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Automatic guidance systems in agricultural autonomous robotic machine: A review

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Abstract
A brief review of the automatic guidance system is described in this paper. The navigation system includes different navigation sensors, vision sensors and computational methods for the development of automated guided vehicles. These navigation systems have been used for vehicle steering control systems. The developed machine is guided by different sensor-based and vision-based technology having RTK-DGPS navigation system that whole system will be useful for performing several agricultural operations such as tilling, spraying of pesticides, granular fertilizer application, weeding, harvesting, etc. Vision-based and sensor-based technologies are becoming very popular for guidance systems of the agricultural automated guided vehicle. Several types of research have been invented and many prototypes developed based on these guidance systems but have not proceeded into commercialization yet. IoT in agriculture, robotics, artificial intelligence and other sensor and vision-based technologies will augment the realization of agricultural vehicle automation in the future.

Keywords: Automatic guidance system, vision-based, sensor-based, navigation

Introduction

The concept of a fully autonomous machine for agricultural operations is far away from new, i.e. driverless tractor using leader cable guidance systems was originated in the 1950s (Morgan, 1958). For several years, robotic systems have been used for industrial production and in warehouses, wherever controlled surroundings are often secured**.** In agriculture and forestry, research into driverless machines has been a vision initiated in the early 1960s with basic research on projects on automatic steered systems and autonomous tractors (Wilson, 2000). A combined application of novel sensor systems, communication technologies, geographical information systems (GIS) and global positioning systems (GPS) have enabled researchers to develop new autonomous machines for different crops in the agriculture and horticulture sector as well as for landscape management**.**

In the 1980s, the potential for combining computers with image sensors provided opportunities for machine vision-based guidance systems. In the mid of 1980s, researchers at Michigan State University and Texas A & M University had explored the machine vision guidance system. In 1997, agricultural automation has become a significant issue together with the support of precision agriculture. The potential benefits of automated agricultural machines have increased productivity, application accuracy and enhanced operator safety. Additionally, the rapid advancement in electronics, computers, and computing technologies has inspired renewed interest in the development of machine guidance systems.

Automated guidance control aims to steer the machine following the desired path automatically. It requires a guidance system to be able to detect machine posture, create a proper steering signal and steer the machine according to the signal. The posture is named as the position and orientation of the machine (Kanayama and Hartman, 1989). Different guidance sensing systems, including mechanical, optical, radio, ultrasonic and leader cable systems have been developed for agricultural machines during the past several decades (Richey, 1959; Kirk *et al*., 1976) [22, 14]. Within the past two decades, vision sensors and GPS sensors are value-added to the list of available guidance sensors. Although, each system uses different technologies to guide machines.

Review on Automatic Guidance Systems

Guidance is the "driver" of a machine. It takes input from the navigation system and uses targeting information to send signals to the steering systems that will allow the machine to reach its destination.

Generally, three types of guidance systems have been used namely Sensor-based guidance system, Vision-based guidance system and RKT-DGPS based autonomous field navigation system.

Sensor-Based Guidance Systems

In the sensor-based guidance system, different types of sensors have been used for sensing the plant or row. Sensors are used as input devices in which sensors sense the plant or row and send commands to the microcontroller for signal processing and create output for agricultural operation.

Shivaprasad *et al*. (2014) [25] developed a robot for seed sowing and fertilizer application to reduce manpower, time-consuming, and increase productivity. The robot system was used to develop the process of cultivating agricultural land without using manpower. The robot was designed for performing several tasks like plowing the land, seed sowing, watering to the plant, fertilizing and navigation using a microcontroller. The obstacle was detected by using an ultrasonic sensor. The robot was navigated in forward and reverse direction as well as turning right and left directions. Satisfactory performance was found during testing with lateral movement accuracy of 10 cm.

Celen *et al.* (2015) [5] designed an autonomous agricultural robot to navigate in between rows with the help of an ultrasonic sensor. The robot was designed independently to drive through the row crops in a field. The offset of the robot was detected in real-time and corrected that offset error for guiding the robot inside the crop row and also turned at the end of the rows to the adjacent row automatically. The white diluted paint was used to drop onto the soil during the movement of the robot. The paint helped to visualize the path of robot movement. The offset was derived from the distance between the paint and the real center of the rows. Experimental results showed that algorithms of row guidance and headland turn were according to the parameters measured and analyzed such as the offset for row guidance and the difference between the motion trajectory and the expected trajectory. The accuracy of row guidance was ±70 mm at the speed of 1 m/s.

Jorge (2017) [12] developed an object avoidance robot (alseTv1) which used three HC-SR04 ultrasonic sensors to detect potential obstacles and correct its trajectory in the Arduino Nano microcontroller. AlseTv1 was the first succession of a sophisticated project which would make the integrated and advanced robot using Raspberry Pi, Raspberry Pi camera module, AMG8833 Grid-Eye infrared array sensor to process signals from different sensors.

Shinde and Awati (2017) [24] developed an automatic seed sowing machine using battery-powered wheels and an inbuilt DC motor. There was a provision of an alarm system for detecting the level of storage seed. The seed sowing machine was detected obstacles very easily using an ultrasonic sensor. Buzzer was indicated when any obstacle comes in the in-front of the machine or diverts path. A seed was fall from the seed drum in each complete rotation of the rotating wheel. The seed dropping process was taken place smoothly as well as without wastage of seeds. The alarm was indicated once the whole system ended. This system was worked efficiently with alarming and indicating facilities.

Sowjanya *et al.* (2017) [27] developed a multipurpose autonomous agricultural robotic machine that was controlled through bluetooth for plowing, seed showing, and irrigation systems. It was especially important for the farmworkers in the potentially harmful area for safety and health. The robot was used to minimize manpower, making proper irrigation and efficient utilization of resources. The robot was mainly useful for weed control and management, fertilizer application based on soil conditions and requirements and soil sensors for drip irrigation in rainy areas.

Saravanan *et al.* (2018) [23] developed an automatic seed sowing robot operated by clean energy for chickpeas seed which minimized the working cost and the time for digging. A proximity sensor was used in this robot to convert rotations to distance with a 12V battery, which then gave the necessary power to a DC motor. This power was then transmitted to the shaft to drive the wheels and further reduction of labor dependency. IR sensors were used to maneuver the robot in the field. Seed sowing and digging robot moved on different ground contours and performs digging and sowing the seed. The low cost of the machine as well as its ability to carry out sowing and fertilizing simultaneously was certainly a boon to the farmers which was saving much of their time. Results showed almost 60% saving in operational cost and 15% saving in seed requirements.

Vision-Based Row Following Systems

Gerrish *et al.* (1997) [7] tried to implement a vision guidance system on a Case 7190 MFD tractor at Michigan State University. The camera was mounted 2.8 m above from the ground level on the left side of the machine with a tilting 15° below the horizon and a facing beyond the machine. When the zoom angle was correctly set, the optical cone angles were found accordingly 20.2° in the lateral direction and 16.8° in the forward direction. The automatic guidance system was tested in a straight row at tractor speeds of 4.8 and 12.9 km/h. Results were drawn in both speeds. The maximum tracking errors were found as 6.1 and 12.2 cm respectively at the speed of 4.8 and 12.9 km/h.

Sogaard and Olsen (2003) [26] described a method based on computer vision for the detection and localization of crop rows, especially of small-grain crops. The method was proposed to use an automatic guidance system in agricultural machinery i.e., an automatic guidance system deployed in an inter-row cultivator. The computer vision system consisted of a color vision camera and a computer. The camera focused on the field surface from an inclined angle to obtain images that covered up to about five rows simultaneously. New images were continuously transferred to the computer, which processed them and calculated the necessary lateral movements of the implement. The processing method was not included a segmentation step, which was found in most of the other methods for plant detection. The segmentation step was replaced by the computation of the center of gravity for row segments in the image. This approach proved to reduce the computational burden of the image processing software. The estimation of the orientation and the lateral position of the center lines of the rows was accomplished by weighted linear regression. The accuracy of estimation was determined by comparing the calculated row centerline with the position of a reference string, which was placed parallel to the row along the centerline of an adjacent inter-row space. Experiments indicated that the row position could be estimated with an accuracy of about ± 6 mm to approximately ± 12 mm depending on the crop.

Reid *et al.* (2004) [21] developed a row segmentation algorithm based on *k*-means clustering to segment crop rows. A vision-based automatic guidance system for row-crop applications was used for finding guidance information from crop row structure and achieving accurate control of the machine. They described a robust procedure to obtain a guidance directrix. The procedure included row segmentation by *K*-means clustering algorithm, row detection by a moment algorithm, and guidance line selection by a cost function. Two image data sets, one taken from a soybean field and the other taken from a cornfield, were used to evaluate the accuracy of the proposed image processing procedure. The average RMS offset error from 30 soybean images was 1.0 cm with an average cost of 4.99 ₹. In contrast, the average RMS offset error from 15 corn images was 2.4 cm with an average cost of 7.27 ₹. The proposed image processing procedure was implemented on the vision-based guidance of the tractor. An automatic guided tractor was able to perform cultivation operations in both straight and curved rows**.**

Will *et al*. (2005) [31] applied the Hough transform and connectivity analysis in the image processing technique and found an appropriate pathway in the field. Pre- and post-processing of the image of the tractor's forward view were crucial for an effective application of the Hough transform. Pre-processing included the determination of a suitable region of interest (RoI), appropriate dynamic thresholding, and midpoint encoding. Post-processing incorporated the connectivity analysis algorithm to obtain the best-estimated lines, which represented the detected crop rows. The lines generated by the crop row detection method were consistent with a qualitative evaluation of actual crop row locations and allowed correct signals for wheel steering. This method was tested with other crops aligned in rows to determine its full versatility and robustness. The Hough transform was used to detect row crops and the connectivity analysis was implemented to recognize the most appropriate path from all possible choices. This system was implemented in an agricultural tractor which was tested in both laboratory and field experiments. The methodology devised was used to overcome image noise problems and successfully determine the proper trajectory for the tractor.

Subramanian *et al.* (2006) [28] developed an autonomous guidance system for use in a citrus grove. A common tractor as a machine was used for this study**.** Machine vision and laser radar (lidar) were individually used for guidance and a rotary encoder was used to provide feedback on the steering angle. A PID controller was developed to diminish the path error. The machine's guidance accuracy was tested by inflexible test paths constructed of common hay bales**.** Path tracking performance was observed. The guidance system guided the tractor automatically through straight and curved paths**.** An average error of 2.8 cm using machine vision guidance and an average error of 2.5 cm using radar guidance were observed when the machine was tested in a curved path at a speed of 3.1 km/h. The guidance system has guided the machine successfully in a citrus grove alleyway.

Bakker *et al.* (2008) [2] developed a new approach for row recognition based on grey-scale Hough transform on intelligently merged images resulting in a considerable improvement of the speed of image processing. A color camera was used to obtain images from an experimental sugar beet field in a greenhouse. The color images were transformed into greyscale images resulting in good contrast between plant material and soil background. Three different transformation methods were compared. The greyscale images were divided into three sections that are merged into one image, creating less data while still having information of three rows. It was shown that the algorithm was able to find the row at various growth stages. The mean error between the estimated and real crop row per measurement series varied from 5 to 198 mm. An average error from the crop row detection was about 22 mm. High errors were found mainly due to factors that did not occur in a good manner or observed in the limited number and size of crop plants, overexposure of the camera, and the presence of algae. Inaccuracies created by footprints was indicated that the linear structures in the soil surface in a real field might be created problems that should be considered in further investigations. In two measurement series that was not suffered from these error sources, the algorithm was able to find the row with mean errors of 5 and 11 mm with standard deviations of 6 and 11 mm. The image processing time varied from 0.5 to 1.3 s per image.

Xue and Xu (2010) [33] designed an autonomous agricultural robot platform based on a vision-based row guidance method to drive through the row crops in a field. The offset and heading angle of the robot platform were detected in real-time to guide the platform based on recognition of a crop row using machine vision. The preliminary experiments of the row guidance system were implemented in a vegetable field. Algorithms of row identification and row guidance were effective according to the parameters measured and analyzed, such as heading angle, offset for row guidance, the difference between the motion trajectory of the robot and the expected trajectory. The accuracy of row guidance was up to ± 35 mm, which meant that the robot worked with high accuracy.

Pajares *et al.* (2011) [19] developed a computer vision system to successfully discriminate between weed patches and crop rows under uncontrolled lighting in real-time. The system consisted of two independent subsystems, a fast image processing delivering results in real-time (Fast Image Processing, FIP), and slower and more accurate processing (Robust Crop Row Detection, *RCRD*) that was used to correct the first subsystem's mistakes. Tested on different maize fields and during different years, the system successfully detected an average of 95% of weeds and 80% of crops under different illumination, soil humidity, and weed/crop growth conditions. Moreover, the system showed to produce acceptable results even under very difficult conditions, such as in presence of dramatic sowing errors or abrupt camera movements.

Cruz *et al.* (2012) [6] developed a crop row detection method in the maize fields having high weed pressure. The vision-based system was designed and installed on a mobile agricultural machine. The image processing consisted of three main processes which were, Image segmentation was based on the application of a vegetation index, the double thresholding based on Otsu's method to achieve the separation of weed and crop and last, applied the least-squares linear regression in crop row detection for line adjustment. Crop and weed separation was effective and the crop row detection was favourably compared against the classical approach based on the Hough transform.

Pajares *et al.* (2013) [20] evaluated a vision-based automatic expert system for the accuracy of crop row detection in maize fields. The vision system was designed for a mobile agricultural robot with considering vibrations, gyros and uncontrolled movements. Crop row was identified by applying geometrical parameters under image perspective projection in a vision-based technique. The first one was intended for separating green plants (crops and weeds) from the rest of the others (i.e. soil, stones, and others). The second one was based on the system geometry where the expected crop lines were mapped onto the image and then a correction was applied through the well-tested and robust methodology. They designed an automatic method for crop/row detection in the maize field by applying automatic thresholding as the first step for plants identification. In a second stage, they applied the Theilsen estimator for accurate crop row detection.

Wang *et al.* (2013) [30] proposed a path recognition method for an agricultural robot vision-based navigation system under a weed environment. The soil background was eliminated by image segmentation based on color components. The weed noise was filtered by deleting small-area objects in the binary image. The crop centerlines and navigation path were extracted through Hough transformation. Experimental results showed that weed noise was eliminated from the field image. The path recognition method in the research was practical and accurate for vision-based robot navigation. The method proposed in the research was aimed at a straight-line navigation path, which was of little curvature. Further, research would be focused on navigation paths with big curvature.

Adeel and Khurram (2014) [1] developed a small size low-cost interactive robot for precision farming. The robot had a computer vision technique to automate the process of navigation. To maintain the course of action, the robot followed the rows of the crop in the field through an image processing algorithm. In this algorithm, the binary image was first split into several horizontal strips and then with the help of the vertical projection method, row position was estimated and finally detected the rows by using Hough transformation.

Jianbo *et al.* (2014) [10] developed a new method for path detection suitable for rice, rapeseed and wheat high crop stubble tilling conditions. First, the distribution characteristics of rice, rapeseed, and wheat high crop stubble images in paddy fields were analyzed based on the RGB color model. The color images were converted into grey images using custom factor combination R+G-2B. Then, the grey images were segmented from the soil background using luminance mean texture descriptor and the binary image through custom shear binary image algorithm was cut to remove big noise blobs in high crop stubble’s tilled area. Finally, a navigation path from navigation points was derived by using the least square method. The experimental results indicated that the navigation path detection algorithm was fast and effective to obtain navigation paths in rice, rapeseed and wheat high crop stubble tilling conditions with up to 96.7% of segmentation accuracy within 0.6 s processing time.

Jiang *et al.* (2014) [11] evaluated a robust crop row detection algorithm for the vision-based agricultural machinery guidance system. The algorithm consisted of five steps: Gray-level transformation, binarization, candidate center points estimation, real center points confirmation and crop rows detection. That experimental system was compared to Standard Hough Transform (SHT) and demonstrated the proposed method outperforms SHT either in detection rate, detection accuracy and computation time. The developed algorithm had required about 61 ms to recognize crop row for a 640 × 480 pixels image, while the detection rate and accuracy were reached 93% and 0.0063° accordingly.

Chang and Lin (2018) [4] developed a smart agricultural machine vision-based system for weeding and variable-rate irrigation agricultural operations. To develop a small-scale smart agricultural machine, the proposed computer vision and multi-tasking combined processes that were automatically done weeding and perform variable rate irrigation within a cultivated field. Image processing techniques such as HSV (hue (H), saturation (S), value (V)) color conversion, estimation of thresholds during the binary segmentation process, and morphology operator procedures were used for confirming the position of the weed and plant. Those results were used to perform weeding and watering operations. The data regarding the wet distribution area of surface soil (WDAS) and the moisture content of the soil was provided to a fuzzy logic controller, which drives pumps to perform variable rate irrigation and to attain water savings. The proposed system was implemented in small machines. The experimental results showed that the proposed image processing system could classify plants and weeds in real-time with an average of greater than 90% classification rate that allowed the machine for weeding by an average weeding rate of 90% and watering by maintaining the moisture content of the deep soil at 80 ± 10%.

RTK-DGPS Based Autonomous Field Navigation Systems

O'Connor *et al.* (1996) developed carrier-phase differential GPS for the steering of a John Deere 7800 series tractor at Stanford University, California**.** A four antennae system was provided for enhancing the heading high accuracy of 0.1° and offset accurately 2.5 cm at a speed of 3.25 km⁄h in straight rows.

Nagasaka *et al.* (2004) [16] developed an autonomous guidance system in rice transplanter using a global positioning system (GPS) and gyroscopes. The real-time kinematic global positioning system (RTK GPS) was employed in the automated six-row rice transplanter for precise positioning. Fiber optic gyroscope (FOG) sensors were used for measuring direction. The actuators were used to control steering, engine throttle, brake, clutch, etc. The RTK GPS achieved 2 cm precision at a 10 Hz data output rate. The FOG sensors were employed to maintain machine inclination. RTK GPS position data were influenced by machine inclination and corrected by the FOG sensor data. FOG sensor drift was corrected by referring to the position data. The influence of drift and deviation from the desired path was eliminated by regulating the yaw angle and machine speed. Heading angle drift was calculated. A simple proportional steering controller was used in the autonomous guidance system. The deviation from the desired path was around 5.5 cm at a speed of 0.7 m/s after correcting for the yaw angle offset. The maximum deviation from the desired path was less than 12 cm which did not include the first 2 m after starting operation. The operation was accurate enough for the rice transplanting. However, they could not obtain enough accuracy for spraying or mechanical weeding operations after rice transplanting because the machine must travel between the crop rows. For this, it is necessary to improve the turn control algorithm and steering controller to obtain more precise operations.

Bakker *et al.* (2011) [3] developed an autonomous robot platform having RTK-DGPS based autonomous field navigation system for a sugar beet crop. It was consisted of including automated row-end turns to provide a method for crop row mapping combining machine vision and to evaluate the benefits of the behavior-based reactive layer in a hybrid deliberate systems architecture. Two experiments were performed simultaneously i.e., the following pre-defined paths reformed from crop row positions based on RTK-DGPS and crop row mapping by combining vision-based row detection with RTK-DGPS information. The standard deviation, mean, minimum and maximum lateral error of the robot were 1.6, 0.1, −4.5 and 3.4 cm, respectively at a speed of 0.3 m/s. The standard deviation, mean, minimum and maximum of the heading error were 0.008, 0.000, −0.022 and 0.023 rad, respectively while following a straight path on the field with RTK-DGPS.

Unal and Topakci (2015) [29] designed and developed a remote-control and GPS-guided robot for precision farming. It was designed to control the robot via the internet and image processing techniques. The joystick was used to control the movements of the robot in any direction or speed. Real-time video transmission to the remote computer was accomplished with a camera placed on the machine. The navigation software was developed for autonomous steering. Results showed that the linear target point precision was valued from 10 to 12 cm and the distributed target point precision was valued from 15 to 17 cm.

Pablo *et al.* (2020) [18] mentioned different kinds of robots and their application below Table:

Table 1: Type of robots and their applications

Sr. No	Name of robot	Application
1	Bonirob/2009	Steering scheme: Independent steering and traction wheels in 1-DOF legs (wheel-legs) Applications: General agricultural tasks A concept was similar to the intelligent phone scheme that gives third parties the possibility to integrate their modules for specific applications
2	Ecorobotics/2014	Steering scheme: Independent steering and traction wheels Application: Robot run by vision sensors/camera to detect the position of weeds in between the rows and kills by two robotics arms.
3	AgBot II/2014	Steering scheme: Two front skid steering wheels and two rear caster wheels Applications: Fertilizer application in large horticultural crops, weed management, detection and classification. Destroy weeds using mechanical or chemical devices
4	Ladybird/2015	Steering scheme: Independent steering wheels Applications: Crop assessment using hyperspectral cameras, panoramic and stereovision cameras, LIDAR, and GPS, thermal and infrared detecting systems
5	Greenbot/Precision Makers 2015	Steering scheme: Independent steering and traction wheels. Applications: Regular agricultural and horticultural operations
6	Casar/2016	Steering scheme: Independent steering and traction wheels Applications: Autonomous robot used in enclosed fruit plantations and vineyards. Pest and soil management, fertilization, harvesting, and transport activities.
7	Rippa/2016	Steering scheme: Independent steering and traction wheels Applications: Robot used in the vegetable growing industry, Spot spraying of micro-dose weedicides to destroy weeds.
8	Vibro Crop Robotti/2017	Steering scheme: Skid steering wheels Applications: Precision farming in seed sowing and row crop cleaning mechanically
9	Ceeol/2019	Steering scheme: Skid steering trucks Applications: Furrow preparation, fertilizer application, weeding, harvesting and soil analysis
10	Naio/2019	Steering scheme: Independent steering and traction wheels Applications: Leaf thinning and trimming in vineyards

Benefits of Automation in Agriculture

Goense (2003) discussed the comparison between an autonomous machine and conventional machinery. The autonomous machine was equipped with several implements having working widths from 50 to 120 cm. He presented that if an autonomous machine was utilized at 23 hours a day, it would be economically feasible with a slight increase in the price of the navigation system or with a slight reduction in labor cost. He also discussed several other changes that will affect the final result, such as the fraction of labor time needed out of the total machine time and the machine tracking system, which provided better utilization of machine working width and there was no need for operator’s rest allowance.

Have (2004) [9] analyzed the effects of automation on machinery sizes and costs for soil tillage operation and crop establishment. He found that the ratios between an autonomous tractor and a traditional tractor, in terms of cost, labor requirement and daily working hours required were accordingly 1.2, 0.2, and 2 times. The analysis showed that the manual control shift to automatic control would decrease the tractor size, implement sizes and investments up to half, decrease the tractor investment to about 60% and decrease the annual tractor plus machinery costs to approximately 65%.

Conclusion

Vision-based and sensor-based technology has been implemented several decades ago. RTK-DGPS and Radar (lidar) have also been used widely for the automatic guidance system since many years ago. Mostly automated guided vehicles and agricultural robots have been developed in overseas countries that are very costly as per their methodology used and materials procurements and market segmentations. In overseas countries, large farmers have large farm capacities for agricultural production and that is one of the reasons for the utilization of robotics and AGVs in several agricultural operations. While in the case of developing countries especially in India, The researchers are doing their remarkable efforts for the development of robotics and AGVs in Indian farming suitable conditions. ICAR has initiated a World bank funded institutional development program under the NAHEP scheme. In this program, several institutions have been recognized for this program implementation to fulfill the vision of ICAR. By this NAHEP-IDP program, the research on robotics, AGVs and UAVs have been started with keeping the suitability of Indian farming conditions. Robots and AGVs have not been commercialized in India yet due to lack of awareness, nonsuitability of Indian farming conditions, insufficient and inefficient components availability at low cost and small and marginal farmers being dominant in India. But based on rapidly ongoing research undertaken by ICAR institutions and other private organizations, it is likely to be taken place soon. For boosting this research capability, this paper is very useful for carrying forward the research.

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