A Review on Field Agricultural Robots

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ABSTRACT

The Nigerian farmers face problems of pest management, weed management, crop health management, labour shortages, resource waste and enviromental damage due to use of heavy machinery. Providing solutions to these problems are of utmost importance. This paper presents a brief review of agricultural robots with emphasis on outdoor mobile robots. The review looks at the history and the present trends in the field and subsequently highlights the design essentials for an agricultural mobile robot. The design challenges such as the dynamic farm enviroment, the path planning and navigation problem is discussed. Current state of developed robots is also breifly higlighted.

Keywords: *agricultural, design, mobile, robots, solutions.*

1 INTRODUCTION

Agriculture in Nigeria has been stuck in the past for quite a while, with farmers in the country still using primitive tools for their farming needs. The country is still struggling to implement mechanized farming, with heavy machinery that researchers show have negative impact on the soil (Wolkoski and Lowery, 2008) and causes wastage. Heavy machinery causes soil compaction and eventual produce loss of up to 50 % (Wolkoski and Lowery, 2008). Application of chemical pesticides is usually done generally causing waste of resources (Harvey, 2017), coupled with waste of fuel used to run the machinery. Researchers are opting for smaller smart vehicles (Pederse et al., 2008) and more efficient methods of farming around the world to solve these problems. There is also the problem of dwindling agricultural labour force (Roser, 2019). Agricultural Robots are used in farm for executing various tasks ranging from crop scouting and eventual pest control, weed control, crop harvesting, targeted pesticide application, intricate pruning, intelligent milking, plant phenotyping and sorting with favourable results (Yaghoubi et al., 2013). The current state of field robots is still far from being able to solve the enumerated problems, however the paper is a brief appraisal of agricultural robots, their classifications, active research areas and the current trends and challenges present in the design of wheeled fields robots.

2 HISTORY OF AGRICULTURAL ROBOTS

Researchers have been trying to make robots since the ancient times when the Egyptians made water clocks (Bedini, 1962) with human figurines that strike bells to indicate time. Al Jazari dubbed as the father of robotics (by some authors) described practical autonomous robots in his book titled "The book of knowledge of ingenious mechanical devices" as far back as the 1200s. Leonardo Da Vinci's mechanical Knight and Nikola Tesla's wirelessly controlled torpedo were all early attempts in the field of robotics in general.

Essential strides recorded in the introduction of robots in the field of agriculture began in the 1920s (Yaghoubi, et al., 2013) with the attempts at inventing autonomous systems used in the farms, mostly attached to the tractors. Tractors that could autonomously be driven were attempted in the 1950s and 60s (Nistala, 2006). An example was an invention in the era was of a tractor steering attached to a barrel in the middle of the field, other attempts were made but relied on underground cable run through the field for the tractor movement (Nistala, 2006).

Much development in agricultural robotics was in the 1980s with the immense development in electronic technology. Smaller components were developed (Nistala, 2006) coupled with smarter chips and smaller computers with high computational power. This birthed the renewed interest in implementing autonomous systems in agriculture (Benson, et al., 2003). Researches were mostly based on machine-based vision guidance systems (Ming et al., 2009). Research by Searcy and Reid (1986) showed the possibility of extracting guidance signal of an autonomous vehicle from an image, the research employed a tractor as their test vehicle. Searcy worked with Bradon in 1992 on the navigation systems, succesfully developing computer algorithms necessary to steer an agricultural tractor with record of favourable performance (Brandon and Searcy, 1992). The later decades saw the further decrease in the cost of computers and increased use of electrical and electronic systems for engines, transmissions and steering on agricultural equipment which allowed for the introduction of precision agriculture (Hassall, 2009).

3 RESEARCH TRENDS IN THE FIELD OF AGRICULTURAL ROBOTICS

Robots in agriculture covers many applications, which makes the mechanical, electronic and software components of each robot unique for the task to be executed. Fruit and vegetable harvesting robots have especially gained attention among researchers. Fragile fruits with low resistance to damage, such as tomatoes, oranges or strawberries are not harvested by vigorous branch shaking methods as compared to damage resistant fruits like olives and almonds, therefore delicate grippers have to be attached to manipulators for their harvest. Tree branch shaking form of fruit harvesting also causes the detachment of unripe and immature fruits, solving this problem will necessitate the use of visual based control, advanced image processing techniques and appropriate gripper design (Shamshiri et al., 2018) for harvest of the right fruit. Figure 1 shows an illustration of these requirement embedded in a typical fruit picking robot.

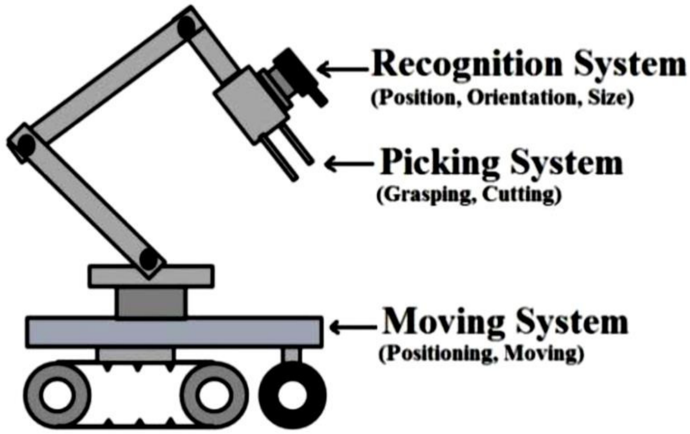

Figure 1. A fruit picking robot (Source: Bachche, 2015)

Hemming et al. (2014) developed a robot harvester for sweet-peppers used in greenhouses, its manipulator prototype has nine degrees-of-freedom to assure maximum flexibility. The chassis moves in between the crop rows on a rail system. Shamshiri and Wan Ishak (2012) worked on an oil palm manipulator harvester, applying nonlinear Lyapunov based control method for joint angles tracking. A two-link oil palm harvesting robot manipulator was used for the analysis. Some other works were the cucumber harvester developed by Van Henten et al. (2002), mango, almond, apple, strawberry, cherry fruit and tomoato harvesters as reported by Shamshiri et al. (2018). Oberti et al. (2013) used multi spectral imaging disease detection method for their selective spraying robot, it was deployed for grapevines. The robot was characterised with a manipulator configured to six degrees of freedom for increased positioning and more accurate precision-spraying. They recorded a considerable reduction of pesticide use from 65% to 85% when compared to the conventional mass spraying method. Gonzalez-de-Soto et al. (2016) presented the features of a robot patch sprayer which uses a real-time machine vision system that can detect weeds and a swift response spraying mechanism to act accordingly. Tests by the team showed the patch sprayer treated about 99.5% of the weeds detected. Young et al. (2019) developed a mobile robot to collect phenotypic data, the system was designed to collect data from individual plants for further analysis. It used stereo imaging techniques to ascertain plant height, and an incorporated depth sensor measured stem width near the base of each plant. The six-legged robot flowerpot developed 2014 is one of the most advanced agricultural robots. The robot is highly intelligent and is able to mobilize the plant in its care by moving it to and away from the sun rays. The robot is also programmed to indicate when the plant needs water by dancing (Goldman, 2018).

Some commercially available agricultural robots presently in the markets include; the Ecorobotix which is a solar powered autonomous drone, it uses its solar power to operate for 24 hours. The robot has a camera which it uses locate and spray weeds. Alexander (2018) reports that the robot uses **90%** less herbicide and is **30%** cheaper than traditional treatments.

Naio Technologies have developed different robots for executing agricultural tasks with the core aim of environmental preservation and protection. Alexander, (2018) stated that the robots could execute farming tasks such as weeding, hoeing, and aid the harvesting processes of various crops. Energid technologies developed Energid Citrus Picking System for fruit picking. The system is reported to be able to pick a fruit with accuracy every 2 to 3 seconds (Alexander, 2018). Another harvesting system is developed by Agrobot. The system is developed for strawberry harvesting. With its 24 robotic arms working wirelessly and an advanced AI system, the Agrobot E-series analyses the strawberries, identifies the ripe ones and picks with high speed and accuracy (Alexander, 2018). Drone technologies are part and parcel of agricultural robot technologies, they play an important role in the monitoring large areas of crops. Agribotix and Precision Hawk are companies that build drones for farm monitoring. Agribotix has developed cheap drones for farmers, to collect crop data over time, or in real-time. The drones have the capability to take precise aerial photos or record videos of the farm, some of the drones have infrared sensors incorporated for measuring the crop health while in the air (Alexander, 2018). PrecisionHawks drones on the other hand have artificial intelligence paired with multispectral, hyperspectral, and LiDar technology for in-depth crop analysis (Alexander, 2018).

4 CLASSIFICATIONS OF AGRICULTURAL ROBOTS

There are vastly different classifications of agricultural robots, these classifications are mostly done with respect to the kind of tasks these robots can accomplish. Three key categories of field mobile robots will be briefly touched upon here.
Harvesters: Kurhade et al. (2015) highlighted some techniques involved in automated harvesting. These techniques are employed depending on the nature of the fruits being picked or harvested; mechanical shaking robots, robots that use machine vision by colour, those that use shape detection and robots that use 3D imaging. Mechanical shakers have been researched and used since the 1960s. The shakers are of different categories themselves, these include limb shakers, air blast, canopy shakers and trunk shakers (Kurhade et al., 2015). Puttemans et al. (2016) recorded positive results in strawberry picking using the colour vision technique as opposed to some other fruits. Machine vision by shapes is most suitable for citurs fruit picking (Kurhade et al., 2015), because the fruits are easily ditiguinshable from the branches when harvesting. 3D technique has been used for the harvesting of Rosa Damascena (Kohan et al., 2011), sweet pepper (Wouter Bac, 2015; Lehnert et al., 2017), and cucumbers (Kurhade et al., 2015) to moderate success.

Pest and weed controllers: The first step of pest control is by identification, the majority of diseases are detectable (Avarind et al., 2017) making it good for visual recognition systems to detect. Pesticide application which is the second step causes high waste of resources (Aravind et al., 2017) which is why many systems have been researched and implemented in variuos farms. Aravind et al. (2017) described a fully enclosed, manually propelled platform that is equipped with a diffused fluorescent lamp and a multi-spectral camera for pest detection and another pest control robot equipped with infrared sensors for obstacle avoidance, video camera module for vision, and a sprayer module with a spray head that is adjustable according to required spray height.
Weed control is very paramount in agriculture as weed competes with plants for nutrition. It has been repeoted that weed can reduce yeild by 71% (Slaughter et al., 2008) if not properly controlled. Robots have been developed for this sole purpose. The core technologies employed for weed controllers are row guidiance systems, a form of machine vision mechanism for recognising plant species, weed removal mechanism and a Global Positioning System (GPS) mapping (Slaughter et al., 2008). There are some notable weed controlling robots in the market now. The Robocrop developed by Garford farm machinery, the IC-Cultivator by Machinefabriek Steketee and a mechanical hoeing robot designed by F. Poulsen Engineering Aps all have incorporated cameras and some form of blade mechanism to destroy weed when located (Siemens, 2014).

Phenotyping robots: Phenotyping robots have gained attention for the important role they play allowing researchers understand environmental and gene function effects in crop breeding and development (Zhang et al., 2016). Robots use machine vision and remote sensing to acquire various plant traits without invading or destroying the plant. At present automatic, multifunctional high throughput phenotyping systems have been developed (Zhang et al., 2016). Examples of these platforms are the Traitmill a functional platform for cereals phenotypic analysis (Reuzeau et al., 2006) and the Plant Accelrator from the University of Adelaide, Australia with a though put of 2400 plants a day (Zhang et al., 2016).

5 VIRTUAL EXPERIMENTATION FRAMEWORKS FOR AGRICULTURAL ROBOTS

Simulating robots in the virtual space allows applications to be created for a physical robot without affecting the actual physical robot, consequently saving cost and time. The applications may be transferred onto the physical robot (or rebuilt) without modifications (Shamshiri et al., 2018). Shamshiri et al. (2018) explained the need for incorporating the sciences of horticulture and agronomy to successfully accomplish a task in the virtual environment when it comes to simulating an agricultural robot as opposed to industrial robot simulation. Virtual environments and middleware frameworks such as the Robot Operating System (ROS) (Quigley et al., 2009) offer great opportunities for processing these sensor readings in the third-party software such as the Open Source Computer Vision Library (OpenCV) and MATLAB (Shamshiri et al., 2018). The main drawback of simulation is that the real world may present more complicated situations such as unexpected disturbances to the actuators, or unpredicted noise to the sensors feedback as a result of natural field conditions (Shamshiri et al., 2018). There is a long list of academic and professional simulation platforms that can be adapted and used for agricultural robots as presented by Shamshiri et al. (2018). Examples include Webots developed by Michel (2004), Gazebo from Open Source Robotic foundation (Koenig and Howard, 2004), CARMEN RNT (Montemerlo et al., 2003), Coupled Layer Architecture for Robotic Autonomy (CLARAty) (Jensen, et al., 2014), Microsoft Robotics Developer Studio (MRDS) (Cepeda et al., 2010), Orca (Makarenko et al. 2006), Open Robot Control Software (Orocos) (Bruyninckx, 2001), Player (Gerkey et al., 2001), the Autonomous Mobile Outdoor Robot (AMOR) (Kuhnert, 2008), and Mobotware (Beck et al., 2010). Table 1 shows the general specifications of the most commonly used simulation software for agricultural robotics.

Table 1: General Specifications of The Most Commonly Used Simulation Software for Agricultural Robotics. (Source: Shamshiri et al., 2018)

S/N	Simulation software	Developer	Supported operating systems	Programming language	Application programming interface (API) support	ROS support
1	Webots	Cyberbotics Ltd	Linux, Mac OS, Windows	C++	C, C++, Python, Java, Matlab, ROS	Yes
2	Gazebo	Open Source Robotics Foundation	Linux	C++	C++	Yes
3	Actin	Energid Technologies	Windows, Mac OS, Linux, VxWorks, and RTOS-32. (RTX	C++	Not known	Yes

4	RoboDK	RoboDK	Linux, Mac OS, Windows, Android	Python	C/C++, Python, Matlab	No
5	Morse	Academic community	Linux, BSD, Mac OS	Python	Python	Yes
6	OpenRAVE	OpenRAVE Community	Linux, Mac OS, Windows	C++, Python	C/C++, Python, Matlab	Yes
7	OpenHRP3	AIST	Linux, Windows	C++	C/C++, Python, Java	No
8	ARGoS	Swarmanoid project	Linux and Mac OSX	C++	C++	Yes
9	V-REP	Coppelia Robotics	Linux, Mac OS, Windows	LUA	C/C++, Python, Java, Urbi, Matlab/Octave	Yes

6 DESIGN ESSENTIALS OF AN OUTDOOR AGRICULTURAL ROBOT

Designing an outdoor mobile robot for executing farm related tasks may be looked at in three phases; its mechanical structure, electrical circuit and the software design. First a problem needs to be identified and clear objectives that will lead to its solution. The complete structure will be modelled towards solving the said problem. Tabile et al. (2013) reported the Quality Function Deployment (QFD) method for identifying the design problem and translating it into technical design parameters. The QFD looks at the problem staement and seeks to translate them into design parameters. The results are used as inputs for the functional decompsition method, which starts at a higher level and methodically divides the main objectives into subdivisions until it reaches a level of functional components.

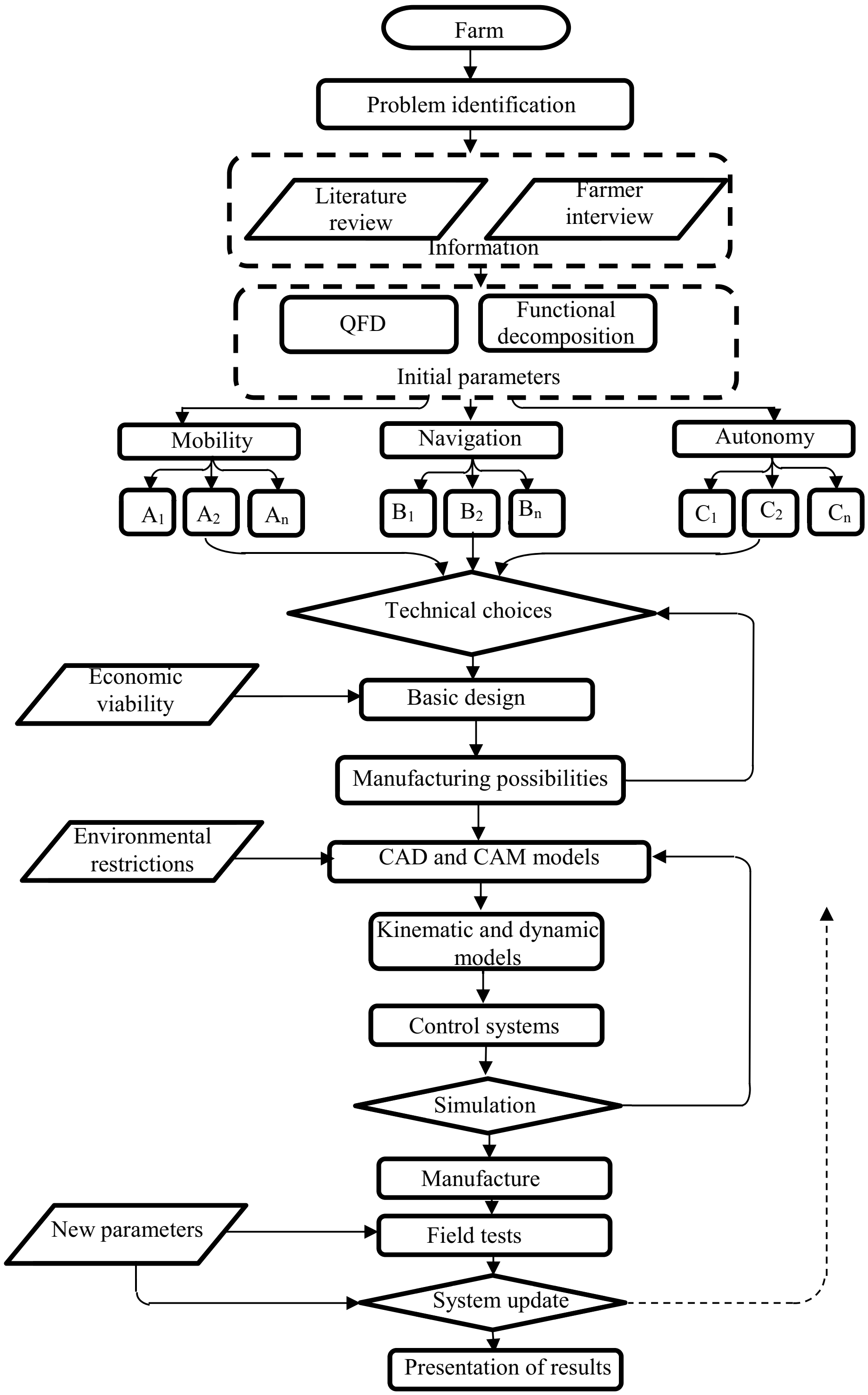

Figure 2: Flow Chart of The Design Process of a Mobile Robot (Source: Tabile et al., 2013)

A flow chart of the design process using QFD is shown in Figure 2. Multiple options are ususally provided from using the QFD method (Tabile et al., 2013), that is when the conceptual design technique will be used to narrow the options down to the needed solution (Tabile et al., 2013).

The virtual platform will then be selected for the model that will be simulated, bearing in mind the platform that will support the model for the simation. From Table 1 (for example), if Webots is selected as the platform for the simulation then the designer musut have C++ background and a Linux, Mac or Windows OS supported system to run the simulations. The simulations are used to see how the robot will behave in the physical plane, opertaional concepts, functional specifications and dynamic analysis under various operating enviroments (Tabile et al., 2013).

Finally, the design process concludes with the development of the kinematic and dynamic models for the robot guidiance. Both of the these along with the virtual prototype is used to develop the mobile robot control architecture (Tabile et al., 2013).

7 DESIGN CHALLENGES OF WHEELED AGRICULTURAL ROBOTS

There are numerous challenges in the design of wheeled agricultural robots, with the greatest being the staggering difference between the virtual and the physical world the robots will operate in. The farm environment is a highly dynamic and unpredictable domain for any system to traverse in autonomously. Not all the characteristics of the physical environment can be fully captured and simulated while modelling and designing the robot. A robot designed by Nakamura et al. (2016) for example often overturned and became immobile during opertaion as it manouvers the muddy terrains of the farms. Another example is the strawberry harvester developed by Qingchun et al. (2012), it was only able to harvest 86 fruit for a 120 trials targetting 100 furits. They attributed the errors to mostly uneven dimensions of the fruits. The problem of accurate automatic guidiance (Cariou et al., 2009) and precise navigation (Gao, et al., 2018) is still very much present in agricultural mobile robots.

The problem often begins from the chassis design comprising of the wheel and the wheel mechanism supports. Chassis meant for the agricultural enviroment need extra buffer suspension device due to the complex terrain structure in the farms (Gao et al., 2018). The navigation problem is only parttly solved according to Gao et al. (2018) with the numerous methods proposed over the years trying to solve it. Gao et al. (2018) listed the global navigation satellite system (GNSS), laser navigation, inertial navigation, electromagnetic navigation, radio navigation, visual navigation and beacon navigation as methods currently used for robot navigation. Global positioning system is generally used to support GNSS in the out door farm environments but its accuracy does not meet the actual demands in the fields (Gao et al., 2018).

Another problem encountered by researchers is the accurate representation of the dynamic environment (Beeson et al., 2008), how to accurately build its map, representing notable land marks reliably for the robot to use for navigation. Payá et al. (2017) summed the current problem of mapping and localsation to be two; mapping and localization of very large dynamic environments and estimating the position and orientation in a space and under real (practical) working conditions. Movement which is a very important characteristic of the wheeled robot possess a serious challenge. The best algorithms for optimum path to be taken by the robots are still researched, but the problem of path planning is still encountered even with the robot's generally low-speed of operation and neglecting dynamic problems (Gao et al., 2018). The current search algorithms developed are unreliable and time consuming (Gao et al., 2018) while obstacle avoidance algorithms have

noticeable limitations including inability to plan path between very close obstacles, turning radius not fully considered which affects data acquisition and robot has to stop for data acquisition (Gao et al., 2018).
Using multiple robots in a single agricultural environment is also another problem described by Gao et al. (2018). The robots must be able to plan their path and communicate with one another in the execution of a unison vision for which they have been designed. For this to occur each of robots must estimate its status and position by self-detect, communicate with other robots in real time, and exchange data correctly and rapidly to ensure orderliness by avoiding collision with other robots during follow-up path planning, but this is still far from fruition (Gao et al., 2018). The farm environment is unlike the structured environment where every little detail can be meticulously planned.

Shamshiri et al. (2018) resigned that for now manual harvesting is still the only solution when it comes to the prevalent problems with robot harvesters. The available record for sweet pepper haervesters has only 33 % success rate and an average of 94 seconds picking time. 6 seconds is the ideal time for commercial implementation. The harvester by Qingchun et al. (2012) was only able to harvest 86 fruit for a 120 trials targetting 100 furits. Field results of a cucumber de-leafing robot an average time of 140 seconds for two leaves plants recorded, which was 35 times longer than manual leaf picking per plan (Shamshiri et al., 2018). Producers still use traditional harvesting methods with examples of 18 billion apples harvested manually every year in Washington and Poland opting to produce over 3 million tons of apples using mass harvesting maachines (Shamshiri et al., 2018). In the area of robot sprayers there is actual promise as automnomus systems have been sucessfully able to reduce considerable amount of pesticides apllied compared to general application methods, but the technology is mostly applicable prior to considerable plant growth or in some cases when the main plant height is between 0.2-0.3 m (Shamshiri et al., 2018).

8 CONCLUSION

The paper has briefly reviewed researches conducted in the field of agricultural robotics, with special attention to mobile outdoor robot designs. The paper has examined the history of agricultural robots and present trends in the area, to provide up to date information for outdoor robot design. Agricultural robots classification have been done based on their peculiar applications. The design essentials have been briefly discussed with much emphasis on the cahllenges still plaguing the field of agricultural robot implementation. Some of the major research hurdles have been highlighted with the major one being the lack adequate representation techniques of the physical world for the robot. Robots implemented in the fields have falled short of farmer expetations compared to existing methods. Some of the areas that have recorded strides despite the cahllenges are pest control, harvesting and phenotyping.

The Nigerian farmers face the same problems of pest damage, weed control, crop health management, labour shortages, resource waste and enviromental damage due to heavy machinery as faced by the rest of the farmers around the world. But the difference being the serious interest in robotic resarch to solve these problems in these other parts. Research into agricultural robotics is very scarce in the country, imposing on our farmers the use of the same farming methods for hundreds of years and this prevents us from reaping the full potential of the farming sector and feeding our teeming populace. This review is aimed at highlighting viable alternative techniques to solve our farm related problems for better more efficient farming.

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