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REVIEW ARTICLE

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Task-based agricultural mobile robots in arable farming: A review

Krishnaswamy R. Aravind[1], Purushothaman Raja[1] and Manuel Pérez-Ruiz[2]

[1]SASTRA University, School of Mechanical Engineering, Thanjavur-613401, Tamil Nadu, India. [2]University of Seville, Area of Agroforestry Engineering, Dept. Aerospace Engineering and Fluid Mechanics, Ctra. Sevilla-Utrera km1, Sevilla 41013, Spain.

Abstract

In agriculture (in the context of this paper, the terms "agriculture" and "farming" refer to only the farming of crops and exclude the farming of animals), smart farming and automated agricultural technology have emerged as promising methodologies for increasing the crop productivity without sacrificing produce quality. The emergence of various robotics technologies has facilitated the application of these techniques in agricultural processes. However, incorporating this technology in farms has proven to be challenging because of the large variations in shape, size, rate and type of growth, type of produce, and environmental requirements for different types of crops. Agricultural processes are chains of systematic, repetitive, and time-dependent tasks. However, some agricultural processes differ based on the type of farming, namely permanent crop farming and arable farming. Permanent crop farming includes permanent crops or woody plants such as orchards and vineyards whereas arable farming includes temporary crops such as wheat and rice. Major operations in open arable farming include tilling, soil analysis, seeding, transplanting, crop scouting, pest control, weed removal and harvesting where robots can assist in performing all of these tasks. Each specific operation requires axillary devices and sensors with specific functions. This article reviews the latest advances in the application of mobile robots in these agricultural operations for open arable farming and provide an overview of the systems and techniques that are used. This article also discusses various challenges for future improvements in using reliable mobile robots for arable farming.

Additional key words: precision agriculture; task-based agricultural robots; soil analysis; seeding; weed detection; harvesting; crop scouting robot

Abbreviations used: AMS (Autonomous Mechanization System); EC (Electrical Conductivity); GEONET (Global positioning system Earth Observation NETwork); GNSS (Global Navigation Satellite System); GPS (Global Positioning System); IMU (Inertial Measurement Unit); LAI (Leaf Area Index); LAIC (Leaf Area Index Calculation); LIDAR (LIght Detection And Ranging); LPG (Liquefied Petroleum Gas); MC (Moisture Content); MRE (Mean Relative Error); NIR (Near Infra-Red); NIRS (Near Infra-Red Spectroscopy); PTO (Power Take-Off); RGB (Red Green Blue); RMSE (Root Mean Square Error); RTK (Real Time Kinematic); RTSS (Real Time Soil Sensing); SOM (Soil Organic Matter); TOF (Time Of Flight); UAV (Unmanned Aerial Vehicle); VOC (Volatile Organic Compound).

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Correspondence should be addressed to P. Raja: raja_sastra@yahoo.com

Introduction

Historically, agriculture has consumed a large amount of energy, and it continues to do so currently. In the past, energy has been extremely inexpensive, and agricultural products have consumed large amount of energy to develop rapidly. The world's population has surpassed 7 billion and is expected to continue to grow in the coming decades, reaching 9 billion in 2050 (Ocampo, 2014). Therefore, agricultural production must continue to increase while consuming the minimum possible amount of resources. Moreover, conventional, imprecise mechanized farming demands relatively more petrochemical energy, the majority of which is already consumed by automobiles and other applications. To address the increasing energy demand, part of the harvest from agricultural crops such as corn and soya beans has been used to produce biofuels; this portion has doubled since 2007 according to the survey "Biofuels Impact on Crop and Food Prices", which was conducted in 2009 (Baier *et al.,* 2009). In light of these problems, precision in the agricultural production processes, from soil tilling to harvesting, is required for the efficient and quality production of crops with the minimum use of resources.

Precision agriculture is a farm management practice that uses modern technologies to observe and respond to farm variability depending on computational analysis of observations (Mandal & Maity, 2013). Technology such as automation can be used in these applications; however, the agricultural operational environment is dynamic, and complex infrastructure and facilities with costly machines are required to completely automate an agricultural process. As an alternative to spending considerable money on infrastructure, a few intelligent mobile robots that each possess specific task capabilities and that are able to move and adapt in the current field can be developed to reduce production costs. A study by Pedersen *et al.* (2008) on the economic feasibility of using robot applications in agriculture indicated a significant reduction in production costs. Introducing robots into agriculture improves sustainability and consistency in agricultural tasks in addition to reducing costs. The precision of robots in tasks such as applying chemicals reduces environmental problems and their harmful effects on humans (Comba *et al.*, 2010).

Agricultural robots can include modified tractors, small ground robots (Blackmore *et al.*, 2004a), and aerial robots. Several reviews have examined agricultural robots, which have been categorized based on several features. Table 1 lists articles in agricultural robots, mainly focusing on the latest trends in the development and use of robots with various features and their descriptions.

Commercially available tractors can be modified into autonomous vehicles by adding the electronics and communication devices necessary for autonomous operation in agricultural fields. Blackmore *et al.* (2004b) implemented an automatic steering system with an initially defined route plan to a modified tractor. Small robots include small modified tractors or completely new robots. Small ground-based robots can assist a human in, for example, harvesting strawberries. These robots can transport strawberries from a worker to an unloading station; workers can spend up to 20% of their time simply walking back and forth from the strawberry field to the unloading station, making automation of this task very useful (Arikapudi *et al.*, 2014). A group of small robots can work together by communicating with each other and the main coordination stations that

Table 1. List of articles on recent trends in agricultural robots

Reference	Description
Research in autonomous agricultural vehicles in Japan (Torii, 2000)	Briefly explains the various applications of image sensors, soft computing, fuzzy control, and cooperative behavior in agricultural robots. Various researches by manufacturers such as Kubota and Mitsubishi are briefly explained.
Agricultural robots- system analysis and economic feasibility (Pedersen *et al*., 2006)	A brief review of various studies on crop scouting, weeding and grass cutting robots. Analyses the economic benefits of using robots over conventional grass cutting machines.
Robotics in crop production (Grift, 2007)	Discusses robots in scouting operations, and other robotic operations and the advantages of using multi-robot systems.
Overview of research on agricultural robots in China (Libin *et al*., 2008)	Discusses various outdoor and indoor robots in various agricultural operations such as grafting, transplanting, spraying, mowing and harvesting in China.
Robotics and automation for crop management: trends and perspective (Comba *et al*., 2010)	A review on robots based on field type, navigation, agricultural operations, navigation and sensor systems along with their future possibilities.
Autonomous robots for agricultural tasks and farm assignment and future trends in agro robots (Yaghoubi *et al*., 2013)	Reviews the use of agricultural robots in fungicide and herbicide applications. Discusses various robots such as Ecobot I (sugar eating robot), Ecobot II (fly eating robot), and Ag Ant (legged robot to attack weeds).
Mobile sensor platforms: categorisation and research application in precision farming (Zecha *et al.*, 2013)	Categorizes agricultural robots based on several factors such as systematic concept, type and method of sensing, size, mobility, propulsion, degree of automation, architecture and information fusion; suggests future directions for such robots.
A brief overview and systematic approach for using agricultural robot in developing countries (Tarannum *et al.*, 2015)	Discusses various robot operations; land preparation, soil observation, seeding & planting, plant observation, harvesting and picking fruit.

Table 2. List of arable crops

Cereals	Industrial crops	Other crops
Maize	Cotton	Vegetables
Wheat	Tobacco	Sugarbeet
Oats	Hops	Melons
Sorghum	Soya	Pulses
Rice	Rape and turnip	Potatoes
Other cereals	Sunflower	Strawberries
	Other oil-seed or fiber crops	Flowers and ornamental plants
	Aromatic plants	Fodder crops
	Medicinal plants	
	Culinary plants	

are monitored by humans (Blackmore *et al.*, 2004a). Aerial robots and unmanned aerial vehicles (UAVs) have limited capacity to carry chemicals and batteries and cannot be used for certain ground-based tasks, such as soil preparation and plant-specific pesticide applications. However, aerial robots are excellent tools for data collection over large fields.

Farming can be categorized based on the crop type. *i.e.,* arable or permanent crops. Farming based on arable crops (as shown in Table 2) is known as arable farming. Arable farming is an important farming type that provides staple foods, medicines, and aromatic plants for the world population. This article mainly addresses the categorization of robots based on the agricultural tasks in open arable farming.

This paper is organized as follows. Five major agricultural tasks in open arable farming are discussed in the “Task-based agricultural robots” section. Research regarding the use of mobile robots in each agricultural task is documented in the following sections: “Tilling robots”, “Soil analysis robots”, “Seeding and transplanting robots”, “Crop scouting and pest, weed, and disease control robots”, and “Harvesting robots”. Based on these studies, the scope for using agricultural robots and the challenges that need to be overcome to achieve reliable, autonomous agricultural mobile robots are discussed in the “Scope and challenges” section. The “Conclusion” section provides insights into future problems faced by agricultural robots.

Task-based agricultural robots

In this article, agricultural tasks are classified into five important operations for open arable farming based on the study by Blackmore *et al.* (2007). The five major operations are shown in Fig. 1; some of the sub-operations shown as part of the major operations might be omitted depending on the crop and the farming type of the country.

Tilling is the first step in the agricultural process; this step involves manipulating the soil by mixing the soil above and below the surface, loosening the soil particles, blending nutrients and making the bed suitable for crop growth. Tilling also benefits crop development by destroying weeds and insect pests (Kladivko, 2001). In some countries, irrigation is included as the step after tilling. Additional irrigation is required at specific intervals throughout the crop growth. Generally, farm irrigation is performed with widely used and efficient automation methods such as central pivot systems, automated sprinklers and drip irrigation. Otherwise, tilling is followed by soil analysis, which is the process of measuring various physical and chemical properties of the soil to evaluate its fertility and physical conditions. In some occasions, soil analysis is also performed during different stages of plant growth to determine the correct nutrients to apply.

After tilling and soil analysis, crops can be grown either by placing seeds in the soil or by transplanting seedlings that were grown in a nursery into the field. Planting requires precision as each plant has specific space requirements and should therefore be placed at specific coordinates relative to the field. This precise positioning helps to generate a map containing the location of each plant, which aids the robots in performing subsequent operations.

Crop scouting is the process of continuously monitoring the field to acquire information on the plant status, disease incidence, and weed and pest infestations, which affect crop growth. Based on the acquired information, a precise control methodology such as herbicide or pesticide applications can be used

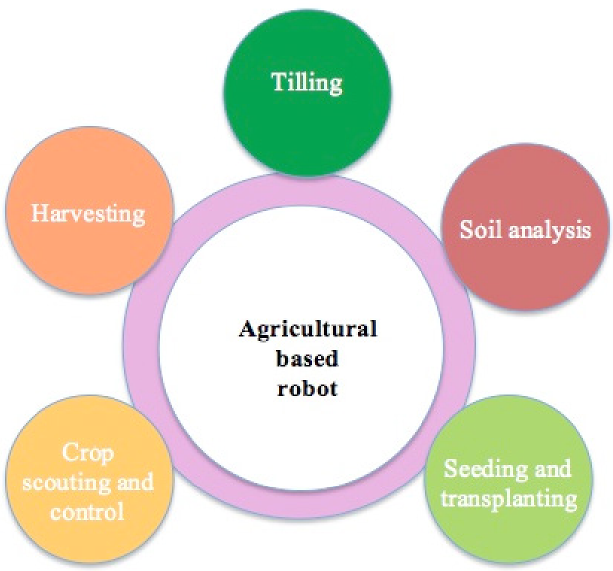

Figure 1. Task-based agricultural robots

Figure 2. Robotra performing a tilling operation

to improve the plant growth. Finally, the crops need to be harvested to obtain the produce; this process depends on the type of crop.

Mobile robots that are categorized based on their ability to perform these five important agricultural processes are known as task-based agricultural robots, as shown in Fig. 1. Research on the individual categories of robots is presented in the following sections.

Tilling robots

Tilling operations consist of primary and secondary tilling. Primary tilling is deep agitation of the soil that produces a rough surface, while secondary tilling is the opposite of primary tilling. Plowing is an example of a primary tilling operation; harrowing, rototilling and cultivating are a few examples of secondary tilling. Primary tilling is followed by secondary tilling to produce a smooth surface. Tilling is a tedious and labor intensive process, making this task a clear target for automation (Sahay, 2006; Micheal & Ojha, 2008). Traditional tractors have sufficient power to pull up the soil because they are heavy and have high torque, but small robots cannot perform this task. Tractors also tend to damage soil through compaction. One of the earliest studies on automatic plowing was conducted by Harries & Ambler (1981) using a conventional tractor with a furrow following transducer and steering servo. This tractor used an opto-electronic sensing technique for turning around the corners; however, the system was not well suited for inclined slopes due to its large displacement errors. Trials conducted using the implemented guidance system and automatic turning control were monitored over 200 runs. The tractor returned to its target position within ± 30 cm over 50% of the time and within ± 60 cm over 75% of the time.

In related research, an existing commercial tractor was modified into an autonomous robot, and additional equipment was attached to it in order to perform agricultural operations. Nagasaka *et al.* (2011) modified a commercial tractor (Yanmar EG65) by fixing a global navigation satellite system (GNSS) antenna for navigation and a DC motor for steering control. The GNSS of the tractor obtains the real-time reference position data from the global positioning systems (GPS) earth observation network system (GEONET) through the mobile phone network; the data then must be corrected for the inclination of the vehicle. The inertial measurement unit (IMU) in the tractor provides information regarding roll, pitch and heading angle. The data from the azimuth sensor, GNSS and IMU are compared to estimate the control parameter that is converted into an actuator command. This control parameter corrects the error in following a particular trajectory. Path planning was performed manually by considering the coordinates of the four corners of a square field and was provided to the tractor as an input.

Matsuo *et al.* (2012) modified a commercially available tractor into a robotic vehicle known as Robotra, as shown in Fig. 2. Robotra was able to perform unmanned tilling operations using its path-planning algorithm. This robot used the real-time kinematic-global navigation satellite system (RTK-GNSS) to provide position information for navigation. RTK (Bakker *et al.*, 2011) is a technique that is used to improve the accuracy of satellite-based positioning systems, such as GNSS, by approximately a few centimeters. Three methods of navigation operation were analyzed: basic, diagonal and round operation methods. Each operation method used a two-step process consisting of path planning and vehicle guidance to follow the path. The evaluation of these three operation methods concluded that the basic operation method can be conveniently performed by a human operator but that the other two methods can be efficiently and accurately performed only by robots since human visual judgment is limited for conducting precise operations in the field.

Soil analysis robots

Soil is the main source of nutrients for plants; therefore, various tests are manually performed in the field by taking samples across the field and then performing statistical analysis to estimate the soil properties. The results of laboratory tests depend on the number and density of the measurement locations. This process costs significant time and money to determine several soil properties. A study by Rossel & McBratney (1998) analyzed and compared the costs of estimating soil properties in the US and Australia. The average cost per sample for analyzing soil pH, carbon, nitrate-nitrogen, phosphorus and potassium were A$18.4, A$22.2, A$29.9, A$22.5 and A$19.4, respectively, in Australia. The costs in Australia were significantly

Figure 3. Bonirob with a soil penetrometer

higher than in the US, and precision agriculture requires more soil samples, resulting in economically inefficient farming. Therefore, an automated real-time measurement system for measuring soil properties can greatly benefit farmers.

Scholz *et al.* (2014) developed an automatic soil penetrometer, which was integrated into an autonomous mobile robot named Bonirob, as shown in Fig. 3. The soil penetrometer has a probing rod with a force sensor that penetrates into the soil to a depth of 80 cm via a linear actuator. This robot is also equipped with surface moisture and temperature sensors and can measure the physical properties of the soil. Their study showed a strong correlation to the data in the commercial penetrologger with a root mean square error (RMSE) of 0.185, 0.145 and 0.120 MPa for soil textures of loamy sand, sand and silt, respectively.

Pobkrut & Kercharoen (2014) developed a soil-sensing survey robot based on an electronic nose to determine certain chemical properties of soil. The robot had six wheels and was equipped with six gas sensors: TGS 825 for hydrogen sulfide; MQ2 for combustible gas; MQ5 for LPG and natural gas; MQ135 for ammonia, benzene and carbon dioxide; TGS 2600 for air contaminants and TGS 2602 for volatile organic compound (VOCs) and odorous gases. The Arduino Mega 256 controller was used to obtain data from the sensors and to control the entire system.

The robot sent the data to the system by using a Zigbee-based wireless network. The robot was tested under real field conditions with different soils, such as sandy soil, sandy soil with fertilizers, loamy soil and loamy soil with fertilizers. The responses of these sensors to various soil conditions were recorded, although further detailed study is needed to correlate the responses with the soil.

A study by Baharom *et al.* (2015) on real-time soil sensing (RTSS) used a visible and near-infrared spectrophotometer to detect the various chemical properties of soil, such as the total carbon, organic matter, total nitrogen, available phosphorus, and moisture content in cultivated paddies. This RTSS process included a halogen lamp as a light source; these lights were guided by an optical fiber to illuminate a 50 mm-diameter area at depths of 10, 15 and 20 cm below the soil surface.

The reflected spectra were then guided to the spectrophotometer by the optical fiber and analyzed. A calibration models was built, and the soil was mapped at all three depths. The highest accuracy of the combined data for the three depths had correlation coefficient (R^2) values of 0.88, 0.83, 0.88, 0.85 and RMSE values of 1.38, 0.26, 0.15, 0.01% for moisture content, organic matter, total carbon and total nitrogen, respectively. The results from this study suggest that combining the data from all three depths provides better prediction accuracy. This RTSS configuration is connected to a commercial tractor and has not yet been tested while attached to an autonomous robot.

A few notable studies on RTSS using commercial, non-autonomous tractors are listed in Table 3. Because these systems are automated, they can potentially interface with robots.

Seeding and transplanting robots

Seeding is the process of planting seeds in the soil so that they are successfully able to germinate. Transplanting involves placing a small plant seedling that has germinated in a particular position in the field based on the specific space requirements of each crop in the field.

Food grains, such as rice and wheat, represent a major types of food that is consumed by people around the world. Haibo *et al.* (2010) developed a precise wheat seeder robot that uses an air suction precision seeding mechanism to accurately drop seeds using an RTK -GNSS module. The precision of the seeding mechanism was ensured by considering the geometric characteristics of wheat seeds. The study analyzed the influence of design and suction speed for precise seeding and identified the process and structures necessary to optimize this precision. Based on the analysis results, the optimum diameter of the suction hole in the metering plate was in the range of approximately 2.0 to 2.8 mm, and the optimum vacuum in air chamber was between approximately 1.8 to 2.8 kPa to ensures the precise placement of the seeds in the soil.

Nagasaka *et al.* (2011) automated the rice transplanter Kubota SPU650 by fixing a GNSS antenna approximately 2 m from the ground surface and by controlling the steering using a servomotor that was connected to the steering axle. Path planning was

Table 3. Related works on automated real-time soil sensing studies

Reference	Sensing equipment	Detection parameters[1]	Results[2]
On-line real time soil sensor (Shibusawa, 2003)	Spectrophotometer	Prediction model for MC, SOM, NO_3-N, pH, EC and soil maps	Evaluated at 860 locations MC (R^2 = 0.95) SOM (R^2 = 0.93 NO_3-N (R^2 = 0.94) pH (R^2 = 0.99) EC (R^2 = 0.93)
Direct measurement of soil chemical properties on the go using ion-selective electrodes (Adamchuk *et al*., 2005)	Ion-selective electrodes	Soil pH, available potassium, NO_3-N, and sodium	RMSE varied from 0.11 to 0.26 pX in the order pH< pK< pNO_3 <pNa (precision) & 0.20 to 0.37 pX (accuracy)
Development of soil pH and lime requirement maps using on the go soil sensors (Lund *et al*., 2005)	Ion-selective pH electrodes, electrical conductivity sensor, near infra-red spectrometer	pH, and lime requirements of the soil	Overall RMSE=0.38 pH. RMSE ranged from 0.28 to 0.55 pH for different fields in USA. The predicted R^2 value was 0.52 kg/ha on the pH map, and R^2 value was 0.83 kg/ha on the pH, EC & NIRS combined map
An automated system for rapid in-field soil nutrient testing (Lobsey *et al*., 2010)	Ion-selective electrodes	Proximal sensing of soil nitrate, potassium and sodium	The predicted R^2 values for nitrate, sodium and potassium were 0.92, 0.99, and 0.99, respectively.
Soil pH mapping with an on the go sensor (Schirrmann *et al*., 2011)	Ion-selective antimony electrodes	Soil pH	The soil pH values from the pH sensor were well correlated with the lab pH ($CaCl_2$) values. After calibration, the mean absolute error varied from 0.28 to 0.48 pH units.
Integrated sensing of soil moisture at the field scale: measuring, modeling and sharing for improve agricultural decision support (Phillips *et al*., 2014)	Hydraprobe II – coaxial impedance dielectric reflectometry	Soil moisture	Using the Penman-Monteith method, the water stress conditions were estimated. Data of the potential evaporation, evapotranspiration & precipitation presented the inputs and outputs throughout the plant growth stages until harvest.

[1]MC, moisture content; SOM, soil organic matter; EC, electrical conductivity. [2]pX: negative base 10 logarithm of specific ion activity. NIRS: near infrared spectroscopy

Table 4. Various works on agricultural robots for seeding and transplanting operation

Reference	Description
Development of a seed-planting robot for the creation of large scale growing flower images (Riesen & Rohrer, 2011)	67% of seed ejected was within a1-cm radius, and 85% fell within 1.5 cm.
Automated three-wheel rice seeding robot operating in dry paddy fields (Ruangurai *et al*., 2015)	GNSS-based positioning was used along with extended Kalman filter-based localization; the average seeding accuracy was 91%.
Command-based self- guided digging and seed sowing rover (Priyadarshini & Sheela, 2015)	Commands were given manually by a mobile phone for navigation and sowing seeds.
Initial field-testing of Thorvald, a versatile robotic platform for agricultural application (Grimstad *et al*., 2015)	Used RTK-GNSS for navigation. Seeding experiments were conducted using different seeding patterns and were analyzed for weed suppression.

Figure 4. Rice transplanter lseki PZ60

performed manually by considering the four corners of a square field, and the path was corrected by measuring the deviation from the desired path. The same authors used another rice transplanter (Iseki PZ60), as shown in Fig. 4, with similar automation and path planning procedures (Nagasaka *et al.*, 2011).

Oksanen (2013) modified a tractor named the APU–Module, as shown in Fig. 5, and successfully conducted trials for the autonomous sowing of spring wheat. This vehicle had the capacity to store seeds for sowing 0.85 ha without any refills. Navigation was performed by using a GNSS-based guidance system. This study indicated many practical problems, such as drops in the GNSS signal because of natural obstacles, errors in satellite communication, and frequent manual intervention. Manual intervention was required to check the seed and the drill settings as the tractor was not able to perform automatic detection and adjustments preventing the complete autonomy of the robot. Recovering the GNSS signal quality required a period of 1 h 27 min and 11-20 interruptions occurred per hectare. The longest continuous operation without intervention was approximately 20 min and the shortest was 2.8 s. The spatial accuracy deviated by approximately 12.5 mm from the mean with respect to the selected path. The mean lateral error was -0.15 cm, and the mean angular error was 0.06°.

Griepentrog *et al.* (2013) retrofitted a Hakotrac 3000 with GNSS for navigation and an electro-hydraulic valve for steering to create an autonomous mechanization system (AMS). Crops were established by interfacing with the data logging system that stored maps for seeding with a grid seeder and punch plater. GNSS was used for the precise placement of seeds in the field. The experimental results showed a mean standard deviation of 2.53 mm; and based on a normal distribution 95% of the data were within 5.1 mm.

Table 4 provides insight regarding some of the other notable studies conducted in the area of seeding and transplanting using agricultural mobile robots.

Crop scouting and pest, weed and disease control robots

In general, crop scouting is the process of assessing an agricultural field through monitoring of factors such as pests, weed growth and diseases, which can restrict the crop growth.

Crop status monitoring robots

Crops exhibit various characteristic features because of genetic factors, aging, responses to environment, pests, and soil fertility. Each characteristic provides information regarding complex traits such as morphology, physiology, growth, ecology, and yield. These complex traits can be assessed by measuring basic quantitative parameters such as leaf length, the leaf area index (LAI), canopy volume, and shoot biomass; and this process is known as plant phenotyping (Li *et al.*, 2014). These parameters can be estimated by using various sensors, including light detection and ranging (LIDAR) or image-capturing devices such as near-infrared (NIR), visible, hyperspectral and multispectral cameras (Fahlgren *et al.*, 2015).

More detailed monitoring of the plant growth status and other characteristics can be achieved using multi-sensor data fusion technology. This technology was tested by developing a non-autonomous phenotyping multi-sensor platform attached to a tractor as a trailer (Busemeyer *et al.*, 2013). The platform was equipped with 3D time-of-flight (3D-TOF) cameras, a color camera, a laser distance sensor, a hyperspectral imaging system and a light curtain imaging system. The repeatability of these sensors for measuring height and coverage density were analyzed and were very high except for the 3D-TOF and laser distance sensor. The accuracy of the light curtain imaging system for determining the height was denoted by an R^2 value of 0.97 and a mean relative error (MRE) of

Figure 5. Wheat-sowing APU-Module

0.024 with a repeatability that had an R^2=0.99 and an MRE=0.11. This platform was also used in a plant breeding trial of 25 different genotypes of triticale. Several characteristics of these plants were deduced by processing the multi-sensor data. The author concluded that this device could be further integrated with an autonomous robot in future studies.

Bonirob, which was introduced in the "Soil analysis robot" section, was studied using this phenotyping system (Ruckelshausen *et al.*, 2009). This robot used sophisticated sensors, such as a 3D-TOF camera, light curtains and hyper spectral imaging devices, to obtain information that can be extracted from the sensory data; and the generalized health status of the plants was then computed using an algorithm. To obtain repeated phenotypic information of each plant in the field, positional accuracy is an important parameter. Weiss & Biber (2011) used Bonirob with 3D LIDAR to detect the plants and to create a 3D point cloud map of an experimental field with model paper plants, plastic plants and maize plants. The detection rate of the plants was 60-70% in outdoor environments with an average positional accuracy of 0.03 m.

Chapman *et al.* (2014) developed a pheno-copter, which is an autonomous robotic helicopter used for plant phenotyping. This device was equipped with two digital cameras and one far infrared camera to analyze images in multiple spectra. One of the experiments estimated the ground cover of hybrid sorghum using the pheno-copter at an elevation of 60 m to determine the correlation between the number of plants per plot and the green cover for 100 plots. The canopy temperature and relative transpiration index in sugarcane under different irrigation conditions were also estimated using the data obtained from visible and thermal cameras. The potential transpiration index for 40 sugarcane clones based on green cover and relative crop temperature were determined by approximation. To quantify the crop lodging of wheat, images from an NIR filtered camera with information on longitude, latitude, elevation and flight log were used to generate a point cloud elevation model, from which the canopy height was estimated.

Córcoles *et al.* (2013) used a quadrotor UAV to estimate LAI in onion crops using a digital photography camera. They also developed LAI calculation (LAIC) software using the artificial neural network. First, the software tool converts red, green, and blue (RGB) into L*a*b image format and use the K-means algorithm for cluster analysis. The selected clusters are provided as inputs to the artificial neural network, which calculates the area covered by leaves. Statistical analysis was conducted using the minimum value, maximum value, standard deviation, mean and coefficient of variation to establish a relationship between LAI and canopy cover. The maximum value of LAI was 56% in the onion crops. The study found that the polynomial model showed better results than the exponential model and that the coefficient of determination was approximately 84%.

Crop pest and disease monitoring and control robots

Incidences of disease from pests and microorganisms affect the output of agricultural products wordwide. The majority of these diseases induce visible symptoms in plants; however, farmers can identify a disease in a large field only when a significant number of plants are infected.

Polder *et al.* (2014) developed a fully enclosed, manually propelled platform that is equipped with a diffused fluorescent lamp and a multi-spectral camera (RGB & NIR). The platform is manually moved over each tulip plant as an image of the plant is obtained. Images in the NIR spectrum help segment the image to differentiate the plant from the soil. Diseased plants among healthy plants are identified using Fisher's linear discriminant classification algorithms. The result is then compared with the enzyme-linked immunosorbent assay (ELISA) score and expert survey results. The results of this study showed that crop experts identified 80% of the diseased plant and misclassified healthy plants as diseased plants 10% of the time. However, the machine vision system correctly identified over 90% of the diseased plant and misclassified 10% of the healthy plants as diseased plants. The author also offered ideas for improving this platform for a robotic system.

Other research has discussed using robots to monitor and identify diseases in the field at an early stage. Pilli *et al.* (2014) developed eAGROBOT to detect diseases in cotton and ground nut plants at an early stage using image processing techniques. A grid data acquisition was used, and sample images were provided as input to a K-means clustering algorithm with varying numbers of nodes for different disease types. A neural network using a single hidden layer with a back propagation technique was used to classify the diseases with highly variable

Table 5. Percentage losses from weed competition in India

Crop	Critical period of crop weed competition	Loss (%)
Rice (transplanted)	4-6 weeks after planting	15-35
Wheat	30-45 days	6-35
Sorghum	40 days	6-40
Groundnut	30-45 days	30-50
Cotton	15-60 days	47.5
Sugarcane	90 days	15-72
Jute	35-42 days	56-87

neurons quantity based on the disease type. The results showed that the Pearson's *r* and *p* values had a poor correlation, while the "contrast of hue" and "correlation of saturation" features showed negative correlation with disease type. The above features along with other textural features (*e.g.*, energy and homogeneity of hue) were used to classify the disease with an accuracy range of 83-96%. Rieder *et al.* (2014) described the preliminary stage of development of a virtual reality-based system for identifying diseases in strawberry plants using a drone. This system includes a 3D user interface to control and monitor the drone, which will assist in studying the phenology of strawberry plants and disease incidence.

Pest infestation and other microbial-based diseases can be controlled by the appropriate application of pesticides. However, misuse of these chemicals can cause pesticide-resistant diseases, and excess application pollutes the environment. Furthermore, the long-term exposure of farmers to these chemicals has harmful effects on the health of farmers. These problems suggest a need for precise applications that are assessed by studying variable rate technology and the site-specific application of pesticides (Bongiovanni & Lowenberg-Deboer, 2004); this precise application can only be achieved by automating the process. Further automation of pesticide application can be achieved by electronic monitors, which measure the application rate and provide a command signal, and rate controllers, which control the rate of application (Zhang & Pierce, 2013).

A study on the precise application of pesticides using an UAV was performed by Faiçal *et al.* (2014). They mainly focused on developing a system architecture using an UAV through simulations. They adjusted the UAV route plan depending on the relative concentration of pesticides in a given area measured using wireless sensor networks for precise application of pesticides. Simulated wireless sensor nodes were positioned at various locations in an experimental field, and the concentration was measured with a color scale varying from green (most concentrated) to red (no pesticide) using the heat map of the field. The behavior of the system was best at a constant light wind of 10 km/h and random gusts of light wind at 10 km/h with no significant difference in measurement at heights of 5 m, 10 m and 20 m. Furthermore, the results show that the chemical dispersion was approximately 14% better for messages sent (from the wireless sensor network to the UAV) every 10 s compared to every 30 s. Sheng (2014) developed a robotic system controlled via wireless network using a mobile phone. The robot was equipped with infrared sensors for obstacle avoidance, a video camera module to obtain visible information, and a sprayer module with a spray head that was adjusted according to the height. The robot was tested on different floors, such as concrete, mud, gravel and grass. The system was able to spray up to a maximum distance of 130 cm with a spray angle of 30–50° and a spray area of 0.88 m^2.

Weed detection and control robots

A weed is an unwanted plant that affects the production and quality of produce on a farm. Weeds compete with crops for resources, which is known as weed competition. According to a survey by Parker & Fryer (1975), production loss from weed competition is estimated to be 11.5% globally, although the loss in individual countries varies because of differing environmental conditions. Table 5 shows the loss of produce due to weeds in India according to the Rice Knowledge Management Portal (http://14.139.94.101/wisy/prsentation/yield_losses.aspx).

Weeds can be classified according to their location in the field; inter-row or intra-row weeds. Inter-row weeds develop between rows of crops, while intra-row weeds develop among crops in the same row.

One of the important challenges of using robots for weed control is identifying weeds from crops. Bonirob was equipped with a multispectral monocular camera, known as JAI AD-130 GE, which captured images with 1.3 million pixels and an image size of 1296 × 966 pixels. This robot was tested on a commercially viable carrot field and had an accuracy of approximately 93.8% when differentiating carrot plants from weeds (Haug *et al.*, 2014). Jensen *et al.* (2012) developed a crop scouting robot known as Armadillo. The robot prototype was developed and tested in a maize field for weed detection, and the researchers. are currently developing a mechanical weeder for the weed removal.

Physically removing weeds is a labor-intensive job that requires constant monitoring during the early stage of crop development. Weeds can also be removed by applying chemical herbicides or by using other techniques, such as mechanical force or heat.

Blasco *et al.* (2002) developed a mobile platform with a manipulator that was equipped with an electrode and a secondary vision system. The primary vision system, which is a color camera with a resolution of 768 × 576 pixels, was attached to the front frame of the robot. The images from the secondary vision system were compared with those of the primary vision to locate weeds and to send spatial coordinates to the electrode for weed removal. The electrical discharge from the electrode destroyed the weed tissues, and the system was able to eliminate 100% of the detected weeds. The system was able to locate 84% of the weeds and 99% of the lettuce plants using its vision system.

Table 6. Other related works in weed detection and removal

Reference	Description
Robotic weed control system for tomatoes (Lee *et al*., 1999)	Developed real-time robotic weed control using machine vision; the results showed that 24.2% of tomato plants were incorrectly identified and that 52.4% of weeds were not sprayed.
Machine vision for a micro weeding robot in a paddy field (Chen *et al*., 2003)	Developed an image processing-based algorithm to determine the travel direction by using a Hough transform for the weeding robot.
Autonomous robotic weed control systems: A review (Slaughter *et al*., 2008)	Described various methods for weed detection and mechanisms for weed removal.
The development and assessment of the accuracy of an autonomous GPS-based system for intra-row mechanical weed control in row crops (Norremark *et al*., 2008)	Developed and improved the accuracy of autonomous hoeing systems for intra-row weed removal using RTK-GPS navigation
Direct application end effector for a precise weed control robot (Jeon & Tian, 2009)	Developed a direct herbicide application end effector interfaced with a mobile robot and 90% of weeds showed symptoms of necrosis.
Design of paddy weeding robot (Yoon & Kim, 2013)	Developed a rotating side sweeper made of an elastic body to remove weeds in paddy fields.
Automatic weed detection system and smart herbicide sprayer robot for corn fields (Kargar & Shirzadifar, 2013)	Developed an algorithm development for weed detection and classification; the algorithm accuracy was 95.89% accurate.
Development of a mechatronic intra-row weeding system with rotational hoeing tools: theoretical approach and simulation (Gobor *et al*., 2013)	Design and analysis of a mobile platform with rotating varying arms that were equipped with blades as an end effector to remove intra-row weeds.
Weed removal in cultivated field by autonomous robot using LABVIEW (Patnaik & Narayanamoorthi, 2015)	Images captured using a static camera were processed for weed identification, and the coordinates of weed were given to a robot for removal.

Chocron *et al.* (2007) developed a flatness-based control for a weed killer robot to remove weeds in a cornfield. This robot had two ultrasonic sensors along two sides at its front. These sensors measured the distance from the robot to the crop along the sides and helped the robot to navigate between rows of crops. The weeds between the crop rows were removed using a hoeing operation with a 40 cm wide hoe carefully driven by the robot. Mechanically removing weeds by hoeing reduces the need for chemical weed killers. The important limitation of this robot is that it cannot remove weeds close to corn crop.

Sogaard & Lund (2007) tested a mobile robot that uses vision sensors for micro-dosing of herbicides to avoid the excessive use of these chemicals. The micro-dosing system consists of 20 uniformly placed tubes that form a micro-boom; the flow of the chemicals is controlled by a solenoid valve. The robot was tested in laboratory conditions with circles of black polyvinyl chloride sheets with a radius of 5.9 mm and densities ranging from 50 to100 circles/m^2 to evaluate the spraying precision. The centroid of the spray on the sheets was 10 mm from the target, and the standard deviations along the longitudinal and transverse directions were 2.5 and 1.8 mm, respectively. The study revealed that the savings of the herbicide glyphosate on *Solanum nigrum* were 536 g/ha; only 4 g/ha were required when using the robot.

Pérez-Ruiz *et al.* (2015) modified a commercial tractor into an autonomous tractor, as shown in Fig. 6. This machine was equipped with several systems, such as an intelligent spraying system and a mechanical and thermal weed control system; the system was designed especially for rows with a width of 0.25 m. A high-level decision-making system controlled a sprayer boom that interfaced with the modified autonomous tractor for variable application of herbicides based on a prescription map and the vehicle location. Experiment were conducted in a winter wheat crop a 0.25-ha field,

Figure 6. Modified New Holland Boomer T3050

as shown in Fig. 7. Application of this robotic system in the field with a weed infestation of 3.24% saved approximately 96.65% of the liquid applied per hectare. As the percentage of the weed infestation increased, the savings in the liquid applied decreased.

The same team used a thermal weed control system of a modified tractor and used an LPG flame as the heat source. The system reduced weeds by 95-99% in maize farming. The study also showed that the production output of a crop was not reduced by the thermal weed control system. Although using of flames to kill weeds is highly effective, it can potentially kill crops and also raises serious safety issues regarding the robot itself.

Nakai & Yamada (2014) developed a robot equipped with a laser range finder and a stereo camera; the robot suppresses weeds by applying mechanical force with a crawler and brush that are the end effector of a robotic arm attached to a tank-type mobile robot. Because the soil surface of a rice field is soft, wet and muddy, the robotic wheels had a continuous or caterpillar track that was 56 mm wide to provide stability and traction for the robot. The robot also had automatic posture control using the laser range finder and a robotic arm using a tilt sensor. Only inter-row weeds can be suppressed by this robot. Table 6 shows additional research on weed detection and removal.

Harvesting robots

Harvesting generally refers to the collection of matured crops from an agricultural field. However, this process varies for different crops. For example, harvesting horticultural crops, such as vegetable or fruit crops, refers to collecting of fruits or vegetables from plants, but this process is different for rice or wheat crops. Harvesting requires considerably greater labor hours; in horticulture, fruits and flowers must be plucked repeatedly from plants as they mature. A robotic harvester must detect the properties of the produce, such as its position, size, surface type, and shape. Additionally, the robot requires mobility to move to a reasonable position and a picking or harvesting mechanism for the harvesting process.

Several semi-automated machines have been built for harvesting, such as harvesters and combine harvesters, to address these problems. Many commercially available harvesters have the ability to interface with tractors using a power take-off (PTO) shaft that uses the power output from the engine. Combine harvesters, which are vehicles that are dedicated to harvesting operation and are operated by humans, have been used to harvest various crops, such as wheat, oats, barley, corn, soya beans, and sunflowers.

An automated combined harvester (Iseki HFG443) was modified by Nagasaka *et al*. (2011) for crops such as rice. Its navigation methodology was similar to the working of an automated tractor and rice transplanter, as explained in the "Seeding and transplanting robot" section. Zhang *et al*. (2013) retrofitted an AG1100 combine harvester with Topcon AGI3 GNSS and IMU receiver for autonomous navigation guided by World Geodetic Sysetm-84 (WGS-84) coordinates for harvesting rice and wheat. The harvester was tested in a 150-m-long experimental path with initial lateral and heading errors of 20 cm and 1.8°, respectively. When the harvester travelled in stable conditions, the lateral error varied within ± 8.3 cm, and the heading error varied within ± 2.5°. Detecting and picking fruits, vegetables or flowers from plants is necessary for other types of crops, such as horticultural crops. Robotic harvesters that pick fruits or vegetables mostly consist of contact-type grippers that are actuated using pneumatic, hydraulic or electric means. Other methodologies, such as cutting the stem with a laser beam, were proposed by Liu *et al.* (2008) to minimize the size and complexity of the end effectors. A focusing lens can focus a high-power, 30-W laser beam from a fiber-coupled laser diode to cut the stem of a single fruit or cluster.

Figure 7. Herbicide application using intelligent boom spray in a wheat field

Chatzimichali *et al.* (2009) designed a robotic harvesting machine for white asparagus. The system consisted of a mobile platform equipped with an asparagus identification system using image processing and a cutting mechanism for harvesting. Antonelli *et al*. (2011) added a developed harvesting module to the robot Zaffy. This harvesting module was equipped with a gripper, a vision system that assisted in positioning, and a pneumatic system for harvesting saffron flowers from plants. This harvesting system successfully made cuts 60% of the time.

Scope and challenges

Many studies in different categories of task-based agricultural robots were presented in the previous sections. By assessing the above research (the "Tilling robots" section through the "Harvesting robot" section), the overall research scope and various challenges that need to be addressed for efficient agricultural production are discussed in this section.

A study by Chamen *et al.* (1994) showed that the soil compaction by tractor operations in a field uses 80-90% of energy in conventional agriculture. This soil compaction requires tilling operations to loosen the soil. If small autonomous machines replace conventional tractors, damage to the soil can be minimized. In this case, the robot can directly drill and place the seeds or plant seedlings without needing to till the soil. A recent study conducted on no-till farming by the US Department of Agriculture (Horowitz *et al.*, 2010) showed that soil that is not tilled retains organic matter and prevents soil erosion. A study by Blackmore (2009) suggests achieving zero draft force and zero compaction on soil minimizes the energy usage for soil operations. Kladivko (2001) also showed that the number of organisms living in the soil significantly increase, which naturally improves soil fertility and minimizes the use of fertilizers. These studies prove that if the entire agricultural process is performed by a small (smart) robot, the frequency of tilling operations decreases. Tilling operations can also be optimized by performing micro-tilling operations since the soil immediately surrounding the seeds influences the seed growth. These micro-tilling implements can be interfaced with a mobile robot. Considerable research has been conducted on RTSS technologies with commercially available non-autonomous tractors (Phillips *et al.*, 2014; Baharom *et al.*, 2015). The challenge is to interface this technology with an agricultural mobile robot to further improve the autonomy of the operations and remove the need for human intervention. Moreover, open farm agriculture is highly dynamic, and unstructured with wide uncertainty, which demands complex systems with complex techniques to perform specific farm operations. A study by Blackmore *et al.* (2007) defined many technical qualities that are required for an autonomous robot. Some of these key qualities include machine size, weight, computational and energetic autonomy, intelligence, external behavior, communication and vehicle system architecture, self-awareness, management, cooperative behavior and mechanization tasks.

Seed placement and transplanting demands high accuracy since other agricultural operations performed by robots depend on this accuracy. Many real-time conditions affect the autonomy of these operations requiring human intervention. Haibo *et al.* (2010) demonstrated the need for frequent human intervention in autonomous tractor operations whenever GNSS fails and whenever coulters, which are required for drilling the soil surface to place seeds, become blocked in moist soil. These frequent interventions make these systems unreliable, and further improvement is needed to achieve complete autonomy. The navigation system should be capable of recognizing the failure of primary navigation sensors and should return to a safe resting position without causing damage to itself or to any other external entity.

In tasks such as crop scouting, the field is sometimes monitored for various purposes using aerial robots. Although aerial robots work for larger fields, they do not provide accurate information about each plant in the field (Chapman *et al.*, 2014). Because farming practices are becoming more precise, information needs to be collected and tasks need to be performed for each plant in the field. The technology of caring for each plant is known as phytotechnology; this technology demands a large database for storing the information of each plant.

More research on real-time robotic disease identification systems is needed for the early treatment of disease and to avoid economic losses. Many image processing techniques have been developed to identify diseases using the visible symptoms exhibited by the plants (Sankaran *et al.*, 2010). However, there is still lack of extensive research on real-time identification of diseases using a robotic platform (Zecha *et al.*, 2013).

Data regarding current weather events such as wind speed can be measured before performing tasks such as harvesting or applying pesticides. If the weather conditions are not favorable, the task can be performed later when the weather improves. More weather-independent robots should be developed that can perform tasks in almost all weather conditions excluding severe weather such as a hailstorm or rain (Blackmore *et al.*, 2007). A significant relationship exists between disease-causing pathogens and weather parameters such as rainfall, humidity, and cloudiness. An affordable disease forecasting model can be developed to predict disease occurrence, and these data can guide robots to prevent unwanted applications of pesticides in the field (Pavan *et al.*, 2011; Kumar, 2014).

Harvesting is a difficult process that differs for each crop. A grain crops is harvested by stripping of the entire plant from the soil and extracting the grain. For horticultural crops, fruits or vegetables need to be harvested using a suitable manipulator and end effector. For example, in harvesting vegetables, the locations of the vegetables in three-dimensional space need to be determined by sensors, and a suitable path for both the mobile robot and the manipulator to reach the produce has to be selected without damaging the plant (Comba *et al.*, 2010). Moreover, selective harvesting of the crops is required based on, for example, the ripening stage of the fruits or the size of the fruits, enabling the robot to pick only the quality fruits (Blackmore *et al.*, 2007).

In the future, several small robots will be needed to perform various tasks in the fields. Each robot in a fleet must constantly communicate with the others to work in harmony; the entire operation may be monitored by humans at a base station. Human interactions with robots should be minimized and should occur at a high level. A framework for integrating multiple robots for autonomous crop protection was proposed by Emmi *et al.* (2014). A master-slave configuration can be used to avoid obstacles and follow a path. A standardized architecture must be created for a fleet of agricultural robots capable of performing different operations.

Conclusions

An overview of recent contributions in the field of agricultural robots in open arable farming was provided in this review paper. Robots categorized based on their operation exhibit a common pattern of functions for executing a task, *e.g.*, navigation, detection, action and occasionally mapping. The navigation function forms the primary requirement of a mobile robot to navigate through the field. Some of the robots described here need constant human intervention due to unreliable guidance systems and communication delays, and many lack-advanced intelligence, and adaptive systems for harsh environmental parameters. Detection requires the measurement of specific parameters using a suitable sensing methodology. Then, actions are taken using an automated farm implement attached to the mobile robot based on the parameter measurements. Uneven soil surfaces, unaffordable weather conditions, and the complex and delicate structure of the crops in arable farming contribute to erratic measurement errors and difficulty in developing a control mechanism to minimize the consequences of errors while performing a task. Improvements in the current technology with the fusion of multiple sensors and intelligent algorithms with an optimized control will yield better performance. New approaches in developing compact automated farm equipment using advanced scientific principles will reduce the size of the robots. Although mapping has been performed by few robots so far, it will become mandatory in the near future for the complete autonomy of agricultural robots. Complete autonomy in arable farming will change farming methods by eliminating a task or by adding a new task. Complete autonomy can be achieved by using multiple robot coordination among several ground-based mobile robots or a combination of ground and aerial mobile robots. The past several decades have proven to be a golden era in agricultural robotics research due to the continuously decreasing price of robotics components such as LIDAR sensors, and controllers, and ground-breaking technology in agricultural research, such as plant phenotyping and phytotechnology. Thanks to large capital investments from leading agricultural companies, universities and governments, rapid changes are expected to occur in the coming years, and successful, intelligent robotic technology is expected to be available in the commercial market.

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References

Adamchuk VI, Lund ED, Sethuramasamyraja B, Morgan MT, Dobermann A, Marx DB, 2005. Direct measurement of soil chemical properties on-the-go using ion-selective electrodes. Comput Electron Agric 48: 272-294. https://doi.org/10.1016/j.compag.2005.05.001

Antonelli MG, Auriti L, Zonel PB, Raparelli T, 2011. Development of a new harvesting module for saffron flower detachment. Romanian Rev Precis Mech Opt Mechatron 39: 163-168.

Arikapudi R, Durand-Petiteville A, Vougioukas S, 2014. Model-based assessment of robotic fruit harvesting cycle times. ASABE Ann Int Meeting Paper No. 1913999.

Baharom SNA, Shibusawa S, Kodaira M, Kanda R, 2015. Multiple-depth mapping of soil properties using a visible and near infrared real-time soil. Eng Agr Environ Food 8: 13-17. https://doi.org/10.1016/j.eaef.2015.01.002

Baier S, Clements M, Griffiths C, Ihrig J, 2009. Biofuels impact on crop and food prices. Int Financ Discuss Papers. Board of Governors of the Federal System. http://www.federalreserve.gov/pubs/ifdp/2009/967/ifdp967.pdf.

Bakker T, van Asselt K, Bontsema J, Müller J, van Straten G, 2011. Autonomous navigation using a robot platform in a sugar beet field. Biosyst Eng 109: 357-368. https://doi.org/10.1016/j.biosystemseng.2011.05.001

Blackmore BS, 2009. New concepts in agricultural automation. HGCA Conference; October 2009.

Blackmore BS, Fountas S, Tang S, Have H, 2004a. Systems requirements for a small autonomous tractor. CIGR J Sci Res Dev Manuscript PM 04: 001.

Blackmore BS, Girepentrog HW, Nielsen H, Norremark M, Resting-Jeppersen J, 2004b. Development of a deterministic autonomous tractor. CIGR Olympics of Agr Eng Int Conf: October 2004.

Blackmore BS, Greipentrog HW, Fountas S, Gemtos TA, 2007. A specification for an autonomous crop production mechanization system. CIGR E- J 2007; Manuscript PM 06032: 9.

Blasco J, Aleixos N, Roger JM, Rabatel G, Moltó E, 2002. Robotics weed control using machine vision. Biosyst Eng 83: 149-157. https://doi.org/10.1006/bioe.2002.0109

Bongiovanni R, Lowenberg-Deboer J, 2004. Precision agriculture and sustainability. Precis Agric 5: 359-387. https://doi.org/10.1023/B:PRAG.0000040806.39604.aa

Busemeyer L, Mentrup D, Möller K, Wunder E, Alheit K, Hahn V, Maurer HP, Reif JC, Würschum T, Müller J, et al., 2013. BreedVision - A multi-sensor platform for non-destructive field-based phenotyping in plant breeding. Sensors 13: 2830-2847. https://doi.org/10.3390/s130302830

Chamen WCT, Dowler D, Leede PR, Longstaff DJ, 1994. Design, operation and performance of a gantry system: experience in arable cropping. J Agric Eng Res 59: 45-60. https://doi.org/10.1006/jaer.1994.1063

Chapman S, Merz T, Chan A, Jackway P, Hrabar S, Dreccer M, Holland E, Zheng B, Ling T, Jimenez-Berni J, 2014. Pheno-copter: A low-altitude, autonomous remote-sensing robotic helicopter for high-throughput field-based phenotyping. Agronomy 4: 279-301. https://doi.org/10.3390/agronomy4020279

Chatzimichali AP, Gerogilas IP, Tourassis VD, 2009. Design of an advanced prototype robot for white asparagus harvesting. IEEE/ASME Int Conf on Advanced Intelligent Mechatronics; July. pp: 887-892.

Chen B, Tojo S, Watanabe K, 2003. Machine vision for a micro weeding robot in a paddy field. Biosyst Eng 85: 393-404. https://doi.org/10.1016/S1537-5110(03)00078-3

Chocron O, Delaleau E, Pleureau JL, 2007. Flatness based control of a mechatronic weed killer autonomous robot. IEEE Int Symp on Indust Electron; June. pp: 2214-2219.

Comba L, Gay P, Piccarolo P, Aimonino RD, 2010. Robotics and automation for crop management: trends and perspective. Int Conf on Work Safety and Risk Prevention in Agro-Food and Forest Systems: September. pp: 471-478.

Córcoles JI, Ortega JF, Hernández D, Moreno MA, 2013. Estimation of leaf area index in onion (Allium cepa L.) using an unmanned aerial vehicle. Biosyst Eng 115: 31-42. https://doi.org/10.1016/j.biosystemseng.2013.02.002

Emmi L, Gonzalez-de-Soto M, Pajares G, Gonzalez-de-Santos P, 2014. New trends in robotics for agriculture: integration and assessment of a real fleet of robots. Sci World J 2014 Article ID: 404059. https://doi.org/10.1155/2014/404059

Fahlgren N, Gehan MA, Baxter I, 2015. Lights, camera, action: high- throughput plant phenotyping is ready for a close-up. Curr Opin Plant Biol 24: 93-99. https://doi.org/10.1016/j.pbi.2015.02.006

Faiçal BS, Costa FG, Pessin G, Ueyama J, Freitas H, Colombo A, Fini PH, Villas L, Osório FS, Vargas PA, et al., 2014. The use of unmanned aerial vehicles and wireless sensor networks for spraying pesticides. J Syst Archit 60: 393-404. https://doi.org/10.1016/j.sysarc.2014.01.004

Gobor Z, Schulze Lammers P, Martinov M, 2013. Development of a mechatronic intra-row weeding system with rotational hoeing tools: Theoretical approach and simulation. Comput Electron Agric 98: 166-174. https://doi.org/10.1016/j.compag.2013.08.008

Griepentrog HW, Dühring Jaeger CL, Paraforos DS, 2013. Robots for field operations with comprehensive multilayer control. Künstl Intell 27: 325-333. https://doi.org/10.1007/s13218-013-0266-z

Grift T, 2007. Robotics in crop production. Encycl Agric Food Biol Eng. DOI: 10.1081/E-EAFE-120043046.

Grimstad L, Phan HNT, Pham CD, Bjugstad N, From PJ, 2015. Initial field-testing of Thorvald, a versatile robotic platform for agricultural applications. Proc of the IROS Workshop on Agri-Food Robotics. October.

Haibo L, Qing L, Yufeng X, Chuijje Y, 2010. Research and development on the key technology of wheat single seed robot. IEEE World Automation Congress; September. pp: 339-343.

Harries GO, Ambler B, 1981. Automatic ploughing: A tractor guidance system using opto-electronic remote sensing techniques and a microprocessor based controller. J Agric Eng Res 26: 33-53. https://doi.org/10.1016/0021-8634(81)90125-6

Haug S, Michaels A, Biber P, Ostermann J, 2014. Plant classification system for crop/weed discrimination without segementation. IEEE Winter Conf on Application of Computer Vision, March. pp: 1142-1149.

Horowitz J, Ebel R, Ueda K, 2010. No-till. Farming is a growing practice. USDA Econ Inform Bull 70. November.

Jensen K, Nielsen SH, Jorgensen RN, Bogild A, Jacobsen NJ, Jorgensen OJ, Hansen CLJ, 2012. A low cost, modular robotics tool carrier for precision agriculture research. Proc Int Conf on Precision Agriculture; July.

Jeon HY, Tian LF, 2009. Direct application end effector for a precise weed control robot. Biosyst Eng 104: 458-464. https://doi.org/10.1016/j.biosystemseng.2009.09.005

Kargar AHB, Shrizadifar AM, 2013. Automatic weed detection system and smart herbicide sprayer robot for corn fields. RSI/ISM Int Conf on Robotics and Mechatronics; February. pp: 13-15.

Kladivko EJ, 2001. Tillage systems and soil ecology. Soil Till Res 61: 61-76. https://doi.org/10.1016/S0167-1987(01)00179-9

Kumar S, 2014. Plant disease management in India: advances and challenges. Afr J Agric Res 9: 1207-1217. https://doi.org/10.5897/AJAR2014.7311

Lee WS, Slaughter DC, Giles DK, 1999. Robotics weed control system for tomatoes. Precis Agric 1: 95-113. https://doi.org/10.1023/A:1009977903204

Li L, Zhang Q, Huang D, 2014. A review of imaging techniques for plant phenotyping. Sensors 14: 20078-20111. https://doi.org/10.3390/s141120078

Libin Z, Qinghua Y, Guanjun B, Yan W, Liyong Q, Feng G, Fang X, 2008. Overview of research on agricultural robots in China. Int J Agric Biol Eng 1: 12-21.

Liu J, Li Z, Li P, Mao H, 2008. Design of a laser stem-cutting device for harvesting robot. IEEE Int Conf on Automation and Logistics; September. pp: 2370-2374.

Lobsey C, Rossel RV, Mcbratney A, 2010. An automated system for rapid in-field soil nutrient testing. 19th World Cong of Soil Science, Soil Solutions for a Change World; August. pp: 9-12.

Lund ED, Adamchuk VI, Collings KL, Drummond PE, Christy CD, 2005. Development of soil pH and lime requirement maps using on-the-go soil sensors. 5th Eur Conf on Precis Agr; July. pp: 457-464.

Mandal S, Maity A, 2013. Precision farming for small agricultural farm: Indian scenario. Am J Exp Agric 3: 200-217. https://doi.org/10.9734/AJEA/2013/2326

Matsuo Y, Yukumoto O, Noguchi N, 2012. Enhanced adaptability of tilling robot (initial report). JARQ 46: 295-303. https://doi.org/10.6090/jarq.46.295

Micheal AM, Ojha TP, 2008. Principles of agricultural engineering, vol. I. Jain, Brothers. 638 pp.

Nagasaka Y, Tamaki K, Nishiwaki K, Saito M, Motobayashi K, Kikuchi Y, Hosokawa H, 2011. Autonomous rice field operation project in NARO. IEEE Int Conf on Mechatronics and Automation; August. pp: 870-874.

Nakai S, Yamada Y, 2014. Development of a weed suppression robot for rice cultivation: weed suppression and posture control. Int J Electr Comput Electron Commun Eng 8: 1736-1740.

Nørremark M, Griepentrog HW, Nielsen J, Søgaard HT, 2008. The development and assessment of the accuracy of an autonomous GPS-based system for intra-row mechanical weed control in row crops. Biosyst Eng 101: 396-410. https://doi.org/10.1016/j.biosystemseng.2008.09.007

Ocampo JA, 2014. Concise report on the world population situation in 2014. Dept. of Economic and Social Affairs Population Division. United Nations, NY. http://www.un.org/en/development/desa/population/publications/trends/concise-report2014.shtml.

Oksanen T, 2013. Accuracy and performance experiences of four wheel steered autonomous agricultural tractor in sowing operation. Int Conf on Field Service Robotics; December. pp: 425-438.

Parker C, Fryer JD, 1975. Weed control problems causing major reduction in world food supplies. FAO Plant Prot Bull 23: 83-95.

Patnaik A, Narayanamoorthi R, 2015. Weed removal in cultivated field by autonomous robot using LabVIEW. IEEE Int Conf on Innovations in Information Embedded and Communication Systems; March. pp: 1-5.

Pavan W, Fraisse CW, Peres NA, 2011. Development of a web-based disease forecasting system for strawberries. Comput Electron Agric 75: 169-175. https://doi.org/10.1016/j.compag.2010.10.013

Pedersen SM, Fountas S, Have H, Blackmore BS, 2006. Agricultural robots—System analysis and economic feasibility. Precis Agric 7: 295-308. https://doi.org/10.1007/s11119-006-9014-9

Pedersen SM, Fountas S, Blackmore S, 2008. Agricultural robots-Applications and economic perspectives, service robot applications. http://www.intechopen.com/books/service_robot_applications/agricultural_robots_-_applications_and_economic_perspectives.

Pérez-Ruiz M, Gonzalez-de-Santos P, Ribeiro A, Fernandez-Quintanilla C, Peruzzi A, Vieri M, Tomic S, Agüera J, 2015. Highlights and preliminary results for autonomous crop protection. Comput Electron Agric 110: 150-161. https://doi.org/10.1016/j.compag.2014.11.010

Phillips AJ, Newlands NK, Liang SHL, Ellert BH, 2014. Integrated sensing of soil mositure at the field scale: measuring, modeling and sharing for improved agricultural decision support. Comput Electron Agric 8: 13-17.

Pilli SK, Nallathambi B, George SJ, Diwanji V, 2014. eAGROBOT - A robot for early crop disease detection using image processing. IEEE Int Conf on Electronics and Communication Systems; February. pp: 1-6.

Pobkrut T, Kerdcharoen T, 2014. Soil sensing survey robots based on electronic nose. Int Conf on Control, Automation and System. pp: 1604-1609. https://doi.org/10.1109/iccas.2014.6987829

Polder G, van der Heijden GWAM, van Doorn J, Baltissen TAHMC, 2014. Automatic detection of tulip breaking virus (TBV) in tulip fields using machine vision. Biosyst Eng 117: 35-42. https://doi.org/10.1016/j.biosystemseng.2013.05.010

Priyadarshini M, Sheela L, 2015. Command based self guided digging and seed sowing rover. Int Conf on Engineering Trends and Science & Humanities; March. pp: 5-9.

Rieder R, Pavan W, Maciel JMC, Fernandes JMC, Pinho MS, 2014. A virtual reality system to monitor and control diseases in strawberry with drones: A project. Proc 7th Int Cong on Environ Model & Software; June. pp: 919-926.

Riesen S, Rohrer L, 2011. Master Thesis on Gardening robotics - Design of a seed planting robot for the creation of large scale growing flower images. Swiss Federal Institute of Technology Zurich.

Rossel RAV, McBratney AB, 1998. Soil chemical analytical accuracy and costs: implications from precision agriculture. Aust J Exp Agric 38: 765-775. https://doi.org/10.1071/EA97158

Ruangurai P, Ekpanyapong M, Pruetong C, Watewai T, 2015. Automated three-wheel rice seeding robot operating in dry paddy fields. Maejo Int J Sci Tech 9: 403-412.

Ruckelshausen A, Biber P, Dorna M, Gremmes H, Klose R, Linz A, Rahe F, Resch R, Thiel M, Trautz D, *et al.*, 2009. Bonirob — An autonomous field robot platform for individual plant phenotyping. Joint Int Agr Conf: July. pp: 841-847.

Sahay J, 2006. Elements of agricultural engineering. Standard Publ & Distrib, New Delhi. 462 pp.

Sankaran S, Mishra A, Ehsani R, Davis C, 2010. A review of advanced techniques for detecting plant diseases. Comput Electron Agric 72: 1-13. https://doi.org/10.1016/j.compag.2010.02.007

Schirrmann M, Gebbers R, Kramer E, Seidel J, 2011. Soil pH mapping with an on-the-go sensor. Sensors 11: 573-598. https://doi.org/10.3390/s110100573

Scholz C, Moeller K, Ruckelshausen A, Hinck S, Goettinger M, 2014. Automatic soil penetrometer measurements and GIS based documentation with the autonomous field robot platform bonirob. Int Conf on Precis Agr; July.

Sheng P, 2014. An intelligent robot system for spraying pesticides. Open Electr Electron Eng J 8: 435-444. https://doi.org/10.2174/1874129001408010435

Shibusawa S, 2003. On line real time sensing. IEEE Int Conf on Advanced Intelligent Mechatronics; July. pp: 1006-1066.

Slaughter DC, Giles DK, Downey D, 2008. Autonomous robotic weed control systems: a review. Comput Electron Agric 61: 63-78. https://doi.org/10.1016/j.compag.2007.05.008

Søgaard HT, Lund I, 2007. Application accuracy of a machine vision-controlled robotic micro-dosing system. Biosyst Eng 96: 315-322. https://doi.org/10.1016/j.biosystemseng.2006.11.009

Tarannum N, Rhaman MK, Khan SA, Shakil SR, 2015. A brief overview and systematic approach for using agricultural robot in developing countries. J Mod Sci Tech 3: 88-101.

Torii T, 2000. Research in autonomous agriculture vehicles in Japan. Comput Electron Agric 25: 133-153. https://doi.org/10.1016/S0168-1699(99)00060-5

Weiss U, Biber P, 2011. Plant detection and mapping for agricultural robots using a 3D LIDAR sensor. Robot Auton Syst 59: 265-273. https://doi.org/10.1016/j.robot.2011.02.011

Yaghoubi S, Akbarzadeh NA, Bazargani SS, Bazargani SS, Bamizan M, Asl MI, 2013. Autonomous robots for agricultural tasks and farm assignment and future trends in agro robots. Int J Mech Mechatron Eng 13: 1-6.

Yoon B, Kim S, 2013. Design of Paddy weeding robot. IEEE Int Symp on Robotics; October: 1-2.

Zecha CW, Link J, Claupein W, 2013. Mobile sensor platforms: categorisation and research applications in precision farming. J Sens Sens Syst 2: 51-72. https://doi.org/10.5194/jsss-2-51-2013

Zhang Q, Pierce FJ, 2013. Agricultural automation: fundamentals and practices. CRC Press, London. 411 pp.

Zhang Z, Noguchi N, Ishii K, Yang L, Zhang C, 2013. Development of a robot combine harvester for wheat and paddy harvesting. IFAC Proc 46: 45-48. https://doi.org/10.3182/20130327-3-jp-3017.00013