. According to Oerke and Dehne (2004), 40% of world food production is lost through diseases, insects and weeds. To achieve high yields in agricultural crop systems, the control of biotic stress is highly relevant. Monitoring diseases and pests during the growing and harvesting stages is essential to

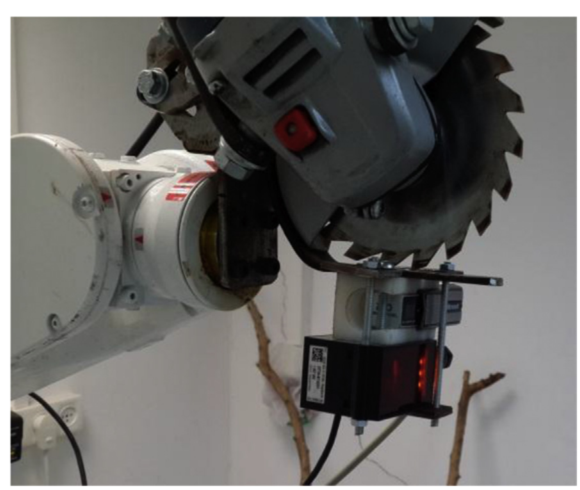

Fig. 3 – Visual servoing end-effector system (Bechar et al., 2014).

fulfilling the plant's production potential, detecting and preventing disease spread, and avoiding significant yield losses. Pest, disease and weed control is a frequently performed and often time-consuming task, which sometimes exposes the HO to the danger of contamination with hazardous chemicals. Automation of spraying or weeding would eliminate the tedious work and replace it with a precise, quality-enhancing, and flexible machine operation (Jorgensen et al., 2006).

Development of systems for weed control, including weed detection and removal, has been one of the major fields of research in agricultural robotics in the last few decades (Choi et al., 2015; Gonzalez-de-Soto, Emmi, Perez-Ruiz et al., 2016; Midtiby, Åstrand, Jørgensen, & Jørgensen, 2016; Oberti et al., 2016; Pantazi, Moshou, & Bravo, 2016; Perez, Lopez, Benlloch, & Christensen, 2000; Thompson, Stafford, & Miller, 1991; Torres-Sospedra & Nebot, 2014). To date, some complete weed-control ARS have been tested under field conditions. The general purpose of weed-control ARS is comprised of four core technologies: guidance, weed detection and identification, precision in-row weed removal, and mapping. Four types of weed-removal mechanisms are suitable for selective in-row weed control by ARS: mechanical, thermal, chemical, and electrical means (Slaughter, Giles, & Downey, 2008). Of these methods, chemical control, e.g., spraying, is the most widely used.

Nishiwaki, Amaha, and Otani (2004) developed an ARS sprayer with a nozzle-positioning mechanism for weed spraying in rice fields. Their results demonstrated $CORT^{+}$, DC^{+} at the natural illumination level for adjusting the detection algorithms accordingly. Slaughter, Giles, and Tauzer (1999) developed a weed-spraying system for road shoulders. Their prototype used a vision system linked to a computer that controlled the spraying system and the selection of spraying-liquid formulation. This system reduced pesticide use by up to 97%. Wiedemann, Ueckert, and McGinty (2002) developed a vision-based selective weed-spraying system mounted on a tractor; its accuracy was comparable to that of a HO. A control system for a selective sprayer was developed by Steward, Tian, and Tang (2002); it was based on machine vision that covered a wide field of view and was able to reach an OV ≤ 3.9 m s^{-1}, generating a DP of 91%. Shin, Kim, and Park (2002) modelled a fuzzy logic algorithm on image processing and ultrasonic sensors for fast spraying in orchards. Jorgensen et al. (2006) modified a remotely controlled slope mower into a robust tool carrier for autonomous outdoor weeding. The real-time weed-control ARS developed by Lamm, Slaughter, and Giles (2002) distinguished grass-like weeds from cotton plants, and applied the chemical spray to the targeted weeds only. This ARS used a mathematical morphology algorithm that was insensitive to occlusion. During OV trials of 0.45 m s^{-1} in 14 commercial cotton fields, the ARS correctly sprayed the weeds with a true/true (TT) result for DP of 88.8%, while correctly rejecting cotton plants with a false/false (FF) result of 78.7%.

Several studies have addressed the use of mechanical means for weed control. Tillett, Hague, and Miles (2002) developed a system for automatically guiding hoes between sugar beet rows at high speed. The system was tested with a 6-m span standard design steerage hoe rear-mounted on a tractor's three-point linkage, and demonstrated DC^{+} for following rows of small and large sugar beet plants. The hoe was tested at an OV of 1.7 m s^{-1} under a variety of crop conditions, ranging from a crop at the two-true-leaf phenological stage infested with 1700 weed m^{-2} at the newly germinating stage, to a relatively clean crop of sugar beets where the beets were large enough to just touch each other within the row. The hoe's lateral $PE_a \pm PE_{sd}$ relative to crop rows was 10 ± 16 mm, while the system was able to cope with a gap of 4 m in the row of plants. Astrand and Baerveldt (2002, 2005) developed a weed-control ARS for sugar beets comprised of three modules: a vision module for the guidance system, a vision module for within-row weed detection, and a selective rotary hoe for mechanical weed removal. The vision module incorporated a sensor-fusion approach that combined spatial context, plant shape and colour features to improve recognition. This ARS was able to follow the row by itself and selectively remove the weeds between plants. The results indicated that the sensor-fusion approach is a robust method to cope with variations in plant appearance and species of weed, but only when the crop plants are large and the weed density is fairly low. The field-test FF results on sugar beet crops showed that 99% of the crop plants were not removed; the TT results showed that 41–53% of the weeds were removed. A mechanical within-row weeder was developed for transplanted crops (Tillett, Hague, Grundy, & Dedousis, 2008) and field trials on cabbage indicated that under normal commercial growing conditions, crop damage levels were low, with weed reductions (TT) in the range of 62–87% within a 240-mm radius zone around the crop plants. Blasco, Aleixos, Roger, Rabatel, and Molte (2002) developed a weeder for transplanted lettuce using a 15-kV discharge electrode mounted on a manipulator and controlled through a weed-detection vision system. In a field test, the vision system detected weeds with a TT score of 84%, and lettuce plants with a FF of 99%, requiring an image-processing time (CT) of 0.5 s. However, the main drawback of this technique was the high-energy consumption required for the high-potential electrode, making this system equivalent to chemical or mechanical systems only for populations <0.5 weed m^{-2} (Vigneault, Benoît, & McLaughlin, 1990). Recently (Gonzalez-de-Santos, 2013), conducted a research project focusing on the design, development, and testing of a new generation of automatic systems and ARS, both for chemical, physical, mechanical and thermal weed management. The aim of the project was to cover a large variety of European products, including agricultural wide-row crops (tomato, maize, strawberry, sunflower and cotton) and close-row crops (winter wheat and barley), and forest plantations of woody perennials. Gonzalez-de-Soto, Emmi, Perez-Ruiz et al. (2016) described the development and assessment of a robotised herbicide patch spraying system capable of working in groups or fleets of autonomous robots. Their robot was assembled on a commercial agricultural vehicle chassis with a direct-injection spraying boom. Their system reliability and accuracy resulted on treatments over 99.5% of the detected weeds (TT). Spraying surface with absence of weed (FT) was approximately 0.5% with respect to the total weed patches area, achieving a significant herbicide savings. The reduction in herbicide use compared to traditional methods was highly dependent on weed abundance. Their study showed a 66%

herbicide saving when the weed population covered about 33% of the surface: this would have been even higher with a lower weed surface covering. A disease-monitoring robot for greenhouse pepper was developed using RGB and multi-spectral cameras and a laser beam sensor mounted on a robotic manipulator (Schor, Bechar, et al., 2016; Schor, Berman, et al., 2016). The system detects powdery mildew (PM) and tomato spotted wilt virus (TSWV) with DP of 95% and 90% respectively and an average CT of 26.7 s per plant. Oberti et al. (2016) applied a selective spraying to treat PM on grapevines. They used a 6-DOF robotic manipulator equipped with a precision-spraying end-effector with an integrated disease-sensing system based on R-G-NIR multispectral imaging. The results indicate that the robot detected and sprayed 85%–100% of the diseased area within the canopy and reduced the pesticide use from 65% to 85% when compared to a conventional homogeneous spraying of the canopy.

Such results demonstrate important progress in weed-control and disease-monitoring performance in the last decade, mainly due to advances in sensor hardware, resulting in decreasing PE_a and PE_{sd}, and increasing DP, ADM, and algorithm and computation power, which improved the operation time under real-time conditions (OT), OV, $CORT^+$, reasoning and information extraction. However, to reach a satisfactory performance, the following gaps need to be addressed. Firstly, the DP and its reliability need to expend to many more variety of weed and be adapted to unstructured and dynamic environments. Secondly, the application with high accuracy needs also to be extend to unstructured and dynamic environments to minimise costs by extending the use of robot to all kind of agricultural surface. Thirdly, the wholeness, or integration of all sub-systems, needs to be improved to enable sustainable performance.

3.5. *Harvesting*

Harvesting/fruit-picking is one of the most common tasks in agriculture and also one of the most demanding and challenging areas for agricultural robotics. The research on harvesting and fruit-picking ARS started more than three decades ago, focusing mainly on open fields and orchard crops such as citrus, apple, cotton, industry tomato, melon and watermelon (Brandt & French, 1983; Ceres et al., 1998; Chen, Ahmad, & Willcutt, 1990; D'Esnon, 1985; Edan, Flash, Shmulevich, Sarig, & Peiper, 1990; Edan & Miles, 1993; Edan, Rogozin, Flash, & Miles, 2000; Harrel & Levi, 1988; Harrell, Adsit, Munilla, & Slaughter, 1990; Umeda, Kubota, & Iida, 1999). Mechanisms, manipulators, end effectors and tools were developed to perform specific operations (Kawamura, Namikawa, Fujiura, & Ura, 1987, 1985; Ceccarelli, Figliolini, Ottaviano, Mata, & Criado, 2000; Ceres et al., 1998; Edan & Miles, 1993; Harrell et al., 1990; Iida, Furube, Namikawa, & Umeda, 1996; Kataoka, Hiroma, & Ota, 1999; Monta, Kondo, & Ting, 1998). Although some progress was made in performing mechanical and physical operations, robotic harvesters did not yet match the human worker's ability, accuracy, success and productivity, and rarely showed the minimal economic justification. The current TT rate of ARS pickers/harvesters is around 75–85% detection of the fruits that need to be picked, but these ARS still often get $CORT^-$ scores due to difficulties avoiding obstacles, and in reaching, grasping and handling fruit in the real-time agricultural environment.

Electronics research in the last decade has generated continuous increases and improvements in computation power and sensors of various types, such as RTK-GPS, 3D cameras, LIDAR, etc. Based on these important advances, the research effort has shifted to modifying and integrating those sensory systems and related algorithms into the fruit-picking ARS technology (Arefi, Motlagh, & Teimourlou, 2010; Bac, Hemming, & Van Henten, 2013; Barnea, Mairon, & Ben-Shahar, 2016; Bulanon, Burks, & Alchanatis, 2009; Bulanon, Kataoka, Ota, & Hiroma, 2002; Dong, Heinemann, & Kasper, 2011; Hannan, Burks, & Bulanon, 2007; Irie, Taguchi, Horie, & Ishimatsu, 2009; Ji et al., 2012; Jiménez, Ceres, & Pons, 2000; Li & Wang, 2013; Mehta & Burks, 2014; Mehta, MacKunis, & Burks, 2016; Nguyen et al., 2016; Sivaraman & Burks, 2006; Yin, Chai, Yang, & Mittal, 2011; Zhao, Gong, Huang, & Liu, 2016), and extending them to additional crops and other agricultural environments, such as greenhouses.

Ceres et al. (1998) presented the Agribot approach, a HRS combining human and machine functions for harvesting apple. The HO detects and identifies each fruit to be harvested using joystick and an IR-laser beam. This signal tells the 3D measurement system to calculate the position of the target. The spherical coordinates, indicating the location of the fruit, include two orthogonal angles and a radius, and are generated within a CT for the position measurement of 29 ms. Since the IR-laser beam attenuates with distance, the measuring range is limited to 2 m, with a $PE_a < 5$ mm. Their objective was to reach a PR equivalent of 1.25 fruit s^{-1} including fruit transfer to the apple bulk container, which corresponds to 2.5 men of manual harvesting productivity, as a minimum to generate an affordable robot. However, while taking into account simultaneous two-arm in operation, their best grasping/detaching operation PR was 0.5 fruit s^{-1}, excluding all other operation included in a complete harvesting cycle.

Jiménez et al. (2000) developed an IR-laser-based range finder to detect spherical objects in non-structured environments based on (Ceres et al., 1998) technology. The image-analysis algorithms associated with their system integrated both range and reflectance information of region primitives respecting sphere characteristics such as crown, contour, convexity and reflectivity. When the global arrangement of the primitives formed circular arcs, the system concluded on the evidence of the presence of a spherical object. The output of this system included the radius, the surface reflectivity and the 3D position of each spherical object detected. Their tests resulted in a DP in the range 80–90% of the visible fruits with 0% false detection when respecting their established rules.

A 3D-vision sensor was developed for robotic harvesting of asparagus (Irie et al., 2009), grapes (Luo et al., 2016) and cherry (Tanigaki et al., 2008). In asparagus, the 3D-vision sensor measured the cross section of all visible plants and determined the target ones (Irie et al., 2009). In cherry, the 3D-vision sensor was equipped with red- and IR-laser diodes. By processing the images from the 3D-vision sensor, the positions of the fruits and obstacles were recognised, and the end-effector trajectory was calculated (Tanigaki et al., 2008). A multi-spectral system with artificial lighting and CART algorithms mitigated disturbances caused by natural lighting conditions for obstacle detection by a sweet pepper ARS harvester. The background was successfully segmented from the vegetation using a threshold at a NIR wavelength. The non-vegetation objects occurring in the scene were removed using a threshold of 447 nm. Vegetation was classified using a CART classifier trained with 46 pixel-based features (Bac et al., 2013). The system detected several plant parts under varying lighting conditions; however, the results were insufficient to construct an accurate obstacle map and generate CORT$^+$.

Yuan et al. (2009) developed a machine-vision algorithm for cucumber detection based on NIR spectral imaging for an ARS harvester. An 850-nm mono-spectral image was captured to solve similar-colour segmentation problems in a complex environment. The region for robotic grasping was established by the grey-level difference between fruit handle and fruit-pedicel. The ARS obtained ADM scores for recognition of 83.3%–100%, while its ASR for acquiring the grasping region was 83.3%. An eye-in-hand sensing system and servo control framework for crop harvesting in dense vegetation was developed using a Baxter robot (Barth, Hemming, & van Henten, 2016). The system was implemented in a sweet pepper plot.

Several harvesting demonstrators have been developed in the last 15 years. Reed, Miles, Butler, Baldwin, and Noble (2001) developed a fresh-market-mushroom harvester manipulator using machine vision and image-analysis algorithms dedicated to produce localisation and sizing. A separate strategy algorithm was developed for selecting the most appropriate picking order of the identified mushrooms. Individual suction-cup end effectors successfully picked the mushroom heads from confined and open spaces, reaching a picking ASR of 80%. Their delicate handling techniques included flexible fingers, high-speed knives and a padded pneumatic gripper system to convey, trim and transfer the mushroom head.

A harvesting device was developed for lettuce heads using a 3-DOF manipulator, an end effector, a lettuce-feeding conveyor, an air blower, a machine-vision device, six photoelectric sensors and a fuzzy logic controller, which gave an ASR of 94% with a CT of about 5 s plant^{-1} (Cho, Chang, Kim, & An, 2002).

Hayashi, Ganno, Ishii, and Tanaka (2002) developed an eggplant robot harvester based on a machine-vision algorithm combining a colour segment operator and a vertical division operator to detect fruits under different lighting conditions. A visual-size feedback fuzzy controller actuating a manipulator, and an end effector including a fruit-grasper, a judger and a peduncle-cutter were also integrated into the demonstrator. The trial, performed under laboratory conditions, resulted in a harvesting ASR of 62.5% and a CT of 64.1 s fruit^{-1}.

Foglia and Reina (2006) developed a cost-effective robotic arm for a radicchio harvester. Their manipulator was composed of a double four-bar linkage manipulator and a special gripper, getting a 10-mm-underground plant-cutting CORT$^+$. Both the manipulator and end effector were pneumatically actuated directly, while the grippers required using flexible air muscle devices. The system used computer vision to localise the plants in the field based on intelligent colour filtering and morphological operations.

During the development of an eventual ARS for harvesting *Gerbera* flowers, algorithms were designed to identify pedicels from digital images produced by a stereo camera system, and for harvesting the targeted pedicels. A 6-DOF industrial robot (plus a 7th linear axis) was assembled with a newly developed pneumatic cutter–gripper. The experimental trials resulted in DP of 72% and 97% for recognition of pedicel from images of various plants and from images of a specific plant, respectively, and a harvest ASR of 80% (Rath & Kawollek, 2009).

For a berry-harvesting task, Hayashi et al. (2010) assembled a system that included a cylindrical manipulator, an end effector, a machine-vision unit, a suction-cup device, a storage unit and a travelling unit. During the evaluation trials, the system obtained a DP of 60% for the peduncle of the target strawberry, and a harvesting ASR of 41.3% of the fruits at the desired maturity level (>80%) when the fruits were picked by the suction device before cutting the peduncle. The CT for harvesting a single fruit was 11.5 s, which included fruit transfer to the tray (Cui, Gejima, Kobayashi, Hiyoshi, & Nagata, 2013). developed a Cartesian-type robot for strawberry in-row hilltop culture. The system consisted of two colour cameras, a harvesting hand, an optic-fibre sensor and a mobile control unit. The system detected the strawberry fruits, evaluated their ripeness, picked the fruits one at a time and cut their peduncles. The detection–harvesting ASR was 93.6% of the fruit at the desired ripeness level of >50%, while the CT reached 16.6 s fruit^{-1}.

Zhao et al. (2011) developed a robotic device for harvesting apples consisting of a 5-DOF PRRRP manipulator (which is one prismatic joint followed by three rotation joints, and ending with another prismatic joint), an end effector and an image-based vision servo control system. The manipulator was geometrically optimised to provide quasi-linear behaviour, simplifying the control strategy. The spoon-shaped end effector, assisted by a pneumatic gripper, harvested apples for an ASR of 77% with a CT of 15 s fruit^{-1}.

(Van Henten et al., 2002) conducted a comprehensive study on a cucumber harvester ARS, from the development of the concept regarding the working environment and system characterisation, to the engineering and economic aspects, and concluded that the CT of a harvest operation should be ≤10 s. The components of the ARS consisted of a 7-DOF manipulator (a P6R redundant manipulator), an end effector that can handle soft fruit without affecting its quality, a thermal cutting device included in the end effector to prevent the spread of viruses through the greenhouse, and a computerised 3D-vision system already performing at a cucumber DP >95% in the greenhouse environment. A motion planner based on the A* algorithm ensured collision-free eye–hand coordination (Van Henten, Schenk, Van Willigenburg, Meuleman, & Barreiro, 2008). The test resulted in an ASR of 74.4% with a harvesting CT of 45–124 s fruit $^{-1}$. Most failures originated from inaccurate positioning of the end effector at the fruit stalk (Van Henten et al., 2002; Van Henten et al., 2003). Based on the failure-type identifications, an approach for rapid and robust calculation of the inverse kinematics (Chapelle & Bidaud, 2004; Craig, 1989) was conducted in a functional model dedicated to their harvesting ARS. An off-line ARS-ability evaluation was performed using 3D information from a cucumber crop obtained in a real greenhouse. An ARS functional model determined the collision-free harvest posture and motion for controlling the manipulator during a harvest mission (Van Henten et al., 2008, 2010). Optimal design of the ARS manipulator was conducted with respect to the time required to perform a collision-free motion during its travel from an initial to target position, as well as the dexterity measure allowing motion corrections in the neighbourhood of the fruit (Van Henten et al. (2009). It was found that: a) use of a 7-DOF manipulator for harvesting cucumbers was not necessary; b) a 4-DOF PPP-Rtype manipulator was sufficient for this type of mission, and c) the 4-DOF PP-RR type manipulator was the most suitable. Finally, the overall conclusion of this project was that although expensive, the methodology used was objective and powerful for evaluating and optimising the kinematic structure of the ARS developed to harvest cucumber (Van Henten et al., 2009).

Fruit picking is one of the most complicated agricultural tasks for ARS. This task consists of several different stages and involves physical contact with the fruit at high location and orientation accuracy, decision-making in real time, detachment of the fruit from the plant without damaging either, and temporarily storing the fruit under safe conditions. The performance of fruit-picking ARS has not improved significantly over the last three decades, yielding on average a DP for acceptable localisation of 85%, for detachment an ASR of 75%, for harvesting an ASR of 66% and a CT of 33 s fruit^{-1} (Bac et al., 2014); moreover, 5% of the fruits and 45% peduncles are damaged. In the harvesting task, the most important gaps to be addressed are: a) a CT that is too long; b) PR and DP that are too low, and c) too many wholeness CORT^{-} results due to the fact that many ARS are still unable to complete their harvesting tasks.

A task that requires similar capabilities to those of the ARS harvester is de-leafing. Van Henten et al. (2006) developed an ARS for removing the leaves from the lower end of cucumber plants growing on a high wire cultivation system. A NIR-based computer-vision system detected the stem, and a specifically developed end effector mounted around the stem used a thermal cutting device to detach the leaves from the stem. Experiments gave a CT of 70 s leaf^{-1}, which is approximately 35 times slower than manual de-leafing.

3.6. *Traceability and geo-positioning*

In precision agriculture, robotic research is mainly focused on mapping and sampling and is a research area with great potential impact (Gimenez et al., 2015). Guo and Zhang (2005) developed a wireless positioning system based on Kalman filtering for automatic sampling and processing of agricultural machinery operational data to provide real-time support for ARS in precision-agriculture operations. Demmel, Ehrl, Rothmund, Spangler, and Auernhammer (2002) developed an in-field data-acquisition system for agricultural machinery based on GPS and standardised communication protocols. This system collected field operational data along with position information at a frequency of 1 Hz, paired the position with the collected data, and used this information to support real-time precision farming operations and/or store it in a personal computer. Many types of information can be collected and paired with GPS information. For example, weed population data paired with GPS information allowed integrating a vision system for weed detection with a selective-spraying ARS (Jeon & Tian, 2009; Jeon, Tian, & Zhu, 2011; Jeon & Zhu, 2012; Jeon, Zhu, Derksen, Ozkan, & Krause, 2011), and a soil information mapping system was developed that required a soil-sampling device and soil parameter extractions (Liu, Crowe, & Roberge, 2009).

Pest control, ground humidity measurements and plant temperature measurements are normally performed manually. A worker equipped with the appropriate instruments traverses every row to update the data required for decision-making about plant-production actions such as irrigation, fertigation, mineral- or pesticide-spraying doses and locations, planting or harvesting time, etc (Ortiz & Olivares, 2006). Automated or autonomous mapping systems reduce manual labour, and enhance sampling location, data mapping and areal resolutions compared to the common weed- and pest-scouting methods (Slaughter et al., 2008).

Researchers have studied the accuracy of automatic RTK-GPS crop seed-mapping systems used during planting, and have demonstrated the potential of such mapping systems to promote precision farming techniques. Ehsani, Upadhyaya, and Mattson (2004) developed a weed-control system based on RTK-GPS and a CCD camera for detecting the leaves of both the crop and the weeds. The processing algorithms subtracted the crop leaves from the image according to a previous mapping. The results showed that the seeds are automatically mapped with a $PE_a \leq 38$ mm from the plant at germination. Griepentrog, Griepentrog, Norremark, Nielsen, and Blackmore (2005) created a precision seed-planting system including a seed-map generator for sugar beet. The system used a RTK-GPS combined with optical seed-drop sensors to identify the eventual plant locations. The PE_a between the GPS seed map and the germinated plant location was 16–43 mm, depending on seedling frequency and vehicle speed, the latter because vehicle bouncing influenced the seed location. Downey, Giles, and Slaughter (2004) developed an automatic weed-mapping system for cotton production using a GPS and a digital video camera mounted on a vehicle travelling along the crop lines. The system achieved a DP of 74% for nut-sedge leaves and 92% for cotton leaves. The main sources of error were occlusion and overlap of weed and cotton plants within the same grid cell and occurrence of brown tissue damage on some cotton leaves.

3.7. *Multi-robot interactions*

In field crop production, the operation of several robots sharing the same task is inevitable in two scenarios. The first scenario involves a relatively low PR of a single ARS compared to the desired task PR, or the existence of a time window in which to complete the task on the total area before some imposed deadline (weather and seasonal conditions, rain forecasting, maximum acceptable maturity of the produce, market requirements, etc.). Enhancing PR may require more than one ARS, leading to the involvement of multiple ARS working within the same space at the same time, e.g., selective weed treatment by spraying herbicides with several systems (Conesa-Muñoz, Gonzalez-de-Soto, Gonzalez-de-Santos, & Ribeiro, 2015). The second scenario involves the requirement of different types of ARS to perform various sub-tasks in the same space at the same time. In agriculture, the second scenario is common since many types of field operations require two or more vehicles to be performed properly. Such ARS incorporate perception systems to acquire information, decision-making systems to interpret and analyse the information, and actuation systems that are responsible for performing the agricultural operations. These systems consist of different sensors, actuators, and computers that work synchronously in a specific architecture for the intended purpose (Emmi, Gonzalez-de-Soto, Pajares, & Gonzalez-de-Santos, 2014a) and require advanced and precise collaboration abilities (Bechar, Nof, & Wachs, 2015). For example, harvesting hay balls on grasslands is generally performed using one dump truck and one tractor equipped with a hayfork, both moving in the field as the harvesting progresses. Similarly, harvesting corn involves a tractor towing a wagon and a harvester filling the wagon (Noguchi, Will, Reid, & Zhang, 2004). Therefore, a master–slave system (MSS) has to control the relative positions of all vehicles involved in a single operation. The 'master' vehicle performs the decision-making functions and sends commands to the 'slave' vehicle. The 'slave' follows the 'master' instructions and reports its own status by transmitting information about its location, orientation, and operating conditions.

Noguchi et al. (2004) developed a MSS with minimal centralised control for mobile ARS performing the same farm operation. They tested the MSS with two tractor ARS in a master–slave relation. Even though the MSS was able to control the two-unit system adequately, it was still far from being a complete system able to control a complex operation requiring a large fleet of ARS, HRS and workers rushing to prepare, fertilise and plant a large field of tomato, broccoli and/or lettuce plants during the late spring season when an important rainfall event was being forecasted to arrive within a short time.

A Cartesian multi-arm robotic harvester is being developed for two-dimensional crops (Zion et al., 2014). The manipulators mounted in parallel on a rectangular frame, traverse laterally across the crop bed as the frame moves along it. Simulations conducted to enable economic optimisation of the robot design, taking into account the costs of robotic arms, labour and operation time and the value of the crop. Emmi, Paredes-Madrid, Ribeiro, Pajares, and Gonzalez-de-Santos (2013) developed a simulation tool to study and evaluate the implementation of precision-agriculture techniques in a virtual 3D world integrating fleets of mobile robots in the execution of precision-agriculture tasks. The simulation tool was able to cope with different mobile robots and agricultural implements, allowed the users to represent realistic characteristics from a defined location, and modelled variable scenarios affecting fleet performance. Nebot, Torres-Sospedra, and Martinez (2011) developed a new control architecture for systems involving a group of heterogeneous robots cooperating to perform a global mission. The architecture coped with scalability, code reuse, hardware abstraction and data distribution among a team of robots. Johnson, Naffin, Puhalla, Sanchez, and Wellington (2009) introduced a team of three tractors and a HO in a peat moss-harvesting operation. The behaviour and actions of the tractors were designed to mimic manual harvest operations while maintaining a safe operating environment. Each of the three tractors was equipped with a bolt-on automation package, and the HO commanded and monitored the mission using a remote interface. The automation package included positioning, planning, and control, as well as coordination and perception systems to preserve field-harvesting order, detect obstacles, and report physical changes in the operating environment. The system performed more than 100 field harvesting missions during one season in a working peat bog, including three complete system tests with the end users.

In recent years, the RHEA project (Gonzalez-de-Santos, 2013; Gonzalez-de-Soto, Emmi, Benavides, Garcia, & Gonzalez-de-Santos, 2016) has been involved in the configuration of a new generation of robotic systems for both chemical and physical management of weeds (Emmi, Gonzalez-De-Soto, Pajares, & Gonzalez-De-Santos, 2014b). The mission consists of an inspection task, performed by aerial units carrying the remote perception system (two Sigma DP2 Merrill cameras, NIR and RGB images), and a treatment task performed by three ground units (Boomer-3050 tractors). The ground units were equipped with an on-board computer, communication equipment, a GPS (RTK) receiver, a camera system, a laser and a spraying system with a 200-l water tank and a 50-l herbicide tank connected to a direct injection system to inject the chemicals into 12 solenoid nozzles activated selectively and located on a 6-m boom. The conclusion of this work was mainly that the external base station equipped with a mission manager controller and a communication system was able to control the multi-robot fleet operation adequately (Gonzalez-de-Soto, Emmi, Perez-Ruiz et al., 2016).

4. Conclusions and future work

Agricultural productivity has significantly increased over the years and is an important target for the application of various types of technologies designed to increase crop yields, improve quality of fresh and processed food, decrease detrimental environmental impacts, and address other aspects of farming. Automation has considerably increased the productivity of agricultural machinery by increasing efficiency, reliability and precision, and reducing the need for human intervention (Schueller, 2006). Field crops are production systems whose products quality is a significant factor (Mizrach et al., 2003), are highly sensitive to mechanical pressure and require gentle, accurate and complex handling operations. Agricultural applications of automation and robotics (ARS) require advanced technologies to deal with complex and highly variable environments and produce (Nof et al., 2013).

Extensive research has focused on the application of ARS to a variety of field operations and technical feasibility has been widely demonstrated. Despite the tremendous effort, however, very few ARS are operational in agricultural production systems. The main limiting factors are production inefficiencies and the lack of economic justification (Bechar & Vigneault, 2016).

The designs, developments and evaluations of agricultural ARS for field operations are highly diverse in terms of objectives, structures, methods, techniques, and sensors. In this context, it is extremely difficult to compare systems and real progress, and transfer developed technology from one application to another. Standardisation of term descriptions and the methodology used for measuring system performance and adequacy of technological requirements is still vital for comparing robot performance, and technical and technological progress. The limiting factors for the commercialisation and assimilation of agricultural ARS are unique to each robotic system and agricultural task. However, there are several mutual gaps that need to be filled, such as poor DP, lack of ADM and low ASR, to suit unstructured and dynamic environments. Research and development of versatile and adaptive algorithms with sensor-fusion ability, integrated into a multi-sensor platform, have to be conducted. Field CT needs to be reduced to reasonable value for a commercial agricultural production system and the PR of the ARS has to be increased to justify economic use. The wholeness or integration of all subsystems needs to be improved to enable sustainable performance and complete operation of the task. Research focusing on each of these gaps and limiting factors is required to move agricultural robotics toward commercialisation.

Development of a feasible agricultural ARS must include creation of sophisticated and intelligent algorithms for sensing, planning and controlling, to cope with the difficult, unstructured and dynamic agricultural environment (Edan & Bechar, 1998), or to integrate a HO into the system, generating a HRS. Such tasks and systems should be reinforced by a HO to solve particular problems of ARS operation in the field (Ceres et al., 1998). The creation and development of innovative algorithms implemented as a tool for solving problems, optimising structure device, and increasing performance of a single ARS task or multi-ARS mission have been powerful in the development and/or optimisation of some ARS designs and operation modes, and have offered objective ways of evaluating kinematic structures of ARS. Although computation is expensive, these research and development methodologies have been found to be powerful in solving complex problems and should be used more frequently, instead of the trial-and-error methods that are used all too often today.

Future studies of the application of automation and robotics to agricultural crop production need to develop several research areas to reach the goal of using ARS, HRS or automatic systems for agricultural field purposes. The information-acquisition system, including the sensor-fusion algorithms and data analysis, should be improved to make them robust, reliable and suited to the dynamic conditions of unstructured agricultural environments.

The size of the systems should be reduced. Small vehicles consume less energy than large ones, and are better suited to stochastic and dynamic requirements. Small vehicles also enable reduced environmental impact by avoiding the over-application of chemicals and overlapping coverage, and their lighter weight and lower ground pressure cause less soil compaction. In addition, smaller systems generally cost less than larger ones.

Development of HRS is considered a reasonable first step on the path to fully ARS. Intensive research is needed on where, when and how to integrate a HO into the system control loop, to define the operator's responsibilities, and to determine how such integration might increase overall system performance and reliability. Furthermore, the success of simultaneous operation of several ARS, or collaboration between ARS, to perform tasks that a single ARS cannot complete, either because of its relatively low PR or because the task involves too many different functions, devices or systems, needs to be assessed.

Machines will inevitably become smarter and fully autonomous; it is only a matter of time (Blackmore, Griepentrog, Fountas, & Gemtos, 2007). However, to achieve these developments and gain the associated benefits, we need to determine how intelligent these machines need to be, and to define their appropriate behaviours. Increases in labour costs and the demand less arduous work, the demands for better quality of life and higher quality produce and the progressively decreasing cost of increasingly powerful computers, electronics and sensors, are all promoting the economic feasibility of agricultural ARS.

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