Localization, Navigation and Activity Planning for Wheeled Agricultural Robots – A Survey

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***Abstract*—High cost, time intensive work, labor shortages and inefficient strategies have raised the need of employing mobile robotics to fully automate agricultural tasks and fulfil the requirements of precision agriculture. In order to perform an agricultural task, the mobile robot goes through a sequence of sub operations and integration of hardware and software systems. Starting with localization, an agricultural robot uses sensor systems to estimate its current position and orientation in field, employs algorithms to find optimal paths and reach target positions. It then uses techniques and models to perform feature recognition and finally executes the agricultural task through an end effector. This article, compiled through scrutinizing the current literature, is a step-by-step approach of the strategies and ways these sub-operations are performed and integrated together. An analysis has also been done on the limitations in each sub operation, available solutions, and the ongoing research focus.**

I. Introduction

Owing to the benefits, the applications and adoption of robots have tremendously increased over the last two decades. Rapid advancements in technology and subsequent industrial revolutions have stipulated the rise and capabilities of robots. This is the reason that advanced robots are not only an integral part of industries but are taking charge in all sectors like services, agriculture, e commerce, healthcare, retail, construction, transport, defense etc. In the last decade from 2009 to 2019, the operational stock of robots in industries increased by more than 166% [1] signifying the expansion of this field. This evolution has also led to the development of several fully functional human-less warehouses and factories which is also known by the name of "lights out manufacturing" [2]–[4]. Furthermore, an unusual increase (38%) has been witnessed in the sale of personal and domestic robots from 2019 to 2020. The data suggests that this increase is expected to continue following the same trend in the coming years with a forecasted annual growth rate of 31% [1]. Georg and Guy [5] studied this trend and evaluated that the reason is not only the decrease in output prices but also it has been seen that increased robot adoption has contributed towards increasing the creativity, productivity and wages of labor.

Moreover, mobile robotics has currently become one of the highly researched fields with the efforts ongoing since 1940s to develop an intelligent system with focus on imitating animals [6]. The field has grown at a much faster pace in the recent years thanks to the development of state of the art sensor systems, advanced artificial intelligence and highly sophisticated software tools like robot operating system (ROS). Traditionally, robots were programmed to follow a predefined sequence of actions in confined work spaces [7]. However, the field has now become much more challenging and research oriented as mobile robots require intelligence and autonomy to take smart actions in complex work-spaces. A mobile robot is equipped with sensors and systems that sense the environment and then a central processing unit accordingly generates control signals for actuators to enable locomotion. In such a way, a robot is capable of mapping or remembering a previously unknown environment, localize itself in this environment and move to target locations while ensuring collision free operation [8].

Innovation in mobile robotics have made them an integral part in all industries. Similar is the case for agriculture industry where extensive research is being carried out to enable robots to carry labor intensive tasks. In this regard, Mahmud et al. [9] list out the current as well as future possible applications of agricultural robotics which include planting, inspection, weed control, spraying and harvesting. All of these are physical, repetitive and time-consuming tasks that require intensive human labor. Robots are specifically intended to replace humans in the 4D tasks which are dull, dumb, dangerous or dirty [10] and thus are a perfect solution for the agricultural industry. This is also the reason that the average age of agricultural labor is increasing [11], indicating that these agricultural tasks are now considered inferior and the younger generation is not interested in them. This further signifies the need of research and development of automation in agricultural tasks.

As per the economic point of view, labor accounts for the major cost in agriculture, almost 38% of the total operational cost [12]. Zahid et al. [13] discuss the need for a robotic pruning system in an apple orchard because of the unavailability of labor and its huge cost which accounts for approximately 56% of the total variable cost in their case. The research on agricultural robotics started in 1960s mainly focused on the implementation of guidance systems for agricultural vehicles. Later it was observed that computer vision and GPS are the feasible solutions to achieve it [14]. In addition, food safety, environmental protection and sustainability have become the major concerns in agricultural sector. Increasing world population and food demand has led to the introduction of "Good Agriculture Practices (GAP)" and "Precision Agriculture" [15]. Robotics and automation are the underlying technologies that can enable precision agriculture by fulfilling and adhering to the requirements of correct information, observation, analysis, dose, place, time and equipment [16]. Research has revealed that in future agricultural robots shall not only minimize the operational costs but also reduce wastes, fuel consumption, pollution and environmental impact [17].

Traditionally, agricultural robots have been very expensive with inefficient performance. However Post, Bianco and Yan [18] attempted to build an affordable environment monitoring agriculture robot using off the shelf hardware and open source software. They were able to achieve it at a very affordable price with reasonable efficiency and anticipated that in near future machine vision based intelligent navigation stacks will revolutionize the challenging farming operations at low cost.

The progress in artificial intelligence and the implementation of its models has drastically improved the performance of agricultural mobile robotics and is producing promising research outcomes. Saleem et al. [19] performed a systematic review of the advancements in agricultural tasks performed through machine and deep learning models and presented a framework for an AI powered agricultural robot. According to them, the choice of a machine or deep learning model should be highly dependent on the agricultural task which is intended to be performed by the robot. Correct selection of models resulted in higher accuracy even exceeding 90% for some agricultural tasks.

To perform a task e.g., weeding, pruning, harvesting, monitoring etc. an agricultural robot goes through a series of supporting tasks. Morar et al. [20] described the agricultural robot as a structure of three components: locomotive equipment, manipulating structure and end effector. For this survey, Fig. 1, inspired by [21], presents a general structure of supporting tasks that a robot performs in order to complete the main agriculture task. This structure also gives an idea of information flow between tasks and sensor systems. Thus, to perform an operation (say weed control), a robot performs the supporting task 1 to localize itself in an environment (an agricultural field or greenhouse); plans a path and navigates to target locations (safe navigation between rows of plants); use systems and tools to gather data and detect parameters relevant for the main operational task (image processing or AI methods to distinguish plants from weed); and finally plans the trajectory of the end effector or manipulator and performs the task (a cutter or gripper to pluck out the weeds).

According to the author's knowledge, there is no instance in literature that cover all aspects and sub tasks which together make an operative agricultural robot. Although, several review articles are present but they only cover small parts of the overall functionality. Hence, this survey shall contribute to provide enough knowledge and explain the synchronisation of all these sub tasks that make a complete and functional robot for agriculture. The article is organized to sequentially go through three sections of localization, autonomous navigation and task execution. Each section covers the challenges and limitations faced and provides an overview of the solutions, ongoing research focus and prospects.

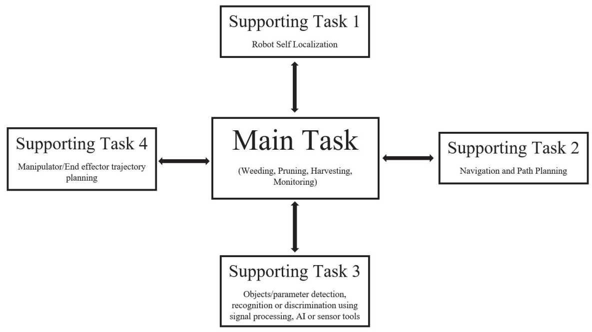

Fig. 1. Framework of an Agricultural Robot [21]

II. Robot Self Localization

For a mobile robot to navigate autonomously, it must have real time information of its location within the work environment. Localization and navigation, although closely linked, are two separate tasks in mobile robotics. Localization is the key problem that is necessary for a self driving robot to be aware of its surroundings and successful navigation is then dependent on it. It requires the timely availability of position and orientation data of a moving robot with respect to a known starting point.

A. Sensor Systems for Localization

From the current available literature, sensor systems that have been primarily used in agricultural robotics for localization include Global Positioning System (GPS), wheel encoders, visual odometry, Laser Imaging Detection and Ranging (LIDAR), Inertial Measurement Units (IMUs) and beacon based systems such as Infrared (IR), ultrasonic waves etc.

1) GPS and variants: Traditionally, global positioning systems (GPS) and compasses have been extensively used for localization. With the availability of GPS for general applications in 1980s, the research in mobile robotics surged, but the resulting systems were inefficient because of the low accuracy and outages caused when the line of sight with the satellite is blocked [22]. The introduction of differential GPS (DGPS) [23] and real time kinematic GPS (RTK GPS) [24] significantly increased the accuracy of GPS systems within a centimeter but this research dates back to early 2000s.

2) Wheel Odometry: Wheel odometry has been often used in mobile robotics in which wheel encoders are used for localization [25]. However, wheel odometry has now become irrelevant for agricultural tasks because of the inherent error sources and wheel slippage [26]. These limitations led to the development of more sophisticated localization technique of visual odometry.

3) Visual Odometry: Visual odometry is an image processing approach in which position and orientation is estimated using a stream of successive images either from a monocular (single) or stereo (multiple) camera system. The application of computer vision-based sensors has gained commercial success in agricultural robotic applications [26], [27] for visual odometry and point cloud data (PCD) formation. Presently, many off-the-shelf machine vision-based systems [28] are available that serve as a source of point cloud data. These sensors have reasonable efficiency and are capable of use in both indoor and outdoor agricultural robots. For instance, Beloev et al. [29] employed Intel's RealSense lineup of vision based depth and tracking cameras for localization and mapping in their precision agricultural robot.

4) Beacon Based Systems: Beacon based systems are another form of localization methods for mobile robotics usually based on infrared or ultrasonic/acoustic applications. In this method, a set of two or more stationary beacons are placed in the environment and another set of two mobile beacons are placed on the robot. One set transmits waves which are received by the other set and based on time the waves took to travel between stationary and mobile beacons, position and orientation of robot is estimated. Kostromins and Osadcuks [30] utilized IR based beacons in agricultural robots and achieved angular accuracy error of 2.89° and a localization error below 7cm. Widodo et al. [31] used the same beacon technology based on sound signals in an agricultural field environment and were able to localize the mobile station within 25mm of actual position.

5) LIDAR: LIDAR has been widely used for localization, but it faces a huge challenge in agricultural field tasks because of the unreliable detection of grass, leaves etc. [32]. For static environments, 2D localization is sufficient. However, Le et al. [32] suggested a completely online 3D version of LIDAR odometry and mapping (LOAM), more suitable for agricultural dynamic environments and proved its worth through simulation and experimentation. Similarly, Weiss and Biber [33] also highlight the advantages of 3D laser sensors for agricultural tasks. According to them, 3D lasers are a more promising solution to form a model of 3D environment also referred to as 3D point cloud data (PCD). This PCD can be used to detect individual plants and then localize the robot to perform agricultural tasks. On the very same principle, Underwood et al. [34] developed a 3D representation of orchard field using 2D LIDARs and obtained perfect localization with an accuracy of 98.2%. This was achieved using tree recognition and matching from within an existing environmental model using markov models based on the statistical and probability theory.

From all the reviewed articles in this section, it can be clearly seen that the trend in last two decades has moved from GPS to LIDAR to computer vision based visual systems and AI tools for robot localization.

B. Localization Methods and Strategies

1) SLAM: Localization of a mobile robot is mainly done in a previously mapped environment. However, agricultural environments are known for their uncertain and unpredictable situations where parameters like terrain and landscape are subject to continuous variability [35]. That is, a formed map shall become irrelevant after continuous changes over time. This raises the need for the methodology of simultaneous localization and mapping (SLAM) for agriculture [36], [37] where a mobile robot continuously forms and updates a model of its environment while localizing itself. Lepej and Rakun [38] analyzed the performance of two SLAM approaches in an agricultural field and tested their feasibility for complex agricultural tasks. Their experiments showed that image registration based techniques performed better than Hector mapping. It is to be mentioned that SLAM is an approach that combines localization with continuous and simultaneous mapping to optimize the locomotion of robot assembly which makes it befitting for agricultural environments [37].

2) Sensor Fusion: With the development of precise sensors and machine vision-based technologies, it has been observed that standalone sensor systems are seldom used as a localization tool, rather multiple forms of sensors are combined to obtain higher accuracy. The combination of data from different sensors in order to increase the accuracy of localization is called sensor fusion. For instance, Bietresato et al. [39] developed a mobile robot to monitor the health and volume of plants using a combination of GPS and sonar sensors to estimate the position. Particle Filter (PF) and Kalman Filter (KF) are two localization algorithms extensively used in fusion of sensor data for agricultural robot localization. Both the algorithms have pros and cons with randomly varying performance depending on the nature of agricultural task. For instance, PF outperforms KF when navigating in an apple orchard rows [40]. There are several other localization algorithms for sensor fusion in agricultural environments, the accuracies of which are compared time and again [41] but it is highly dependent on real world conditions. Sensor fusion is extremely useful to counter for the limitations of one form of sensor with another type of sensor e.g., since vision-based systems have high accuracy but struggle in variable light conditions, Wang et al. [42] fused odometry and vision system's data to localize the robot in outdoor environments. Frequently, IMU data has been noted to be fused with other sensor systems in agricultural robots to improve localization [18], [43].

3) AI and Computer Vision: Recent advancements in computer science and artificial intelligence have opened huge prospects in mobile robotics. However, the field of application of AI for self-localization in agricultural robots is still in the early stages of development. AI tools are extensively being researched upon to optimize the mapping and self-localization specially in outdoor environments. Weinzaepfel et al [44] developed a convolutional neural network (CNN) in which the pose of mobile robot is estimated using only a single RGB image. Given a reference image, the model can form a dense set of 2D to 2D matches, giving a solvable Perspective-n-Point (PnP) problem. Similarly, Cattaneo et al. [45] developed a deep neural network which learned to localize the robot by matching prior PCD data with real time LIDAR data. All these techniques can significantly revolutionize the robotics domain of precision agriculture. From the literature, it has been observed that the frequency of articles focusing on AI based localization of agricultural robot has grown significantly in recent years.

III. Autonomous Navigation

With the timely availability of localization data, an agricultural robot can plan and execute its motion within the work environment. The objective is to implement an optimal navigation algorithm that can find the most suitable path from source to destination. In the area of agriculture mobile robots, navigation and control is the most researched field [46]. Patle et al. [47] performed an organized review of all the navigation strategies and algorithms, the following three conclusions from their study are concerning for navigation of agricultural robots: the research on dynamic environments is very few compared to static environments, research on navigation to a moving goal in dynamic environment is very limited, and less literature is available for multiple robotic systems in an environment as compared to a single robot.

Agricultural environments are characterized by irregularity of terrain and inconsistent surroundings making it a requirement for the autonomous robot to timely adapt to the environmental and kinematic changes without the need for re-calibration [48]. The literature on agricultural navigation dates back to 1990s where several attempts were made to introduce autonomous guidance systems in tractors e.g. in [49] a control and guidance system was installed in the tractor which followed orchard rows and found the trajectory by establishing a relative relation between the tractor and rows and then calculating the lateral and direction error. However, with the progress in technology and availability of computational resources, the research has surged in advanced navigational sensors and algorithms [50]. As of 2021, visual navigation is the most significant, feasible and researched solution for agricultural robots [51].

A. Navigation Strategies and Methods

A robot comprises of two subsystems when looking from the perspective of navigation: the physical control systems such as the steering mechanisms and the computational system consisting the algorithms and models responsible for planning the locomotion [52]. Also, the computational subsystem is responsible for controlling both the kinematics and dynamics of the robot involved in navigation. Ortiz and Olivares [53] described the kinematic and dynamic model used in the development of a vision based navigation system for their agricultural robot. Their robot was able to navigate autonomously through speed control and path tracking by calculating the deviation between a reference straight line and the available path. A very similar approach is used in [54] where the authors performed kinematic and dynamic modeling and simulation of their robot in which the navigation is performed by minimizing the camera offset with respect to a crop field track using the nonlinear model predictive control (NMPC). Gao et al. [55] developed a path planning algorithm for spraying in orchards having an accuracy of 97.5%. They proposed to use an RGB-D camera on their robot to acquire color depth images. A segmentation model was used to detect the row spacing and canopy height from the color depth image and form a region of interest (ROI), the path is then planned as a function of the spraying path to the midpoint of ROI. In a similar experimentation, Ahmadi et al. [56] performed row navigation for crop monitoring through simple camera stream. The robot's movement is controlled with the purpose of keeping the row representing arrow close to the centre of the image. However, in such an approach, the navigation method has been generalized for fields containing strictly parallel rows separated by a specific distance and the concept has not been verified for complexities such as varying distance between rows.

Moreover, Li et al. [51] mounted a stereo vision camera on their robot and employed a novel AI approach. In their setup, deep convolutional neural network was used to train a model with set of images collected in the agricultural field and an improved version of Hough transform method then extracted a visual navigation path. Robot's posture was adjusted based on the correlation between the prior image and actual scene. Aghi et al. [57] used a very similar approach as a backup algorithm for their agricultural robot in which machine learning algorithm was trained on previous image dataset to use for visual navigation.

From all the available literature, it can be clearly seen that over the years the research trend has moved towards AI based navigation as it leads to better efficiency, accuracy and safety of the equipment as well as the crop.

B. Path Planning - Obstacles Avoidance and Algorithms

The path planning of a mobile robot can be divided into global and local planning. Global path planning is responsible for finding the optimal path to target through prior information of environment, whereas local planning, responsible for activities like obstacle avoidance, has little or no prior information of environment and must adapt readily. Local path planning has to be optimized for agricultural robotics because of the challenging dynamic environment [52]. Nguyen and Le [58] developed a path planning algorithm highly optimized for obstacle avoidance in applications of agriculture. The algorithm is independent of global information and the authors guarantee shorter path length and reliability. For a better local planning, Aksamentov et al. [59] have used a convolutional neural network to distinguish between vegetative and non-vegetative obstacles, classify them as passable or non-passable and then navigate accordingly. Similarly, Ball et al. [60] developed a system of visually aided guidance and navigation having novelty based obstacle detection. In this novelty-based detection, prior PCD mapping and global information is matched with the real time data and obstacle is detected through novel image regions.

Gao et al. [61] provide a hierarchy of the path planning search algorithms used in the wheeled agricultural robots. Dijkstra's algorithm is the most used algorithm in static environments but has low efficiency as it traverses all points. A* and D* are more optimized for static and dynamic environments respectively but are computationally expensive. Finally, authors suggest that the latest and immature Theta* and Phi* algorithms are most suitable for agriculture as they are not so complex, consume less computational resource and greatly reduce error. In short, the research on optimal algorithms for navigation is ongoing and is expected to continue with a higher pace in future. Currently, the cost-map based approach is most widely used in local and global path planning and is also used in [60]. A cost grid representation is formed of the environment where the obstacles have the highest values, and the algorithm tries to find the path that sums up to the least cost.

In efforts to develop optimized navigation algorithms for agricultural robotics, Mingjun et al. [62] performed experiments to compare the traditional local map based and CRFNFP (Conditional Random Fields based near-to-far perception framework) based navigation system and concluded that CRFNFP enhances the robot's ability to navigate through long range crop fields with efficient paths. Santos et al. [63] took an interesting approach for path planning in huge crop fields. They took satellite images of vineyards and trained their model to detect a vineyard from an image and extract Occupational Grid Map. A topological map is then created with delimited places and then a simple A* search algorithm is used to find the optimal paths in the map avoiding the delimited nodes.

C. Coverage Path Planning

Coverage path planning is considered one of the most important aspects of navigation and entails that an agriculture robot should cover the whole area with a continuous and sequential operation and without overlapping paths [64]. Hameed et al. [65] numerically developed 3D side to side coverage path planning approach and guaranteed that this approach can cover the entire agricultural field with no overlaps or skips even in rough terrains. Also, one important objective of coverage path planning is to deal with complex agricultural fields at a reduced operation time and increased efficiency [52]. Davoodi et al. [66] studied the feasibility of a group of agricultural robots for coverage planning and monitoring. The field was segmented based on a distributed density function and the robots were deployed to maximize operations at areas of interest. They validated and verified their work using simulation tools. Conesa-Muñoz et al. [67] developed a mathematical model for path planning of multiple robots for weed control. They used combinatorial optimization problem to cover the entire area with optimal transitions given that the field can be split into parallel tracks. All in all, navigation is the key to the robotics field in precision agriculture, with optimal path planning reducing work time, total distance travelled [68], reduced fuel consumption and less environmental impact [69].

IV. Activity planning and task execution

Once the robot has reached its target location after localization and navigation, it can continue with its main agricultural task like weeding, pruning, harvesting, monitoring etc. It includes the detection of parameters that are specific for the task and then using an end effector or specialized structure to execute the task. For example, in a robotic pruner for apple trees [13], the robot must reach the target tree, detect the tree structure, localize the pruning point and then perform the cut sequence using end effector. Considering the harvesting operation of apples, the activity planning and task execution can be subdivided into scanning, approaching, detaching and storing. Fig. 2 [70] provides an overview of the sequence of steps for apple harvesting.

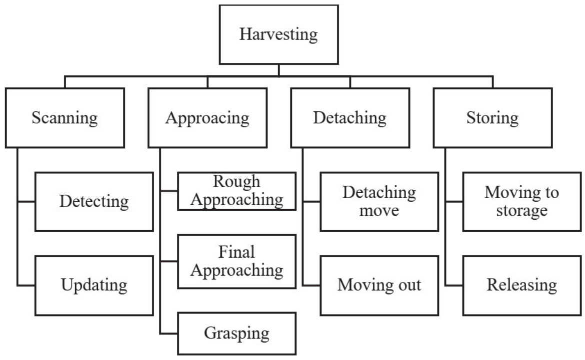

Fig. 2. Sequence of the steps for task (harvesting planning and execution) [70]

In view of this hierarchy of steps, a perfect coordination between the robot platform, detection sensors/systems and grasping mechanisms is required, which is a challenge for agriculture robots [70]. Handling agricultural products is extremely complicated because of their sensitivity to environmental and physical conditions, so they require gentle and accurate operations [21]. Additionally, detection and precisely reaching the correct position is the most difficult part in agricultural robotics and therefore is still performed manually [71] and significantly adds to the cost. Automation in this sub-operation is the essence of agricultural robotics.

The concept of automated industrial tasks is old, however the technology lagged because of the unavailability of sensors and systems. Li et al. [72] in their review signified the dependence of automated agricultural tasks on machine vision based systems. Now that, abundant vision hardware [28] and sophisticated software tools are available, the literature on performing agricultural tasks through feature detection and localization of fruits/plants etc. is maturing speedily. Gongal et al. [73] have provided a comprehensive review of the vision systems (B/W, color, spectral, thermal), features (color, geometric, texture, integration of features) and classification methods (K means clustering, KNN clustering, Bayesian classifier, neural network, support vector machine) used for fruit detection and localization. After successful detection, the localization of fruit is done by 3D reconstruction of environment using laser rangers, depth cameras, or stereo vision. In [73], their data suggests that detection through integration of several features, classification through support vector machine and localization through laser range finder can help achieve higher accuracies. Overall, AI and image processing techniques are solely the key methods to successful localization of the target subject (fruit, weed etc). However, vision systems are highly dependent on lighting conditions and is the biggest challenge for object detection in agricultural environments.

The end effectors for agricultural tasks are completely different from industrial ones and must be designed and optimized according to the application [74]. The challenges for end-effectors are:

- There is high variability in the shapes and sizes of end products e.g., fruits, branches, plants etc
- The fruits and other vegetation are much softer and can be damaged easily by gripper.
- Pruning and cutting end effectors require accuracy to not damage nearby plants.
- The product may not be stable in a dynamic environment.

Eizicovits et al. [75] proposed a method to grasp objects of variable shapes and sizes which can be extended to agricultural environment. In their method, 3D PCD is used to form grasp pose maps, such that agent perception capabilities are established enabling the grasping of objects from precise locations. Liu et al. [76] constructed models of end effector for vacuum sucking and pulling tomatoes. They proposed that the studies should be extended to incorporate the permissible extent of tensile forces and suction into the operation of end effector.

In addition to conventional single arm manipulators, following alterations [77] have been observed in literature for agricultural tasks:

a) **Multi Arm Manipulators:** They are primarily used to reduce operation time. Lytridis et al. [78] have listed all the relevant literature where multi arm manipulators are used in agricultural tasks (mainly harvesting). It has huge prospects such as approaching and grasping can be done with one arm and cutting with the other arm. Also such manipulators are extremely useful in environments where there is a need of moving away obstacles (leaves etc.) with one arm and grasping with the other.
b) **Soft Manipulators:** Their primary purpose is linked with the safety of agricultural product and nearby objects. These manipulators are inspired by the aspects of human hand such that the end products like fruits are not crushed when grasped by the gripper [79], [80].
c) **Parallel Manipulators:** A single end effector is attached to robot assembly through several arms. They have been extensively used in agricultural tasks [81]–[83]. Although extremely complex, they offer high accuracy, speed and payload capacity.
d) **Redundant Manipulators:** These manipulators have high degree of freedom (DOF) to avoid any joint limitations when reaching a target. They have abundant applications in agriculture [84]–[86]. where they need to avoid dense obstacles (leaves, branches etc.) in complex environments.

V. Conclusions and Future Directions

Mobile Robots are now finding large scale applications in agricultural sector, thanks to the advancements in sensor systems and software. This research field is important as it not only contributes towards reducing costs, labor shortages and work time as well as preserves environment by reducing waste, pollution and fuel consumption. This paper followed through the series of sub tasks that a robot goes through to perform a main agricultural task such as harvesting, pruning, monitoring etc and provided sufficient knowledge on these aspects through reviewing the current available literature.

Localization and pose estimation is an essential prerequisite and extremely challenging because of the unstructured nature of agricultural environments. Several sensor systems and a number of algorithms are available that are capable of highly accurate localization. However the challenges of dynamic environment and inconsistencies have raised the need of improved localization methods and thus extensive research is being carried out to come up with agriculture specific localization methods. Current research focus is the fusion of tested AI techniques with more precise 3D reconstruction (through LIDARS, depth cameras etc.). In future work, researchers are focusing on coming up with advanced AI methods such as semantic segmentation of tress, fruits etc and then incorporating this data into forming maps. The resulting SLAM approach with dense maps is expected to have highly improved localization.

Abundant literature is available on the navigation and path planning phase. Most of the agricultural robots navigate by detection of rows in crop fields and are incapable of planning paths through complex areas. That is why, the recent focus has been to use AI with vision systems to execute intelligent path planning and optimize obstacle detection. Currently, the systems detect neglect-able obstacles such as grass, leaves and branches that needs to be solved in order to further shorten the travelling paths. Also, some applications (seeding, monitoring etc) require full farm area coverage that is a potential area for algorithms' improvement.

The final and most important steps of object recognition (e.g., fruit detection) and task execution requires complete and perfectly synchronized system integration. The parameter detection phase is done through vision systems and machine learning but faces a huge challenge of light variability in environment. Research on end manipulators is also needed to come up with human-hand like tendencies to deal the product appropriately no matter the softness, shape or size. Various configurations of end effectors and manipulators are discussed that are developed for agricultural specific tasks but these are still far from natural levels. Finally, a stronger relation should be developed between the cost, time and labor savings as an incentive of agricultural robots for precision agriculture.

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