#7606 A REVIEW ON SENSOR BASED ROBOTIC AGRICULTURE: IMPROVING TRADITIONAL AGRICULTURE PRACTICES

S.C. Karad, Prabhat Kumar and G.U Shinde
National Agriculture Higher Education Project, ICAR, New Delhi
Centre of Excellence for Digital Farming Solutions Enhancing Productivity by Robots, Drones, and AGVs (DFSRDA)
Vasantrao Naik Marathwada Krishi Vidyapeeth, (431402) Parbhani
srfic.nahep.vnmkv@gmail.com, +919370728496

ABSTRACT

Agribot is advanced mechatronic applicant machinery that serves precision agricultural practices and works independently with logical programs duly coded with several set of operational task in the field. This is automated device that expedites accuracy and speed of every task of field operations associated with the farming. The most important characteristics of sensors in Agribot applications are such that it must be Robust, Smart, Low-cost , with strong signal interpretation. The issues of Sensor Fusion, Robust algorithms and overall quick response to activate the mechanism are important quality parameters. The operational task like properties and contains sensing, paste detection and paste management, plant properties sensing and climate monitoring issues are very important while designing a hardware and software deigning in Agribot. The weed detection in which cameras, machine vision and image processing like methods and tools are developed and need to be very précises and specific as traditional practices are challenging with an expected output such as operation cost and time must be saving with high quality agricultural production capacity and economic for Indian farming system. So sensors are the core components of Agribot where in the cost of the device can be minimised so that there will be a digital farming practices by smart farm machinery. The present paper introduces a overall review about sensors used in weeding, insect and disease detection, spraying and harvesting like operations.

Keywords: Precision Agriculture, Digital Farming, Field Operation, Autonomous vehicles & Sensors, DOF, Machine Vision

INTRODUCTION

Agriculture is the most dominant sector which affects the GDP of every nation in the world map. To soothe hunger and bridge demand and supply gap surely there is a need for precision agriculture. Hi Tech agriculture technology outstandingly transformed almost every field operations procedure both in crop and livestock systems in today's time. Use of these technologies with sensor development is a need of an hour. Due to revolution in agriculture robotics technology, minimum investment required in terms of time and efforts related with operation and production cost. Operations involved in agriculture enhanced because of, evolution in software development, machine vision and multivariate data processing. Additionally, there is improvement in equipment and machinery associated with field operations optimized real time scenarios faced by farmers. In today’s time there is a dearth of human labours extensively required in field operations. Management of weed in intra row and harvesting is very tedious when it is done with traditional farm equipment and machines. As a consequence, labour arability crop field operations accelerated with the help of robots [Marinoudi et. al. (2019)]. Some of complexities associated with operation and performance of advanced robotics used in the field operation. These complexities should be addressed to transform the applicability of robotics in agriculture. While building a perfect robotic solution for complex operations for the field, cost operation analysis, advantages and disadvantages should be given priority [Pedersen *et.al.* (2006)]. Other factors are also anxiously needed to execute any prominent task to suffice the need of requirement which includes adaption capacity, smartness, networking and capability of communication, less length and weight [Blackmore et. al. (2008)]. Smaller self-dependent autonomous machines are preferred to perform soil erosion and associated problems rather use of big farm machineries [Fountas et. al. (2010)]. Divide any big operation into small steps of operation before fully atomizing any task related with field operations. To cope up complex conditions involved in the field, there is a need to optimize all small operations [Fountas et. al. (2020)]. There are some frequently observed troubles commonly faced by robots while performing field operations which include assessment of terrain [Reina *et.al. (*2017), Fernandes & Garcia *et.al. (*2018)], plan and path [Bochtis *et.al. (*2009),Bochtis *et.al. (*2015),Yang & Noguchi *et.al.* (2012)] human observation - detection problem [Yang & Noguchi (2012)], and light-footed robots [Yang *et al.* (2004)]. Troubles in tasks related field operations are mainly associated with Inputs of utility and crop specific specifications related with their physiology, anatomy and architecture and pest - disease detection. To implement full autonomous application to any field operations, difficulties are always part and parcel. While implementing any robotic solution common difficulties are frequently with actuation, intelligence, navigation and vision of robotic systems. Some multifaceted robotics responsibilities and tasks associated with field operations which agribots won't perform well includes harvesting, seeding, management of weeds, interaction, purning, navigation and assessment of systems [Aravind, *et al*. (2017)]. Some arable land farming operation set has been examined [R Shamshiri (2018)]. Proper attitude review has been a very integral part of commercially available agribots [Fountas *et al.* 2020]. Examination is essential for agribots, for study of farm environment and to see exact technique of operation [Tsolaki et al. (2019)]. Most advanced agribots have seen for weed management agribot in the field which is autonomously operated for weed related operation [Slaughter *et al*., (2008)]. Similarly, straw berry related study and operation has been done by these agribots [Defterli (2016)]. However, holistic study of agribots architecture and operation is essential, because there are different types of field operations related to various types of crops and controlled environment. Primary challenges of agribots are associated with weather adaptable structures which are evolved to fulfil various needs of crops and their respective field operations. Weather agribots structures are accurate to cope up the challenges concerned with autonomy of actuation. This paper will try to give review about the traditional agriculture practice improvements based on sensors used in agribots.

MATERIALS AND METHODS

Correlational survey has been done for sensors used for weeding, insect and disease detection, spraying and for harvesting applications has been studied. For this review paper several research articles were downloaded from renowned peer reviewed journals and then papers as per the sensor's application category divided into four applications. While reading papers focus has been given to sensors and types of crops these strategies used for each application. Afterwards, in the (Table 1) weed detection types are presented such as chemical and mechanical. Additionally, crop disease and insect detection are categorized in the column number three of (Table 2). (Table 3) mentions about spraying mechanism two modes such as present and absent. At the end in (Table 4) is depicting harvesting application rate of picking fruit in column number three, categorized into two modes such as present or absent with their speed. These studies conducted while writing this research paper will be a torchbearer to shade light to see how sensors revolutionized every traditional practice in conjunction with field operation. The role of sensors in various applications is discussed as follows.

Weeding

Amongst all field operation related tasks, wedding tasks are quite repetitive and time consuming in nature. More than 40% hard work required by farmers is to collect weed manually [Labrada et. al. (2006)]. There are certain crops that are quite disturbing to farmers and labours and so it took lots of money to do that manually. This kind of field operation will have some of the very bad effect over the health of farmers because of manual herbicide sprayed over crops. As a result yield will be less because of spraying without knowing the difference between the crops and weed. There is a huge loss up to 61.5% in the yield of wheat and maize and 33.7% actual yield loss because of heavy use of pest [orke et. al.(2006)]. So to avoid such huge losses weeding robots is the solution [Utstumo et. al (2018)]. These weed robots are usually classified into two types: chemical and mechanical. These robots 100% efficiently and effectively can detect the weed in the crop field row and can spray the exact amount of herbicide required [Utstumo et. al (2018)]. Weeding robots can [Asterix. (2020)]. spot the weed very precisely in the range of 98% [Van Evert et. al (2006)]. Some of the commercial robots can spot and destroy the weed very precisely with the accuracy of 85%. Commercial chemical weeding robots [EcoRobotix (2020)] are less in performance compared with mechanical types [Klose et. al. (2008)].

Cameras which are internet enabled are widely used. Listed cameras such as RGB and IR are widely used. Sensors like optical and acoustic distance sensors, laser, gyroscope and IMU mentioned in the literature. Sensors integrated with robotics systems can increase the performance of weed detection in both chemical and mechanical types. Herbicide with weed refers to weed extraction by chemical method which is famous than mechanical type because of less work done required by it. But spraying more will have some bad toxic impact over the health of individuals involved in these operations. So, precision spraying is the best solution for spraying chemicals in an accurate amount and in precise quantity over the weed. This is attained by integrating sensors with robots with machine vision applications which are highly capable to detect weeds. In the end even though there are good solutions available in the market, still there is a lot to do to increase efficiency. That includes correct navigation guidance and simulation systems with the help of deep learning, so as to make the exact decision at the correct time.

There is only one point which comes in between greater accuracy of robotic systems. Accurate identification of most accurate weed from field is a challenge for such system. Sensors and cameras integrated with robotics systems like vision cameras and sensors measuring distance could be a very great help for precision detection and spraying on weeds. There is huge scope for advancement of weed detects in their early stage like sprouting using soil EC sensors.

Table 1. Sensor-based weed detection application.

Sensors Used	Crops	Weed Detection & Type	Cited Work
Cameras, optical and acoustic distance sensors	Maize	Yes, Chemical	Klose, *et al* (2008)
RGB infrared camera	Carrot	Partly, Chemical	Utstumo, *et al* (2018)
Webcam, solid-state gyroscope	Potato, corn	Partly, Chemical	Van *et al* (2006)
Color camera	Sugar beet	Yes, Mechanical	Bakker,*et al* (2006)
Color camera, artificial vision, compass	Beetroot	Yes, Chemical	EcoRobotix
Color camera, Sensor Watch	Tomato	Partly, Chemical	Lee *et al*., (1999)

Insect and Disease Detection

Disease and Insect detection recently gained great momentum because of scope in the sensors based robotic machine vision system. Traditional practices took lots of time, money, labour and again fewer yields. If we can predict any disease of any crop early and advance surely that would avoid the economic burden of farmers. Monitoring with the help of these advanced system, insects can be detected which are usually below leaf, underground and which are extremely difficult to locate by human eye. In Table 2 we have categorized sensors, crops and then crop disease identification with accuracy would be a great help for future study. From study we can see that all colour cameras like multi spectral, hyperspectral and some of digital cameras which are less costly also be used in some of research papers. Those are of high cost and would require high GPU computing power to process images and train models to give precise results in less time. Digital shade cameras detected viruses like wilt in pepper plants and mildew powdery in tomato with high accuracy. Multispectral also been given great accuracy for such disease detection [Fountas *et. al.* (2020), Scho *et. al.* (2017)]. In olive trees, Xylela fastidious detected promptly with the help of sensors [Rey *et. al.* (2019)].

RGB camera sensors usually used in strawberry to detect Powdery mildew [Mahmud, *et al* (2019)]. Rice RGB camera used to detect Pyralidae insects in Tomato [Liu *et al*. (2019)]. Two DSLR cameras (one in BNDVI mode), a multispectral camera, a hyperspectral system in visible and NIR range, a thermal camera, LiDAR, an IMU sensor used to detect Xylella fastidiosa bacterium in Olive tree [Rey *et al* 2019)]. The groundnut RGB camera Cotton (Bacterial blight, magnesium deficiency) can be used to detect (leaf spot & anthracnose) groundnut in cotton [Pilli *et al* (2015)]. The RGB camera, multispectral camera, laser sensor can be used to detect tomato spotted wilt virus & Powdery mildew virus in Bell pepper [Fountas *et al* (2020), Schor *et al* (2020)]. There are some of troubles faced while detecting disease and insects on different crops those include: first is lack of image based on detection of models as per specified in the datasets; second is processing time from large sets of image datasets of multispectral, hyperspectral, thermal and RGB camera; and third is, uneven light conditions present in various crop fields. [Zheng, *et al*., (2019)] to cope with these real time difficulties we should use sensor vision based modern technology [Barth *et al*., (2018)].

Table 2. Sensor based disease and insect detection application.

Sensor Used	Crop	Crop Disease	Cited Work
RGB camera, multispectral camera, laser sensor	Bell pepper	tomato spotted wilt virus & Powdery mildew	[Fountas *et al* (2020), Schor *et al* (2020)]
groundnut RGB camera Cotton (Bacterial blight, magnesium deficiency),	Cotton	(leaf spot & anthracnose) groundnut	Pilli *et al* (2015)
Two DSLR cameras (one in BNDVI mode), a multispectral camera, a hyperspectral system in visible and NIR range, a thermal camera, LiDAR, an IMU sensor(*)	Olive tree	Xylella fastidiosa bacterium	[Rey *et al* 2019)
rice RGB camera	Tomato	Pyralidae insect	Liu *et al*. (2019)
RGB camera	Strawberry	Powdery mildew	Mahmud, *et al* (2019)

One of the difficulties is uneven light conditions and that can be reduced using some of the novel imaging modalities about light to detect some of the insects and diseases on crops [Mahmud, et al. (2019)]. There other difficulties too apart from lightning conditions which are some of insect morphology related with imaging constraints such as shadow etc. For detection of bugs under the plant on the crop beneath the soil requires some of the advance mechanism to detect that precisely and that is the challenge.

Spraying

Even though we manage to control the toxic effect of active substances like herbicide and liquid fertilizer which we use for spraying application over pests and insects in the field. There is a risk associated with the health of farmers even if we use some advanced robotic for applications. Precautionary measures should be taken. Spraying agri drones and agribots can avoid such risks. Traditional spraying accuracy has been replaced by sensor integrated machine vision intelligence nowadays. Using these practices with the help of drones and agriculture robots, we can attain precise spraying over rightly spotted part of crops in the field operations. So as a result of homogenous spraying, we will get proportionate yield in less time. Research papers have been reviewed for sensor applications in spraying applications which are shown in Table 3. Some of the processes were corrected which are used in the greenhouse in association with robots [Sammons *et al.* (2005)], robots which are working in very alignment of crop rows [Singh, *et al* (2005)]. Sensors which detect the correct spot used with robots always increase the accuracy of precision spraying [Oberti *et al.* (2013), Underwood, *et al* (2015)]. Nozzles are used with spraying devices associated with Agri drones [Sammons *et al*. (2005, Sogaard, & Lund (2007)], also that nozzles could be used with the end effector with manipulator other types of agribots to attain variety DOF applications ranging from 3 DOF [Slaughter *et al.* (2008)], [Underwood, *et al.* (2015)] to 9 DOF [Oberti *et al.* (2013)].

Table 3. Sensor-based spraying application.

Sensors Used	Crop	Presence or absent of real time Detection	Cited Work
Thermal IR camera Hyperspectral camera, stereo vision, monocular color camera	Vegetable crops	Present	Underwood, *et al* (2015)
Robot controller	Cantaloupe	Absent	Mahmud *et al* (2019)
infra-red sensors , Bump sensors, induction sensors	Cucumber	Absent	ammons *et al.* (2005)
Ultrasonic sensor, color TV camera	Grapevine	Absent	Ogawa,*et al* (2003)
RGB camera, R-G-NIR multispectral camera	Grapevine	Present	[Oberti *et al* (2013),]

Also, in some of the applications, spraying time and machine effectiveness plays an important role.These suggestions should be taken in positive mode to optimize existing systems [Mahmud *et al* (2019)]. Other parameters should also be taken considerations to optimize existing mechanism such as machine error [Sánchez-Hermosilla *et al.* (2010), Singh *et al.* (2008)], parameter of performance metrics [Oberti *et al* (2013)], actual [Sammons *et al*. (2005, Sánchez-Hermosilla *et al.* (2010) Ogawa, *et al.* (2013)] and real time detection and spraying capabilities [Underwood, *et al* (2015)].

Harvesting

Harvesting is one of the most repetitive field operations out of all the other applications mentioned in this paper. Some of the research universities and companies are taking efforts to automate these repetitive applications. Based on literature review found, two types of robotics harvesting applications which are Bulk type and second is selective type. Selective type application is a need of the hour which is point of attraction to everyone because of its fastest and precise operational results. Performance of these selective kinds of harvesting robots can be measured based on the objects effective picking speed and picking charge [Hayashi, *et al.* (2014)].These applications of harvesting with the help of sensor machine vision-based robotics should be done in precise given type without affecting crops and plant. Cash crops like strawberries suffer lots of manufacturing and labour cost in some stage of harvesting [Qingchun *et al.,* (2012), Feng *et al*., (2012)]. So, to overcome that, strawberries harvesting robots is a solution [Hayashi *et al*. (2014) Hayashi *et al*. (2014), Xiong *et al.* (2019]. Strawberries selection speed of harvester robots is 7.5 to 8.6 seconds per strawberries and claimed speed is about 8 second per this fruit in line of crop [Xiong *et al* (2019)], 5 second per fruit strawberries picking speed mentioned in [Arima, *et al*., (2004)]. Only speed is immature, what matters is accuracy of picking fruit. Traditional harvesting practices over acers of acres of land cost more to growers, so to avoid cost and exertion of robotics harvesting is a solution. Performance metrics of harvesting robots is also an important point to be considered for harvesting [Shiigi, *et al*., (2008)].

Table 4. Sensor-based harvesting application.

Sensors Used	**Crop**	**Rate and picking speed (present/ Absent)**	**Cited Work**
CCD cameras, vacuum sensor	watermelon	66.7%, Absent	Pilarski, *et al*. (2002)
CCD camera, photoelectric sensor 62.5%	eggplant	64.1 sec/eggplant, Present	Hayashi,*et al* (2002)
black and white CCD cameras, proximity sensor, far and near vision sensors	melon	15 sec/fruit, Present	Umeda *et al* (1999
Pressure sensor, 2 convergent IR sensors, telemeter, cameras	various fruits	2 sec/fruit (only grasp & detach), Absent	[Ceres *et al.* (1998)]
synchronized CCD cameras	cucumber	45 sec/cucumber, Absent	[Van Henten, *et al* (2002)]
Camera, laser sensor	cherry tomato	8 sec/tomato bunch, Present	[Feng *et al.* (2018)]
Binocular stereo vision system, laser sensor	tomato	15 sec/tomato, Present	[Lili, *et al*., (2017)]
Stereo camera, playstation camera	tomato	23 sec/tomato, Present	[Yaguchi *et al* (2016)]
Color CCD cameras, reflection-type photoelectric sensor	strawberry	8.6 sec/fruit, Present	Defterli, (2016)
Sonar camera sensor, binocular camera	strawberry	31.3 sec/fruit, Present	Defterli, (2016)
3D vision sensor with two sets of slit laser projectors & a TV camera	asparagus	13.7 sec/asparagus, Absent	Cerescon
Laser sensor, vision	mushroom	sensor 6.7 sec/mushroom, Present	[Siciliano & Khatib (2016)]
3D vision sensor with red, IR laser diodes, pressure sensor	cherry	14 sec/fruit, Absent	Tanigaki *et al.* (2008)
High-frequency light, camera	apple tree	9 sec/fruit, Present	Baeten,*et al* (2008)
Color camera, gyroscope	alfalfa, sudan	2 ha/h (alfalfa), Absent	Rowley (2009)]

Some examples are dogtooth [Dogtooth], Independent harvester selection strawberry [Sammons *et al.* (2005)] end effector based [Agrobot E-Series.] and harvesting robotics [Octinion.]. Harvesters are used for other plants, fruits and crops such as apples and tomatoes. For instance, apple harvesters are very easy to pluck apples by recognizing apples by their color with the help of robotics vision based grippers. Fastest of such harvester has speed of 7.5sec steps per apple [Silwal,*et al.,* (2016)] for keeping it requires 9 sec per apple [Baeten, *et al* (2008)] such machine has 90% around accuracy in dense orchids [FR Robotics] and apple [Bulanon & Kataoka et. al. (2010)]. Vegetable crops such as tomato and potato, tomato harvester is used for plucking it for a quickest speed of around 24 seconds [Yaguchi *et al.*

(2016)], with 87% of picking price [Lili *et al.* (2017)]. Without moving a tomato bunch 8seconds per tomato speed also achieved by tomato harvester [Feng *et al* (2018)]. Commercial tomato harvesters are also good such as [Metomotion.] and Root-AI [Root-AI.]. For citrus family fruit like oranges, citrus harvester is also used with the speed of 3 seconds per orange [Energid]. For cherry orchid the speed is like 14 seconds per cherry orchards [Tanigaki, *et al.* (2008)]. For manually plucking fruit requires some more time [Ceres *et al.* (1998)]. Cucumber harvester claimed speed of around 45 seconds per it with 80% accuracy [Van Henten, *et al* (2002)]. For eggplant harvester it took 64 seconds per it with accuracy of 62% [Hayashi, *et al* (2002)]. Size and weight of object has affect over accuracy and precision of plucking them. Harvester of commercial plucking of pumpkin and cabbage [Edan, *et al*. (2002)] is also used and robotic system is also designed. For melon and watermelon, melon robotic harvester has around 86 % accuracy [Umeda *et al* (1999)], with 67% of selection rate [Pilarski, *et al*. (2002)]. Harvester machine, designed for Sorghum showed 2 hector acer fastest speed of harvesting it [Rowley et. al. (2009)]. Mushroom harvester shown 70% accuracy [Siciliano, & Khatib (2016)] damages were avoided and cost loss was made up with the help of these robotics applications.

In summary, Harvester robots are of two types one which is mounted on tractor used for apple [Baeten, *et al.* (2008)] and other type is strawberries manual harvester [Xiong *et al*., (2019)] and remaining type is independent one. Two types of picking structures such as suction vacuum type and other is gripping gripper type. Gripper type is with a casual joints and links used to pluck item by the force enabled mechanism of end effector with manipulator [Abundant Robotics]. Whereas suction vacuum type can able to pull and twist and then pluck the item. The gripper's arms is one of the advance structure helpful for plucking fruit in harvesting application [Agrobot E-Series], peduncle type arms [Hayashi *et al*. (2014)] and fruit is plucked off with gripper or vacuum suction [Yaguchi *et al.* (2016), Zapotezny & Lehnert (2019), Agrobot E-Series.]. For localization of fruit is very important in machine vision using sensors such as RGB cameras, time of flight sensors, infrared sensors [Xiong *et al*. (2019), Agrobot E-Series.] or laser sensors [Feng, *et al.* (2018)] and other robots uses [Cerescon] Proximity sensors instead of cameras. Manipulators were commonly used in harvesting applications which has degree of freedom movements ranging from 2 DOF to 7 DOF.

CONCLUSIONS

Sensors and cameras integrated with robotics systems like vision cameras would be very great help for precision detection and spraying on weeds. There is huge scope for advancement of weed detects in their early stage like sprouting using soil EC sensors. There other difficulties too apart from lightning imaging constraints such as shadow etc. some of the advance mechanism to detect bugs under the plant on the crop beneath the soil requires that precisely and that is the challenge. Some of the applications, spraying time and machine effectiveness play an important role and that suggestions should be taken in positive mode to optimize existing systems. Other parameters should also be taken into like machine error parameter of performance metrics actual and real time detection and spraying capabilities. Manipulators were commonly used in harvesting applications which works in degree of freedom between 2 DOF to 7 DOF. From this paper we can say that sensors useful in agribots applications on Weed Detection, Spraying, Disease and Insect Detection and harvesting. Out of these four applications harvesting application has much more ahead in sensor development associated with vision-based agriculture robots. Whereas less sensors used in the rest of applications. Specifically, for weed detection application we found there is huge scope for full autonomous sensor-based weed detection and for its effective efficiency. However, weed control done by mechanical type than chemical one. Even though for insect and disease detection application has good result accuracy but the work done on limited crop is very less.

Image processing should be immediately linked with processing strategies, communication way, vision structures and the extent of the photographs. A key task related to the robotic imaginative and prescient structures is to offer uniform lighting situations via synthetic illumination methods. In future we need to increase decision support system of these applications and there is need of new algorithm development in relation with sensor based robotic system.

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