

Robots poised to revolutionise agriculture

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Abstract

Purpose – This paper aims to provide details of a number of recent and significant agricultural robot research and development activities.

Design/methodology/approach – Following an introduction, this first provides a brief overview of agricultural robot research. It then discusses a number of specific activities involving robots for precision weed control and fertiliser application. A selection of harvesting robots and allied technological developments is then considered and is followed by concluding comments.

Findings – Agricultural robots are the topic of an extensive research and development effort. Several autonomous robots aimed at precision weed control and fertiliser application have reached the pre-production stage. Equally, harvesting robots are at an advanced stage of development. Both classes exploit state-of-the-art machine vision and image processing technologies which are the topic of a major research effort. These developments will contribute to the forecasted rapid growth in the agricultural robot markets during the next decade.

Originality/value – Robots are expected to play a significant role in meeting the ever increasing demand for food, and this paper provides details of some recent agricultural robot research and development activities.

Keywords Robots, Agriculture, Agrochemicals, Food production, Harvesting

Paper type Technical paper

Introduction

Twenty-first century agriculture faces a number of significant and unprecedented challenges. These include shortages of human labour, the desire for national food security, unpredictable climatic variability, pressures on farmland from urbanisation, reduction in land fertility from erosion or poor management and growing public expectations for ever more sustainable agricultural practices. Further, according to the United Nations, the global population is forecast to rise from its present level of 7.4 billion to reach 9.55 billion by 2050 and 11.2 billion in 2100. This will require agricultural production to be increased dramatically but without causing irreparable environmental damage. Many concepts have been proposed to address these issues such as the widespread use of genetically modified crops, improved herbicides and fertilisers, precision agriculture and, more speculatively, the recently proposed indoor vertical farming. While there will be no universally applicable solution, it is recognised that robotics is one of the technologies that will play a central role. The use of robots in precision agriculture has been discussed previously in this journal (Bogue, 2013), and this article takes a broader view and considers a number of research activities and developments that are likely to stimulate the agricultural robot markets.

Overview of research

Agricultural robots have been the topic of an extensive research and development effort for many decades and are being studied by numerous groups from around the world. Research continues to gather pace and recent years have seen a growing number of field trials with pre-production prototypes and a limited degree of commercialisation. Most importantly, the availability of light detection and ranging (LIDAR), global positioning system (GPS) and allied location technologies, often derived from better funded field of research such as the military and driverless cars, has led to autonomous operation becoming technically feasible and cost-effective. In some instances, research aims to “robotise” conventional agricultural machines by eliminating the human operator and conferring a degree of autonomy, although much work involves “ground up” custom designs. This latter approach is more complex because in addition to developing the actuators, sensors, control systems and end effectors required to accomplish the intended task, together with the technologies to confer autonomous operation, it also involves all of the issues associated with mobility, namely, power sources, steering and braking mechanisms and drive trains.

Robots have the potential to conduct the majority of the tasks presently undertaken by conventional agricultural machines or humans and cover the entire process from ground preparation and seeding, through fertilisation and weed control to harvesting. Perceived benefits include less reliance on human labour, improved productivity, lower production costs and reduced environmental impact.

Precision weed control and fertiliser application

Weed control is a vital process and the economic implications are considerable. For example, Australia spends AU\$1.5bn/

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Industrial Robot: An International Journal
43/5 (2016) 450–456
© Emerald Group Publishing Limited [ISSN 0143-991X]
[DOI 10.1108/IR-05-2016-0142]

Received 11 May 2016
Accepted 12 May 2016

year on weeding-related operations and losses to the nation's agricultural production are estimated at AU\$2.5bn/year. However, because of mounting environmental concerns, blanket spraying with herbicides is becoming ever less acceptable and a growing body of research seeks to develop alternative and less environmentally damaging technologies. Equally, reducing the quantities of fertilisers used has both economic and environmental benefits.

An example of a “ground up” development which seeks to address these issues is the Ladybird robot (Figure 1). Developed at the Australian Centre for Field Robotics (ACFR) at the University of Sydney, the aim was to design an autonomous robot that could be used by farmers to optimise their crop yield. For environmental reasons, diesel power was rejected in favour of lithium iron phosphate batteries that could be recharged in the field from curved solar panels mounted on “wings” on each side of the robot. The curve allows light to be captured efficiently because the sun's position varies and changes with the seasons, and the wings can be raised or lowered to accommodate varying crop heights. The wings also shade the vision system on the underside of the robot and prevent it from being affected by changes in ambient light. The drive train is based on four electric motors and each has two mechanically decoupled axes to orient and drive the wheels which confer the robot with a high degree of manoeuvrability. The Ladybird can move at about 3 mph for between 7 and 9 h on batteries alone, and, on sunny days, solar energy can recharge the batteries, allowing it to operate indefinitely. Autonomous navigation is achieved through the use of a combined GPS/INS (inertial navigation system). As the robot moves, a forward and rear facing LIDAR and a high resolution, spherical digital video camera capture features of the surroundings. These data are fed to an on-board processor, allowing the robot to identify and avoid obstacles and detect the rows of crops. To classify and analyse the crop, image sensors capture data as the robot traverses a field. A stereo camera creates RGB images of the crops and a hyperspectral imaging camera (400-900 nm) captures IR and UV data. The spectral information allows the system to identify the shape and colour of the crops, and their spectral

Figure 1 The Ladybird robot



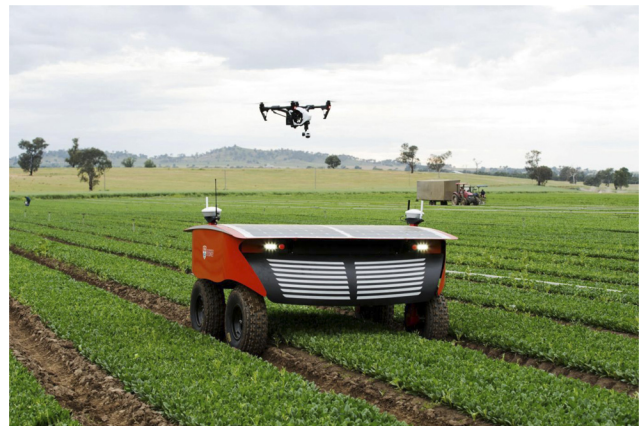
Source: Australian Centre for Field Robotics, University of Sydney

fingerprints provide data on their health through the use of one of a number of previously trained machine learning algorithms. The height of the crops is determined with a laser sensor. To control weeds and to fertilise the crops, the robot is fitted with a spraying end effector attached to a Universal Robots UR5 six-axis robot arm. When another machine learning algorithm has identified a weed, its co-ordinates are transferred to the robotic system which can position itself directly over the weed. A controlled quantity of herbicide is then applied in exactly the correct position. Equally, if the software identifies a plant in poor health from its spectral characteristics, the robotic arm can deliver an appropriate quantity of fertiliser to it. One of the key challenges is planning the paths for a robot arm to allow many individual weeds to be processed quickly and details of an algorithm used by the group can be found in Lee *et al.* (2014).

Most recently, the ACFR group has developed a robot for intelligent perception and precision application (RIPPA) which is smaller than the Ladybird but uses much of its technology (Figure 2). It is equipped with the variable injection intelligent precision applicator which, like the technology on the Ladybird, delivers controlled and localised quantities of agrochemicals. In 2016, trials were conducted in Cowra, NSW, where the robot autonomously drove up and down crop rows with an accuracy of 4 cm using satellite-based location corrections. The robot completed over 21 h of continuous operation using solar and battery power and a video clip can be viewed at www.youtube.com/watch?v=W7AMytvA3XI&feature=youtu.be. The RIPPA has now reached a commercial prototype stage.

Allied work at the Queensland University of Technology (QUT) involves the development of a small agricultural robot, the AgBot II. This is 3 m wide, 2 m long and 1.4 m high, and, like the RIPPA, it is equipped with an array of cameras and sensors. It is designed to operate autonomously and detect and classify weeds and manage them either chemically or mechanically, as well as applying fertilisers for site-specific crop management. QUT is starting a dialogue with potential commercial partners.

Figure 2 The RIPPA robot



Source: Australian Centre for Field Robotics, University of Sydney

These highly localised and controlled applications of agrochemicals are an example of precision agriculture, and, in addition to cost saving because of reduced usage, there are clear environmental benefits. AgBot II, RIPPA and other similar robots represent an emerging generation of agricultural machines specifically designed for advanced crop management and can also use novel weed destruction methods based on, for example, mechanical and thermal principles rather than herbicides. It is estimated that the use of multiple, relatively low-cost robots rather than a single, large and expensive tractor could reduce the cost of weed management in terms of energy, labour and agrochemical usage by up to 40 per cent. Further, small and lightweight robots reduce damage to the soil through compaction. However, deploying multiple robots is not without its problems, amongst which is the cost of the individual units, preventing collisions between them, communicating with each-other and various safety issues. The EU-wide RHEA project (Robot Fleets for Agriculture and Forestry Management) addressed some of the issues and aimed to develop robotic fleets (Figure 3) for weed control and pesticide management in agriculture and forestry. In contrast to the developments discussed above, the robots were not developed ground-up but based on a modified New Holland Boomer 3050 tractor unit. These were equipped with machine vision-based weed and crop row detection systems; a laser rangefinder to detect obstacles; a GPS/IMU (inertial measurement unit); communication equipment linking the operator station, the mobile units and user-portable devices; a controller to compute the steering, throttle and braking for path tracking; and additional power supplies based on a fuel cell and solar panels. The overall system architecture is shown in Figure 4. A series of field trials have been successfully conducted and the robots were able to detect up to 90 per cent of weed patches and by using a combination of physical

Figure 3 The RHEA fleet of agricultural robots



Source: Emmi *et al.*, New Trends in Robotics for Agriculture: Integration and Assessment of a Real Fleet of Robots, *The Scientific World Journal*, Vol. 2014, Article ID 404059, doi:10.1155/2014/404059

and chemical means, they can eliminate up to 90 per cent of the detected weeds, reducing chemical consumption by 75 per cent when compared to current practices. The final project report can be viewed at http://cordis.europa.eu/result/rcn/164052_en.html and further technical details can be found in Emmi *et al.* (2014).

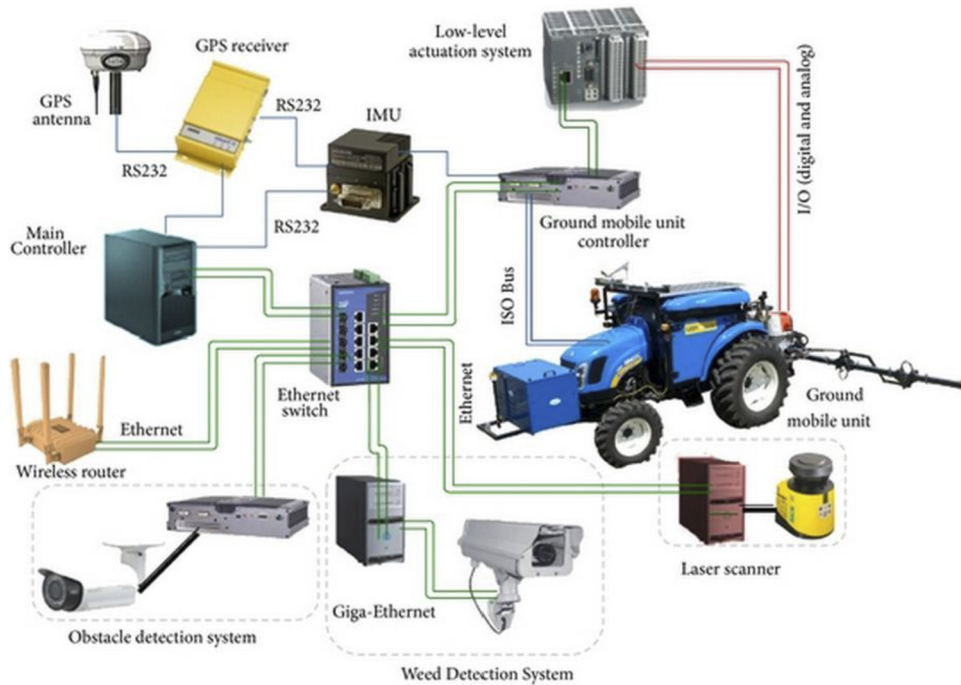
Harvesting robots

Harvesting processes are highly labour-intensive and anticipated future labour shortages have stimulated interest in automated systems since the late 1960s (Schertz and Brown, 1968). Since then numerous prototype robots have been developed to harvest and pick a variety of fruits and vegetables such as apples, grapes, melons, cucumbers, peppers and strawberries, both in open fields and within closed environments such as greenhouses.

One of the most complex and costly elements of many of these robots is the vision system that frequently involves several different types of cameras. This issue is being addressed by a group from the Spanish University of Lleida who have demonstrated a prototype fruit picking system by combining a robotic arm with a low-cost stereo-vision camera located in the gripper (Font *et al.*, 2014). The image acquisition device is a Minoru 3D USB Webcam and the robotic arm was created from ABS with a 3D printer and includes six DC gear motors and a microcontroller for velocity and speed control. The robotic arm is composed of five linked elements and a manually interchangeable gripper. Laboratory tests showed that using reddish pears as targets, the system required an average time of 16 s to detect and grip a pear, although 95 per cent of this time arose from mechanical limitations of the robotic arm. Figure 5 shows a schematic of the robotic arm and the gripper with the in-built imaging device.

The algorithms used with vision systems are also the topic of an extensive research effort and whether operating outside or within greenhouses, the ability to locate, recognise and characterise crops and weeds is clearly vital. In the harvesting context, one of the most critical issues is identifying crops that may overlap or be subject to varying lighting conditions. Workers from China's Shanghai Jiao Tong University are addressing this problem in the context of robotic tomato harvesting. They have developed a tomato recognition algorithm based on multiple feature images and image fusion. Details can be found in Zhao *et al.* (2016). During laboratory trials, the algorithm successfully recognised 93 per cent of the target tomatoes out of a sample of 200, and Figure 6 shows some results of applying these algorithms to growing tomatoes. Another Chinese group, from Jiangsu University, recently reported a technique for detecting apples under highly variable lighting conditions (Ji *et al.*, 2016). Experimental results show that the maximum segmentation error is 3 per cent and the average recognition time is less than 0.7 s, which, the authors claim, can meet the requirements of a real-time picking robot. This development is potentially very significant because apple picking robots have been the topic of research for many years, but all prototype systems have been too complex, costly, unreliable and slow; humans can pick apples at a rate of around one/second, but most robots struggle to better one every 5-10 s. Recognising the

Figure 4 The RHEA system architecture



Source: Emmi *et al.*, New Trends in Robotics for Agriculture: Integration and Assessment of a Real Fleet of Robots, *The Scientific World Journal*, Vol. 2014, Article ID 404059, doi:10.1155/2014/404059

Figure 5 The robotic arm (left); the robot arm-mounted imager and gripper (right)

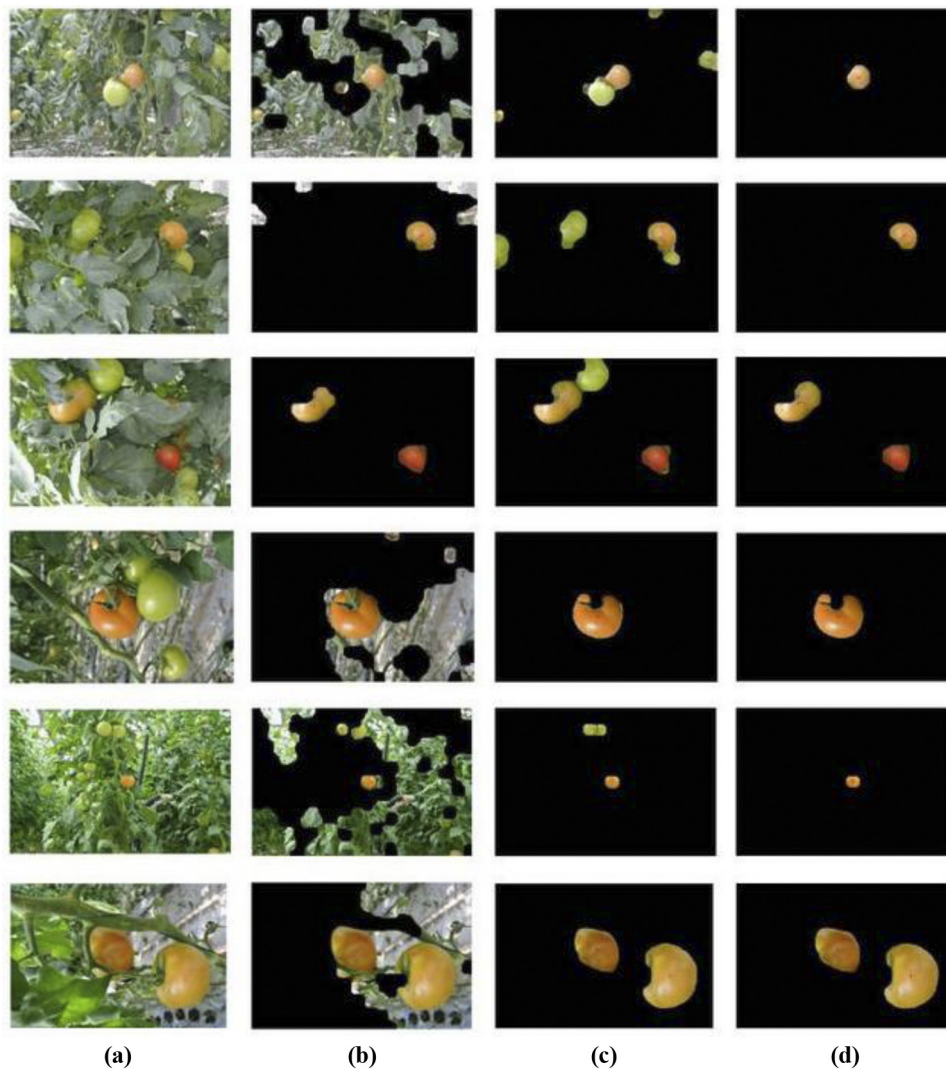


Source: Font *et al.*, *Sensors* 2014, 14 (7), pp. 11,557-11579, doi:10.3390/s140711557

potential of a workable apple picking robot, in 2013, the US Department of Agriculture awarded a research team from Washington State University a \$548,000 grant as part of its National Robotics Initiative to conduct such a development. The robot uses relatively conventional imaging technology and algorithms to recognise colours, shapes and textures of the fruit and the tree but reflecting the difficulties posed by fruit overlaps etc. rather than

developing ever-more complex algorithms the group's system will include a human operator. Any apples missed by the system are selected by a human who views an image of the tree on a computer screen. Touching the unpicked apples on-screen identifies them and directs the robotic arm to locate and harvest them.

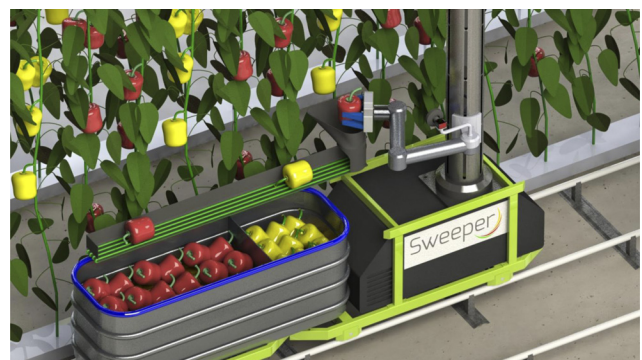
A €4m, EU-funded project, Sweet Pepper Harvesting Robot, commenced in 2015 and has the ambitious aim of

Figure 6 Tomato recognition techniques

Notes: Column (a) shows the original images with tomatoes in plant canopies. Images in columns (b), (c) and (d) show the results of three recognition methods using a*-component images, I-component images and fusion images, respectively; Credit: Zhao et al., *Sensors* 2016, 16 (2), 173; doi: 10.3390/s16020173

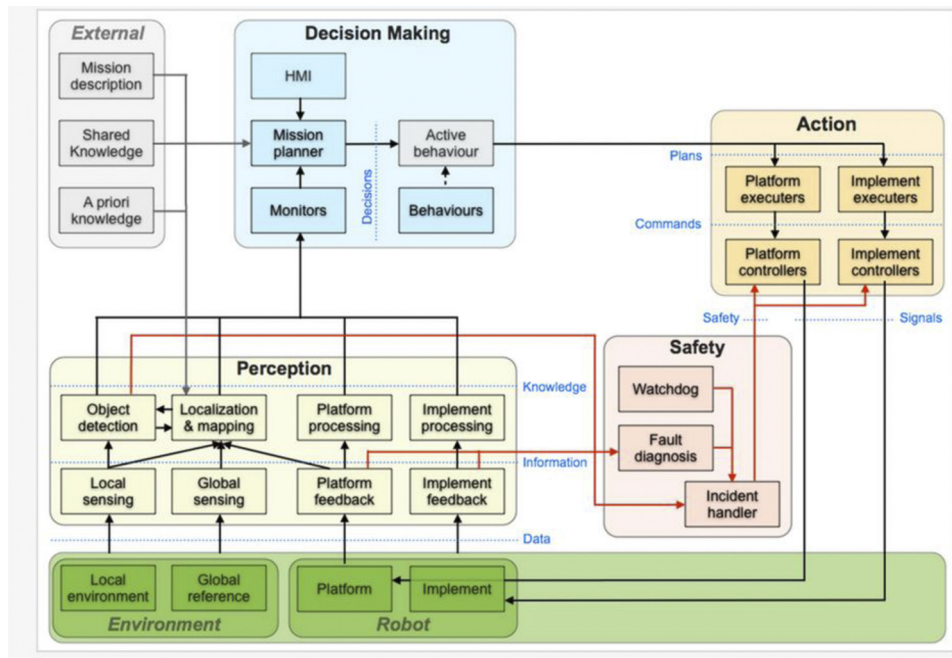
developing and commercialising the first robot for harvesting peppers in greenhouses. This is a significant application because 1.3 million tons of peppers are harvested each year in Europe. The project involves six partners from four European countries and builds on the machine vision, gripping and other technologies developed previously in the EU-funded CROPS project. The robot will run on a rail system within a greenhouse and has a snake-like arm with six DOF, equipped with a gripper. A schematic is shown in Figure 7. To harvest a pepper, the robot will first use cameras and pattern recognition techniques to locate it. Once a target has been identified, its colour is analysed to determine whether it is ripe and the robot then begins to move its articulated arm towards it and picks it with the end effector.

Workers from the University of Southern Denmark note that the literature contains little on the software techniques

Figure 7 Schematic of the robotic pepper harvesting system

Source: SWEEPER

Figure 8 The FroboMind architecture



Notes: The software modules are grouped into Perception, Decision-Making, Action and Safety layers. The blue dashed lines indicate the data interfaces between layers and modules

Source: Jensen *et al.*, Robotics 2014, 3 (2), pp. 207-234, doi:10.3390/robotics3020207

used in agricultural robots, potentially leading to duplication of effort. They argue that the lack of a common, open software platform for field robotics research is inhibiting the rate of agricultural robot developments (Jensen *et al.*, 2014). Accordingly, they have designed FroboMind, a software platform tailored to robots in precision agriculture which provides the means of using the same generic platform across different projects. FroboMind is open-source and is available for royalty-free commercial use. It is implemented in ROS and runs on Ubuntu Linux and the architecture is shown in Figure 8. Examples of current applications are autonomous crop scouting, precision spraying, mechanical weeding and grass cutting, as well as humanitarian demining and land surveying.

Concluding comments

Many agricultural robot developments have reached the pre-production prototype stage, there have been numerous successful field trials and some projects have the specific aim of achieving commercialisation. This process is gradually gathering pace but the market is forecast to expand very dramatically during the next decade. According to a report from Tractica, annual shipments will reach 992,000 units world-wide by 2024, up from 33,000 in 2015. Much of this will comprise relatively well-proven devices, with driverless tractors, dairy robots and drones all taking significant market shares, but the report also notes the demand for robots for more complex tasks such as harvesting, pruning, weeding and spraying. Although this article has only touched on the extensive body of agricultural robot research, it illustrates that

considerable progress is being made, particularly in the critical machine vision/image processing technologies that will enable these complex tasks to be realised. Equally, the majority of the technological challenges relating to autonomy have been solved and legal and safety considerations are the major factors inhibiting the deployment of robotic tractors and similar devices, but, in all probability, these issues will be resolved with the imminent arrival of driverless cars. Progress by the research community, combined with several recent product announcements by robot and agricultural equipment manufacturers, suggests that the markets will indeed exhibit rapid growth during the next decade.

References

- Bogue, R.W. (2013), "Can robots help to feed the world?", *Industrial Robot*, Vol. 40 No. 1, pp. 4-9, available at: <http://dx.doi.org/10.1108/01439911311294200>
- Emmi, L., Gonzalez-de-Soto, M., Pajares, G. and Gonzalez-de-Santos, P. (2014), "New trends in robotics for agriculture: integration and assessment of a real fleet of robots", *The Scientific World Journal*, Vol. 2014, p. 21, doi: <http://dx.doi.org/10.1155/2014/404059>.
- Font, D., Pallejà, T., Tresanchez, M., Runcan, D., Moreno, J., Martínez, D., Teixidó, M. and Palacín, J. (2014), "a proposal for automatic fruit harvesting by combining a low cost stereovision camera and a robotic arm", *Sensors*, Vol. 14 No. 7, pp. 11557-11579, doi: [10.3390/s140711557](http://dx.doi.org/10.3390/s140711557).
- Jensen, K., Larsen, M., Nielsen, S.H., Larsen, L.B., Olsen, K.S. and Jørgensen, R.N. (2014), "Towards an

- open software platform for field robots in precision agriculture”, *Robotics*, Vol. 3 No. 2, pp. 207-234, doi: [10.3390/robotics3020207](https://doi.org/10.3390/robotics3020207).
- Ji, W., Meng, X., Tao, Y., Xu, B. and Zhao, D. (2016), “Fast segmentation of colour apple image under all-weather natural conditions for vision recognition of picking robots”, *International Journal of Advanced Robotic Systems*, Vol. 13 No. 24, doi: [10.5772/62265](https://doi.org/10.5772/62265).
- Lee, J.J.H., Frey, K., Fitch, R. and Sukkarieh, S. (2014), “Fast Path Planning for Precision Weeding”, *Proceedings of Australasian Conference on Robotics and Automation, 2-4 December 2014, The University of Melbourne, Melbourne*.

- Schertz, C.E. and Brown, G.K. (1968), “Basic considerations in mechanizing citrus harvest”, *Transactions of the ASAE*, Vol. 11 No. 3, pp. 343-346, doi: [10.13031/2013.39405](https://doi.org/10.13031/2013.39405).
- Zhao, Y., Gong, L., Huang, Y. and Liu, C. (2016), “Robust tomato recognition for robotic harvesting using feature images fusion”, *Sensors*, Vol. 16 No. 2, doi: [10.3390/s16020173](https://doi.org/10.3390/s16020173).

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