A REVIEW OF AUTONOMOUS NAVIGATION SYSTEMS IN AGRICULTURAL ENVIRONMENTS

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ABSTRACT
Mobile robots operating in agricultural environments have been a significant subject for researchers. The rapid advancement in communication, sensors and computing technologies has provided important progress in the field of agricultural autonomous robot guidance systems. Automated agricultural robots save labour costs, prevent people from performing risky operations, and provide the farmer with up-to-date and precise information to assist management decisions. The research on mobile robot navigation systems in agricultural environments consists of designing suitable systems for sensing, mapping, localisation, path planning, and obstacle avoidance. The navigation algorithm must use sensory information to determine a suitable trajectory, make a decision, and move correctly within its environment without collision. In this paper, an overview of navigation systems for autonomous agricultural vehicles is presented and discussed. The key elements are navigational sensors, computational techniques, and navigation control strategies. The selection, coordination, and combination of the optimal sensors to provide the basic information for mobile robot navigation are critical processes. Powerful algorithms are used for feature extraction, data processing and fusion. For autonomous navigation, steering controllers provide an appropriate steering action to automatically drive vehicles. Navigation of mobile robots in outdoor environments such as agricultural applications is still an open problem. The design of efficient and robust sensing and control systems for agricultural mobile robots is required to overcome the difficulties due to the weather conditions, dynamic environments, unexpected obstacles, terrain nature variations and vegetation.

Keywords: Agriculture, autonomous, control, laser, localisation, mapping, mobile robot, navigation, sensing, vision.

INTRODUCTION
Mobile robot systems have been introduced in different indoor and outdoor agricultural environments. These robots play a significant role in many agricultural applications since they reduce human labour and enhance the operation safety. The need for autonomous navigation systems of mobile robots has been recognised in different agricultural tasks such as planting, spraying, fertilizing, cultivating, harvesting, thinning, weeding, and inspection. In recent years, advanced technology has encouraged many researchers to develop more intelligent and adaptable vehicles. These vehicles should have sufficient amount of intelligence in order to behave sensibly for long time, whilst achieving specific tasks.

The design of mobile robots operating in outdoor environments such as agricultural applications is still a challenging subject. Navigation in agricultural environments presents difficulties due to the changes in weather conditions and variations of the nature of the terrain and vegetation. These environment characteristics have to be addressed and require the design and conception of efficient and robust sensing and control systems. The autonomy of the mobile robot is obtained by means of sensing the environment and employing appropriate control algorithms for specified task. The design of the robot and control algorithms needs to be planned and optimised before the robot executes the task. Comprehensive knowledge of the robot facilities and limitations, the environment characteristics, and the task requirements, is necessary to obtain good outcomes.

Previous reviews have demonstrated different aspects related to autonomous navigation of mobile robots in agricultural environments. The review paper by Rovira-Más (2010) analysed a variety of typical environments and situations encountered in agriculture and suggested suitable sensor architectures to meet the requirements of agricultural robots to perform different tasks. Grift et al.

(2008) presented a review study of agricultural automation technologies and addressed the topics of sensing and perception, reasoning and learning, data communication and task planning and execution. In the paper reported by Li et al. (2009), a review of agricultural vehicle guidance technologies has been presented. The authors focused on navigation sensors, computational methods, navigation planners and steering controllers.

The objective of this review paper is to provide an overview of recent innovations in autonomous navigation systems in agricultural environments. This paper focuses on global research in autonomous navigation techniques in the past 15 years. Autonomous navigation system for agricultural mobile robot consists of mobile robot navigation sensors, computational methods, and navigation control strategies. Figure 1 summarizes the basic elements of the autonomous navigation system of agricultural mobile robots.

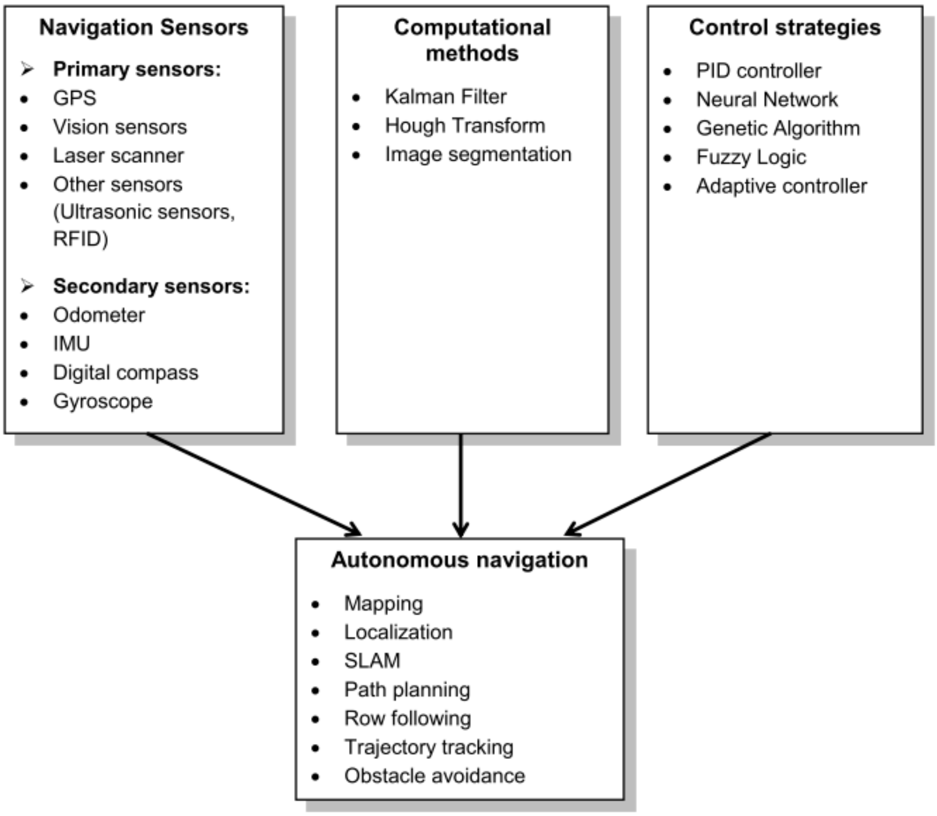

Figure 1: Basic elements of autonomous navigation system for agricultural mobile robots

PAPER OUTLINE

The paper is organised as follows. The following section describes some of the inherent difficulties and advantages for developing autonomous navigation in agriculture and explains the main aspects related to the autonomous navigation task in agricultural environments. The paper then reviews the literature according to what is believed to be the most important elements of autonomous navigation system for agricultural robots. The work reviewed is divided into three sections namely

- Mobile robot navigation sensors.
- Computational methods.
- Navigational control strategies.

The major focus in these three categories will be to distinguish between autonomous navigation in crop rows in the field and tree rows in the orchard. Finally, a summary of the significant conclusions of the reviewed literature is presented.

MOBILE ROBOT NAVIGATION IN AGRICULTURAL ENVIRONMENTS

Agricultural environments consist of various elements such as plants, trees, weed, soil, objects, and landmarks. This diversity creates some difficulties and complications in the mobile robot navigation process. For example, the cultivated areas are large and the ground surfaces are usually uneven. Weather conditions such as rain, dust, fog, and sun light may affect the data acquired by mobile robot sensors. The plant colour may change during different growth stages and the quality of soil may vary from one place to another. However, the agricultural environments provide some simplicity. For example, most crops/trees from the same kind are planted in straight rows and the intervals between the rows are almost equal. The landmarks that already exist in the field can be used as stationary landmarks for localization and navigation algorithms (Li et al. 2009). Figure 2a shows a view between two tree rows in an orchard, while example of crop rows is depicted in Figure 2b.

(a) **(b)**

Figure 2: (a) Tree rows; (b) Crop rows

Autonomous navigation is one of the important issues in mobile robots applications. The task of the navigation is to guide the robot safely and autonomously within different environments. The robot's navigation ability relies on complex sensor systems and intelligent control algorithms. The robot must be capable of sensing and detecting the surroundings firstly then analysing and modelling it. Navigation of the mobile robot in agricultural environments requires consideration of the position of the mobile robot and detecting the surrounding area and obstacles. The mobile robot should be able to avoid occasional unexpected obstacles such as dead or alive animals, fallen tree branches, and fence post. It is necessary to have a system for detection, mapping, position estimation, and navigation around any such object.

Many researchers have proposed automated or semi-automated agricultural robots that could explore their environment and build a map of the environment. The combination of different sensors has been employed to increase the robustness of the map. If the map of the environment was perfect, the robot can easily determine its position and orientation at each time. Localisation and map learning are interdependent processes because accurate localisation is necessary for building a good map, and having an accurate map is essential for good localisation. Simultaneous localisation and mapping (SLAM) is the technique used by autonomous vehicles to build up a map within an unknown environment, while at the same time using this map to localise their current location. Path planning is needed for automatic operation to find an optimal path from starting point to the goal position so that no collisions with obstacles occur.

Since most crops are planted in rows, an important step is to develop a row detection algorithm, which allows the mobile robot to accurately navigate along the row. In row recognition process, the problem is to find accurate features that are stable under different environmental conditions. The row detection process is accompanied with some difficulties such as incomplete rows, missing plants, and irregular shape and size of the plants along the row. In addition, the presence of weed along the row might distort the process of row recognition by adding some noise to the row structure (Åstrand & Baerveldt 2005).

MOBILE ROBOT NAVIGATION SENSORS

The use of sensors in agricultural vehicles has been increased rapidly in the recent years. Navigation sensors provide information about the vehicle states (position, orientation, speed, etc.) and the objects in the surrounding environment. Some guidance sensors provide information for absolute positioning and others only provide relative positioning. Different sensors such as Global Positioning System (GPS), vision, and laser range scanner are used in autonomous mobile robot systems as primary sensing systems. Ultrasonic sensors and RFID have also been reported in the literature as primary sensors but are less common. Other sensors such as odometer, inertial measurement unit (IMU), digital compass, and gyroscope are typically used as secondary sensors to complement the primary sensing systems.

Global positioning system (GPS)-based navigation

Global Positioning System based guidance technology has been widely used for many agricultural tasks. GPS guidance systems provide absolute position measurements which used to navigate the mobile robot to perform many field applications. To increase the accuracy of the conventional GPS navigation system, additional technologies have been developed by many institutions. The more recently developed systems are the Differential Global Positioning System (DGPS) and Real-Time Kinematic Global Positioning System (RTK-GPS) which require that the GPS base station be located within a specific distance from the agricultural robot receiver.

Research has been reported using the RTK-GPS as the only positioning sensor for the automatic steering system of agricultural vehicles (Stoll & Kutzbach 2000; Thuilot et al. 2001). Regardless of the kind of GPS, this navigational technology has some limitations when the GPS system is used as the single position sensor for autonomous navigation of mobile robots. Therefore, a GPS often combined with other sensors to provide more accurate navigation information (Hellström 2002). Examples of combining RTK-GPS with inertial measurement unit (IMU) can be found in (Eaton et al. 2010; Kise et al. 2002). Research has been developed using RTK-GPS and fibre optic gyroscope (FOG) sensors for autonomous agricultural vehicles (Nagasaka et al. 2004; Noguchi et al. 2002). The work of Nørremark et al. (2008) proposed the use of RTK-GPS with tilt sensor to develop autonomous system for intra-row weed control.

The most common problems with using GPS for navigation involve obstruction of line-of-sight to satellites, multi-path issues and interference from other RF sources (Hellström 2002). In some orchards, GPS cannot be effectively used for localization and navigation since the agricultural robots frequently move under the tree canopy, which blocks the satellite signals to the GPS receiver (Li et al. 2009). For these reasons, many researchers are developing autonomous navigation systems for mobile robots in agricultural environments without using the GPS as a primary sensor for navigation.

Vision-based navigation

Vision sensors have been widely used in mobile robot navigation because of the cost effectiveness of vision sensors and their capability to provide huge information that can be utilised to generate steering control signals for the agricultural mobile robots. Vision systems are becoming more common in outdoor agricultural applications such as localisation, map construction, autonomous navigation, path following, inspection, monitoring, and obstacle avoidance. One big disadvantage using vision sensors is the influence by varying ambient lightening conditions especially in outdoor environments.

Researchers have explored the use of different vision sensors to find guidance paths on crop rows. For instance, detecting the position and orientation of the crop rows relative to the vehicle and detecting the edges along harvested crops. They mainly focused on the development of different image segmentation techniques to extract the guidance information for crop rows applications. Billingsley and Schoenfisch (1997) investigated a vision-based guidance system which is relatively insensitive to additional visual noise from weeds. The algorithm developed by the authors used tracking window within the image to decrease the processing time and row-fitting algorithm to fit the best line for crop rows. An automatic row-following control system for a weeding cultivator that uses colour CCD camera was investigated by Okamoto et al. (2002). This system used the crop row images to determine the offset between the cultivator and the target crop row. The prediction of the offset improved the accuracy of row following. Benson et al. (2003) reported a machine vision-based guidance system for grain harvester using a single monochrome camera. The guidance algorithm was based on the lateral position of the crop cut edge and was capable of accurately locating crop rows. An example of row segmentation algorithm to obtain a guidance information to steer a tractor using monochrome CCD camera was proposed in (Han et al. 2004). The algorithm was acceptable for real-time vision guidance in term of its accuracy. Ortiz and Olivares (2006) suggested an approach to solve the autonomous navigation problem using a camera. The features extracted from the images used to map the plantation rows, within which the robot must navigate. Gottschalk et al. (2010) developed an autonomous field inspection vehicle using a webcam to navigate between two crop rows. The relative vehicle position was determined by image segmentation and classification and extracting geometrical lines corresponding to the crop rows. Researchers reported the use of spectral filters to enhance the detection of vision-based guidance systems for row crop following application (Åstrand & Baerveldt 2005; Kaizu & Imou 2008). These systems achieved good performance in detecting plants in near-infrared (NIR) images. Figure 3 shows the threshold image made from NIR image.

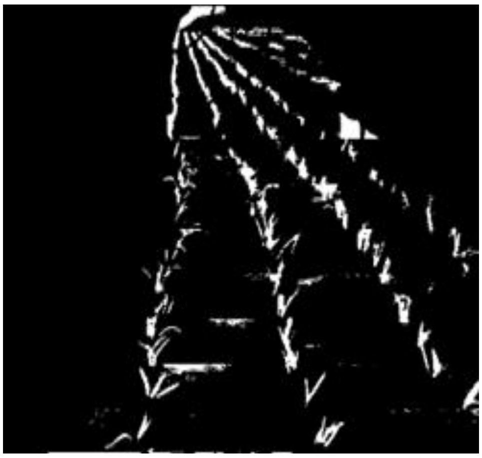

Figure 3: Threshold image from NIR image, reproduced from (Kaizu & Imou 2008)

Research on autonomous navigation of mobile robots for tree row following in groves and orchards is relatively rare. The difficulty of finding a possible path between rows lies in discrete planting of trees which breaks visual continuity of a row and adds complexity to the segmentation methods. A number of vision-based autonomous navigation systems have been developed for tree row following (Ayala et al. 2008; Gao et al. 2010; Torres-Sospedra & Nebot 2011; Zhang et al. 2012). These systems used different image segmentation and classification methods to extract the useful information for navigation and focused on optimizing the classification methods. They typically used line detection methods to locate guidance paths.

Stereo vision systems are also researched for autonomous navigation in agricultural application to provide a 3D field images by combining two field images taken simultaneously. The precision and maximum depth values are limited by the baseline between the two camera centres, and the accuracy of the distance measurements decreases as depth increases (Weiss & Biber 2011). Research has been done on developing stereo-based crop row detection systems (Kise et al. 2005; Rovira-Más et al. 2008). The results showed that stereo perception can provide the level of details and accuracy needed in construction of 3D field maps, localisation and autonomous navigation.

Laser scanner-based navigation

Navigation using laser scanners has been the source of countless research contributions. This is mainly because the laser scanners have the benefits of high resolution and large field of view. The laser scanner is one of the most popular devices in outdoor applications. It determines the relative distance of objects in the surrounding area by measuring time of flight of laser pulses. One important advantage of laser sensors over visual systems is the ability of providing robust ranging data for object detection and localisation. This enables the robot to operate more reliably at different weather and ambient illumination conditions.

Studies have been reported on the utilisation of laser sensors for crop row detection to extract guidance directions. They used various methods for line detection and sensor data fusion. The laser sensor is used as the navigation sensor and usually combined with other sensors using suitable data fusion algorithms. Satow et al. (2004) investigated an automatic crop row guidance system for tractor using a laser sensor able to detect the height and the position of crop rows. An autonomous robot tractor was developed by Yokota et al. (2005) to gather surrounding spatial information about crop growth and yield using laser scanner. Weiss and Biber (2011) used 3D LIDAR sensor for detection and segmentation of plants and ground to perform localisation, mapping and navigation for autonomous agricultural robot. In the work developed by Ahamed et al. (2011), 2D laser data was used simultaneously for growth monitoring and autonomous navigation with artificial landmarks.

Researchers have also investigated the potential uses of laser sensors for tree row detection in orchards and groves. Laser scanner data can be used to detect different components of the tree rows (e.g. trunk, stem, and canopy), whilst typically only plant canopy can be detected for row crops. Hansen et al. (2011) and Libby and Kantor (2011) used the laser scanner to detect the dense canopy of the tree rows. However, Libby and Kantor (2011) found that the use of reflective tapes to detect the ends of the rows as shown in Figure 4 reduced processing time and enhanced row detection. Hamner et al. (2010) suggested a method to detect trunk and/or canopy of the trees for tree row recognition. Hough transform then was implemented to extract point and line features to navigate the agricultural vehicle between the rows. In the study reported by Guivant et al. (2002), laser scanner was used to perform SLAM algorithm using the trunks of the trees as point features.

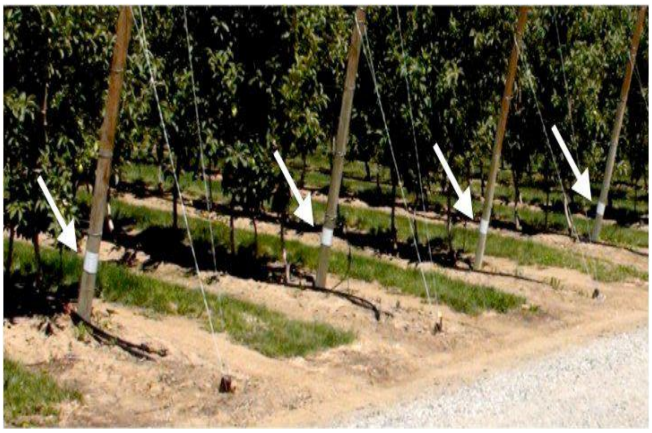

Figure 4 : Reflective tape placed around posts at the ends of rows, reproduced from (Libby & Kantor 2011)

Laser scanner was used in some studies to determine distances and bearing angles of the trees and obstacles in the orchard, then line detecting methods were used to detect the tree rows and to provide the lateral and heading errors between the robot and orchard rows (Andersen et al. 2010; Barawid Jr et al. 2007; Hamner et al. 2010; Tsubota et al. 2004). Figure 5 shows an outline of the orchard rows recognition using Hough transform. The distances and angles of the trees measured by the laser scanner were used to estimate the position and orientation of the agricultural mobile robots using different data fusion algorithms (Christiansen 2011; Hansen et al. 2011; Libby & Kantor 2011) .

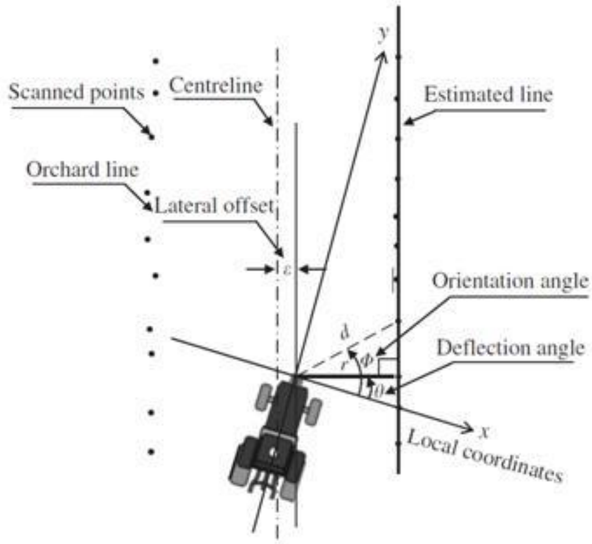

Figure 5: Outline of the orchard rows recognition using Hough transform, reproduced from (Barawid Jr et al. 2007)

Laser scanner and vision based navigation

In some semi-natural environments like fields or orchards, both vision camera and laser range scanner can be used as primary sensors for autonomous navigation. Integration of both machine vision and laser scanner provides more robust guidance for autonomous navigation system of the mobile robot, as well as increases object detection capability. The work of Subramanian et al. (2006) presents an autonomous guidance system based on machine vision and laser radar for guidance and a rotary encoder to provide feedback on the steering angle. The guidance system guided the tractor automatically through straight and curved paths. A combination of laser scanner and camera has been used to develop SLAM-based system (Auat Cheein et al. 2011; Debain et al. 2010). Debain et al. (2010) used Extended Kalman Filter (EKF) for data fusion, whereas Auat Cheein et al. (2011) used Extended Information Filter (EIF) and found that it is more appropriate for real time application because EIF improves the processing time.

Other sensors

Ultrasonic sensors have been introduced in some studies for plant recognition to navigate the mobile robot in agricultural environments. However, their use is restricted in outdoor application since they require the objects to be perpendicular to the sensor for the ultrasonic echoes to be reflected back properly. Toda et al. (1999) presented a sonar-based crop row mapping technique to identify the maize row to navigate the robot in an agricultural environment. Harper and McKerrow (2001) used ultrasonic sensors for plant recognition for navigation task. They applied correlation of echoes from many orientations to enhance the accuracy of plant recognition. The work of Iida and Burks (2002) presented the use of ultrasonic sensors to measure the relative position between a tractor and tree canopy for navigation of the tractor in the orchard. In the paper presented by Ampatzidis et al. (2009), a novel location technology based on radio frequency identification (RFID) has been proposed for yield mapping system. Special passive RFID tags attached to the trees and bins and a RFID reader located on the harvesting platform were utilised to identify the trees and the bins.

COMPUTATIONAL METHODS

Powerful algorithms and methods are necessary to extract key features from the environment to automatically drive vehicles. Different computational techniques are used to deal with sensor data fusion to provide the required information for agricultural vehicle autonomous navigation. The most commonly used computational methods in the literature are Kalman filter, Hough transform and image segmentation.

Kalman filter
Kalman filter (KF) provides a robust mathematical method for multi-sensors data fusion in real time. The multiple measurements that have been gathered over time, containing random variation (noise) are combined mathematically to estimate the states of the system at each time instant. This method not only can estimate the previous or the present state, but also can predict the future status. The standard version of the KF is designed to be applied to processes that can be described by linear stochastic differential equations. In most cases, mobile robot systems have nonlinear characteristics. Hence, extensions to this filter have been developed. Extended Kalman filter (EKF) has been adapted to solve the problem of nonlinear systems.

Research has been reported on attempts to use KF to estimate the pose (position and orientation) of the agricultural vehicles, once appropriate models for the vehicle and the sensors are obtained. These studies mainly used the data collected from different sensor. A number of papers proposed the integration of GPS with other sensors using KF to improve the accuracy of the estimated position (Han et al. 2002; Nørremark et al. 2008). KF is commonly used to combine laser data with the data from other sensors for mobile robot localisation in orchards. Libby and Kantor (2011) used two laser scanners and encoders to perform EKF algorithm to localise the mobile robot in orchard environment, whereas Christiansen (2011) used laser scanner, odometer, and IMU to improve the position estimation. EKF is often combined with different optimisation techniques and control strategies to improve its performance. Subramanian et al. (2009) developed a fuzzy logic enhanced KF for sensor fusion for guiding an autonomous vehicle using machine vision, laser radar, IMU, and speed sensor.

SLAM problems can be efficiently solved by using different types of filters reported in the literature. EKF can be considered as the most widely used algorithm to solve the SLAM problem. However, EKF-SLAM has disadvantages of its processing time and computational requirements. The complexity of EKF-SLAM increases with the number of the landmarks and features in the map. EKF has been introduced in some studies to implement SLAM problem (Christiansen 2011; Guivant et al. 2002). Unscented Kalman filter (UKF) can be used as an alternative filter to the EKF to achieve the SLAM algorithm, which shows a better performance than the EKF when dealing with the nonlinearities associated with the process and observation models. On the other hand, the Extended Information filter (EIF) improves the processing time of the SLAM algorithm because of its linear computational cost. Thus, the EIF is more suitable for real time applications (Auat Cheein et al. 2011). The difference between EKF and EIF is that they have different form of the information. EIF uses inverse matrix of the covariance matrix which is known as information matrix in order to express the uncertainty in the SLAM (Yan et al. 2009). Auat Cheein et al. (2011) studied SLAM problem using vision system and laser sensor to detect the olive stems. They implemented optimised EIF-SLAM algorithm which improved the processing and estimation time.

Particle Filter (PF) is also used to solve the SLAM problem. Unlike the EKF, the PF is not restricted to Gaussian processes and it has a better managing of non-linearities associated with the estimation process, but the real time implementation of the PF is still limited (Auat Cheein et al. 2011). Kurashiki et al. (2010) presented a self-localisation algorithm consisting of a 2D laser sensor and a particle filter to handle the sensing uncertainties. Hansen et al. (2011) described the use of three derivative-free filters for mobile robot localisation and navigation in an orchard. The localisation solution uses the tree rows as measurements to correct the pose estimated by the filters. They concluded that the derivative-free filters were more flexible towards changes in the system and measurement model descriptions.

Hough transform
Hough transform is a feature extraction technique used in image analysis, computer vision, and digital image processing. It is used to isolate the features of a particular shape within an image. The classical Hough transform was concerned with the identification of lines in the image, but later it has been improved to identify the locations and orientations of certain types, most commonly circles or ellipses. Row detection is mainly associated with autonomous navigation. As most crops and trees are

cultivated in rows (usually straight lines), most of the image processing algorithms for row detection are based on Hough transform.

Hough transform has been used effectively in many studies for straight line recognition of crop or tree rows using vision or/and laser scanner as navigation sensor (Ayala et al. 2008; Barawid Jr et al. 2007; Gao et al. 2010; Hamner et al. 2010; Leemans & Destain 2006; Torres-Sospedra & Nebot 2011; Tsubota et al. 2004). Figure 6 depicts an example of using Hough transform for detecting tree rows and constructing a path located midway between two rows. In the work of Åstrand and Baerveldt (2005), the authors described a method for robust recognition of plant rows based on the Hough transform that is able to guide agricultural machines. The novelty of their algorithm was that they modelled a plant row with a rectangular box instead of a line.

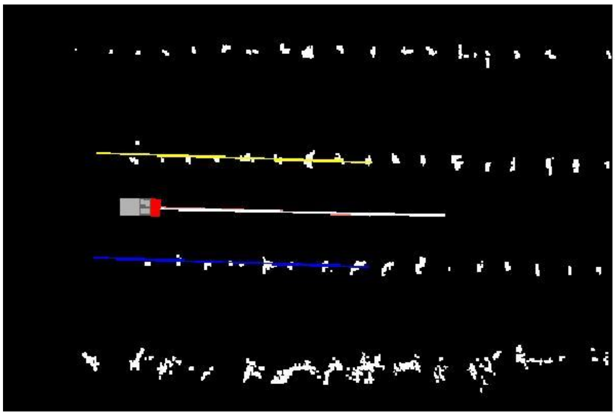

Figure 6: Hough Transform for detecting tree rows, reproduced from (Hamner et al. 2010), in colour

Image segmentation

In computer vision, segmentation refers to the process of partitioning a digital image into multiple regions or set of pixels. It is typically used in mobile robots to locate objects and boundaries (lines, curves, etc.) in images. In agricultural environments, image segmentation techniques are used to separate the objects in different classes (crop, background, weed, trees, etc.) to extract the guidance information for row following.

Various methods of image segmentations have been investigated in the literature to extract the guidance information. Han et al. (2004) developed a row segmentation algorithm based on k-means clustering to steer a tractor in both straight and curved rows. Figure 7 demonstrates the use of k-means clustering algorithm to compute a threshold in the region-of-interest (ROI). Benson et al. (2003) studied the use of histogram based segmentation and edge detection to detect the crop rows. In the paper presented by Gottschalk et al. (2010), a combination of histogram-based method, threshold function, and morphological imaging functions was used for extracting geometrical lines corresponding to the crop rows to calculate the relative vehicle position. Ericson and Astrand (2010) described a method of detecting parallel rows using a combination of an edge-based method and a Hough transform. They presented a novel edge-based method to find lines and further rectangles in the images. Ding et al. (2011) presented a novel method for mature wheat cut and uncut edge line detection, termed wavelet image rotation and projection algorithm. This algorithm calculates two important control parameters, navigation heading angle and lateral position. The study of Torres-Sospedra and Nebot (2011) developed an algorithm which is a combination of edge detection and Hough transform to extract the desired path between the tree rows. In the work presented by Jiang et al. (2011), perceptual colour clustering and morphological image processing have been used to obtain the segmented path, then least-square curve fitting method has been used to obtain the optimal navigation path. Gée et al. (2008) suggested the use of region segmentation method and double Hough transform for crop row recognition. Lulio et al. (2012) used JSEC algorithm with Artificial Neural Networks (ANN) for segmentation and classification of agricultural scenes for navigation problem.

Segmentation with the JSEG passes through three stages: colour space quantization, hit rate regions and similar colour regions merging.

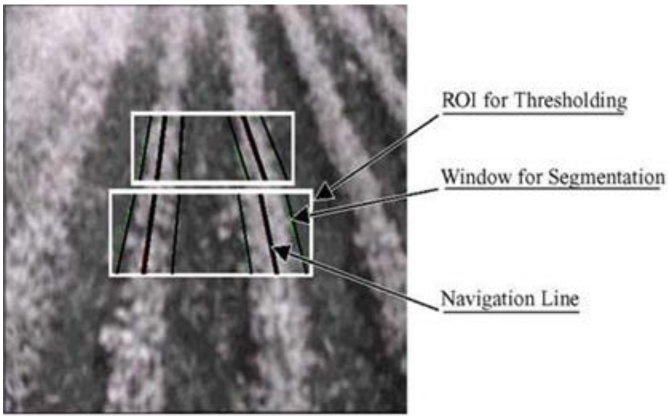

Figure 7: Region-of-interest (ROI) for image thresholding and navigation lines, reproduced from (Han et al. 2004)

NAVIGATION CONTROL STRATEGIES

Steering controller design for agricultural vehicles is a difficult challenge. Agricultural mobile robots usually operate on various types of terrain, even and uneven, or changing and unpredictable terrain. For autonomous navigation, steering controllers should be able to provide necessary steering commands in response to the variation in mobile robot state, travelling speed, ground conditions, and other factors affecting steering dynamics (Li et al. 2009). Different control strategies such as Proportional-Integral-Derivative (PID), Neural Network (NN), Genetic Algorithm (GA), and Fuzzy Logic (FL) have been identified in the literature. An intelligent controller of autonomous mobile robot that can navigate to a target position in known or unknown environments is shown in Figure 8.

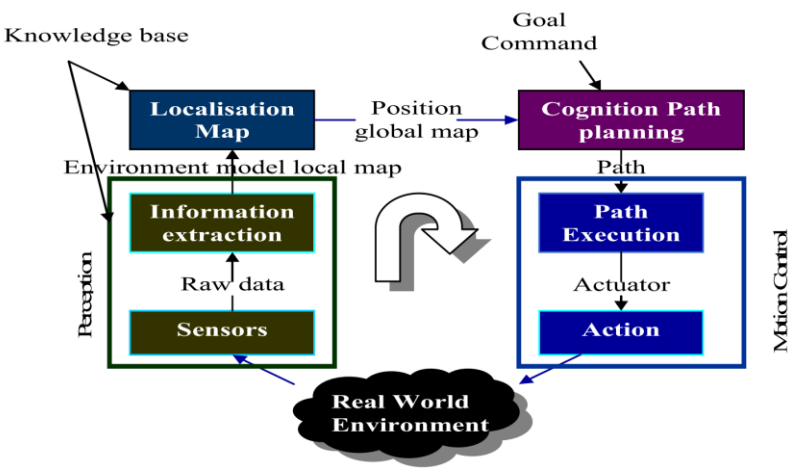

Figure 8: Schematic view of intelligent controller, reproduced from (Singh et al. 2008)

Proportional-Integral-Derivative (PID)

Proportional-Integral-Derivative (PID) controller has been used in many studies for guidance system of mobile robots in agricultural environments. An approach for autonomous navigation problem in agricultural environment using proportional-integral (PI) control for the steering control of the agricultural robot was reported in (Ortiz & Olivares 2006) . The authors concluded that the robot was able to navigate in real plantation with acceptable behaviour. Benson et al. (1998) suggested the design of a PID steering controller for an agricultural tractor guided by a geomagnetic direction sensor. Its closed-loop transfer function was obtained experimentally and the test results showed that this controller achieved satisfactory automated guidance. In the work investigated by Subramanian et al. (2006), a PID controller was developed to minimize the path error and steer the tractor through the alleyway of a citrus grove using the information from the vision system and laser radar. Another example of using PID controller to control the position of a cultivator based on the information from the row recognition system is introduced in (Åstrand & Baerveldt 2005). PID was also proposed in the work of Nørremark et al. (2008) to steer unmanned hoeing system for intra-row weed control.

Neural Network (NN) and/or Genetic Algorithm (GA)
In some agricultural application, NN and/or GA have been applied to control the motion of the mobile robot. Torisu et al. (2002) designed a NN vehicle model instead of a dynamic or kinematic model to express the input-output relationship of vehicle motion on sloping land. Zhu et al. (2005) developed a NN vehicle model for estimating vehicle behaviour on sloping terrain. A training method combined with GA and back propagation algorithm was used to train the NN vehicle model. The tractor was successfully guided along a predetermined path. Ryerson and Zhang (2007) presented a GA-based path planner for machinery operating on agricultural field. GA was chosen to create an optimal path guiding the vehicle to completely cover a field while avoiding all known obstacles.

Fuzzy Logic (FL)
FL control is well suited for controlling a mobile robot because it is capable of making inferences even under uncertainty. It also deals effectively with complex and non-linear processes. FL controller has been implemented in autonomous navigation of mobile robot in agriculture. Toda et al. (1999) presented a navigation method, which employs sonar-based mapping of crop rows and FL control to steer a wheeled mobile robot in an agricultural environment. Benson et al. (2003) suggested the use of FL controller to develop machine vision guidance algorithm to guide an agricultural combine harvester. Results indicated that the algorithm performed accurate cut-edge detection. In the study reported by Rovira-Mas et al. (2005), FL model was proposed to fuse navigational information proceeding from a differential GPS and a machine vision perception engine. Martín et al. (2010) described the implementation of a fuzzy steering controller for safe obstacle avoidance in unmanned navigation of a robot tractor under different ground conditions.

There are different adaptive fuzzy approaches used in outdoor environments such as Neuro-fuzzy and Genetic-Fuzzy techniques which are flexible and can be adapted to agricultural environments. Neuro-fuzzy is the combinations of NN and FL. A NN assists learning and adaptation and FL assists rules generation and decision-making. Marichal et al. (2001) and Zhu and Yang (2007) developed a neuro-fuzzy approach for autonomous mobile robot. A learning algorithm based on NN was developed to tune the fuzzy rules and the membership function automatically. In the research developed by Joshi and Zaveri (2011), a neuro-fuzzy based system was proposed for reactive navigation of a mobile robot using behaviour based control. The proposed algorithm used discrete sampling based optimal training of NN.

In recent years, GA algorithms have been used for automatic learning of fuzzy control rules and membership functions for autonomous navigation of mobile robots. Cho and Lee (2000) used a FL controller for the autonomous operation of an orchard speed sprayer. The developed fuzzy logic controller was optimised using GA. Hagras et al. (2004) presented a fuzzy-genetic techniques for the on-line learning and adaptation of an intelligent robotic navigator system. Such a system could be used by autonomous mobile vehicles navigating in unstructured and changing environments.

CONCLUSION
Historically, agricultural applications have evolved from the use of labour to accomplish most of the agricultural operations to the use of highly automated agricultural equipment. From the literature reviewed, it is argued that using mobile robot with multi-sensor combination (primary and secondary sensors) provides more robust guidance system. The basic idea behind sensor-fusion is that by combining different sensor data, more accurate navigation, mapping, and position estimations of mobile robot can be obtained. On the other hand, using many sensors will add cost and complexity to the system design. From the previous studies, GPS can be unreliable for a closed canopy in an orchard. Camera and laser range scanner can be considered as the most promising sensors used as primary

sensors for guidance. Each one can be used individually or they can be used together with other secondary sensors such as odometer, IMU, digital compass, and gyroscope.

Hough transform with a suitable image segmentation method can be used for mapping the environment and for row detection. For localisation and SLAM, EKF can be considered as the most promising techniques for sensor data fusion which provides accurate estimation of the position and the orientation of the mobile robot.

The literature to date indicates that different control strategies are used for autonomous navigation of mobile robot. PID controller is commonly used in control applications and has a simple structure, but it requires a good system model. Thus, it is unsuitable for highly non-linear robot systems and uncertain environments. Intelligent controllers especially FL controller can be considered as the most promising control algorithms that can control and enable the robot to navigate in real world environment. FL controller integrates human knowledge on vehicle driving in a set of linguistic expressions. It is widely used as steering control for mobile robots due to its simplicity and effectiveness as a non-analytical model that embed human expert knowledge. It can be fused with NN or GA for learning and adaptation. Amongst the adaptive FL approaches, neuro-fuzzy algorithm was found as the most robust technique used for autonomous navigation of the mobile robot.

From the reported literature, autonomous navigation system for mobile robot is taking an increasing presence in agriculture. However, more research needs to be achieved to improve technology, overcome the limitations of fully automated agricultural vehicles and decrease the cost.

ACKNOWLEDGEMENTS
The senior author would like to acknowledge the University of Technology, Baghdad, Iraq for funding the PhD scholarship.

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