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Machine vision for orchard navigation

Josiah Radcliffe, Julie Cox, Duke M. Bulanon*

Northwest Nazarene University, 623 South University Boulevard, Nampa, ID, 83686, United States

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ABSTRACT

Developing a machine vision based autonomous utility vehicle for agricultural application is a challenging task due to changing physical landmarks. While most research thus far has developed algorithms that take advantage of ground structures such as trunks and canopies in the orchard, this research uses the combination of the canopy with the background sky. By focusing on the tree canopy and sky of an orchard row, an unmanned ground vehicle can extract features that can be used for autonomously navigating through the center of the tree rows. This was attempted by using a small-unmanned ground vehicle platform driven by four motors and guided by a machine vision system. The machine vision system is composed of a multispectral camera to capture real-time images and a personal computer to process the images and obtain the features used for autonomous navigation. Laboratory field tests showed that the small vehicle platform system was able to navigate autonomously with an RMS error of 2.35 cm. Field tests using a peach orchard showed that the small vehicle platform system could navigate the rows autonomously with an RMS error of 2.13 cm. The machine vision algorithm developed in this study has the potential to guide small utility vehicles in the orchard in the future.

1. Introduction

Within the next 30 years, the world's population is preparing for a steep increase, bracing for nearly 10 billion inhabitants [1]. With a vastly growing population, the demand for natural food resources needed to sustain this population expands simultaneously. However, with the labor force moving away from manual agriculture, farmers are now needing to develop ways to harvest and produce an increased output of product while harboring the loss of physical manpower [2].

As technology increases, researchers are beginning to implement robotics in the field, creating sustainability for farmers amid declining labor supply and increasing food demand. In addition to using robotics technology, a farmer can also use "precision agriculture" [3]: a way to create efficient cultivation by maximizing production while minimizing costs, which is very compatible with robotics [4]. While in the past, many agriculturalists have been focused on a large output of goods to feed the growing population, currently much of the population is becoming more concerned with how these goods are being produced. People, as well as governments, are caring more and more about the chemicals used in food products, as well as the methods implemented for seeding and harvest. Also, the public and farmers alike are beginning to be concerned with the environmental impacts of agriculture, such as synthetically enhancing crops, harsh chemical weed control, and precision watering. With these needs considered, robots, especially autonomously driven robots, can help the agricultural community achieve these newfound regulations and concerns. By using an autonomous robot, farmers can reduce the manpower and hours needed to do these mundane tasks—like precision weed spraying, seed or row mapping, precision watering, and harvest data gathering—yet still carry out these undertakings precisely. Farmers can also conduct other high-level tasks, as navigation is automated [5]. Other benefits can include increased safety of the harvest and equipment, longer duration of work, as an autonomous vehicle may outlast a human worker, as well as increased productivity [6]. Pederson et al. describes the viability of robotics in the field, by studying vehicles doing three different autonomous tasks in an agricultural setting, and finding that these robots are more economically friendly than the traditional methods of accomplishing the same assignment [7]. By implementing autonomous robots into an agricultural setting, farmers can better use their resources, therefore saving money and economizing a better product for the masses. With these benefits in mind, no longer are autonomous vehicles in the field ideas for the future, but they are becoming feasible, and much needed, option for today [8].

The main challenge for developing an autonomous vehicle on the farm is its navigation system. Navigating a vehicle in a field

* Corresponding author.
E-mail address: dbulanon@nnu.edu (D.M. Bulanon).

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with different crops is not a trivial matter. One vital vehicle on the farm is the tractor. By using a tractor, a farmer can cultivate a wide area at once with a large amount of power. The idea of "driverless tractors" stems back to the 1920's, and gained further momentum in the 1950's and 1960's, with prototypes being guided by large cables in field rows. In the 1980's and 1990's, research for machine vision and computer aid guidance were implemented through research done through Michigan State and Texas A&M universities, as well as automated fruit harvesting at the University of Florida [9]. This research has continued into present North America, with more funding being poured into the agricultural domain, gaining attention from prestigious research academies and personnel looking into various sensors and machines [10]. However, since precision is beginning to outweigh brute force, other types of machinery are also being considered. In some cases, a tractor can seem unreliable for tasks such as turning into narrow rows, or accurate weed spraying or watering. Likewise, a navigational system that may work for a large machine can prove inefficient for a smaller one, which may be needed for precision farming. Another inefficiency with some of this research is that it is often conducted in a controlled laboratory environment, which differs greatly from the outdoor setting for which it would be used [11].

One of the main tasks of autonomous guidance is developing a functional navigation system. The navigation of an autonomously driven vehicle can prove a difficult matter. With different methods, such as global positioning systems, mechanical feelers, dead reckoning, radio frequency identification tags, laser radar, Kalman filter, and machine vision, one has yet to be named the better, as each one has its difficulties [11]. In this paper, a machine vision sensor is proposed to guide a vehicle in a row of trees. The basic concept of machine vision for navigation is the machine vision sensor can measure the relative position of the vehicle concerning a landmark and use that to estimate the vehicle's heading. Usually, the vision sensor is mounted on the vehicle [9]. The position of the vision sensor is dependent on the geometric relationship between the sensor and vehicle, and the field of view of the sensor. One of the common methods of using landmarks is detecting a row of crops on the ground. Benson et al. developed a machine vision system to guide a combine harvester, and it used the lateral position of the crop cut edge as a guidance directrix [12]. One of the difficulties in developing a machine vision for outdoor application is dealing with the varying ambient light condition. A machine vision guidance system for a paddy rice field used a pair of monochrome cameras with different spectral filters to deal with strong reflections on the water [13]. Hague et al. differentiated between vegetation and soil using a near-infrared camera to enhance the high reflectance of plants in the near infrared [11]. In addition to using special filters, different image processing techniques are also explored to take advantage of the geometrical properties of the crops. For example, Tillet and Hague [14] developed a machine vision guidance system for cereal crops using the midpoints of rows extracted from a single view of adjacent row crops. Sogaard and Olsen [15] used a color video camera to detect and localize small-grain crops and calculated the centers of gravity of row segments without using segmentation. Other researchers also used a Hough transform to track rows of transplanted cauliflower field [16].

Much of the current research in machine vision concentrates on ground-based feature recognition solutions, such as processing images of the surface crop, grass edge, planting pattern, or other low landmarks to find a guidance directrix. This is a logical approach specifically for surface crops because they are planted in a certain pattern, and the features of the pattern can be used to guide the vehicle. On the other hand, orchards with fruit trees pose a different challenge. While some researchers have used the overhanging canopy to use as a guide, it calls for a different approach to deal with the challenges. Subramanian et al. [17] developed a machine vision system for citrus groves, and it used adaptive thresholding to deal with the changing illumination and shadows brought about by the canopy. While an agriculture setting, specifically orchards, can prove to be one of the ideal settings for this kind of research due to the environment in which it resides, there are always challenges in the field [18]. In an orchard, the trees and rows are unlikely to change from year to year, yet the trees or vines themselves change from blossoms to fruit throughout the season. Along with the changing trees (changing in color, growth, and foliage), an orchard can have narrow rows and smaller turning radii, as well as uneven terrain with obstacles, such as branches from trimming or else tarps for collecting [19]. Changing settings like this lead to challenges with navigation, especially if that navigation relies on physical barriers as indicators. Along with adapting to these constraints, researchers must develop algorithms that adapt to the season, yet that also remain low cost and simple for farmers to use.

When relying on ground features, they are often subject to change, due to varying environmental factors and the dynamic nature of the crops. This research focuses on looking up, not down, with the camera angles and uses features of the sky and tree canopies in the image processing. By focusing on the tree canopies and sky, the environmental factors decrease drastically. Unlike the trees themselves, the skylines do not change throughout the seasons, and always remains as one of the most luminescent parts of the image, a key in pinpointing an object in image processing. By using the sky as a guidance system, this research provides a unique approach to autonomous navigation using machine vision.

This paper is aimed at finding ways to develop and implement machine vision into the agricultural field, predominantly orchards. The goal of this research is to develop an algorithm to autonomously guide a small robotic ground vehicle platform along an orchard row, following the path of the row using an upward looking camera combined with a controller based on feature recognition from the contrast between the tree canopies and the sky. The autonomous navigation system will be evaluated in laboratory controlled settings and actual field setting using a commercial peach orchard.

2. Material and methods

The block diagram of the unmanned ground vehicle (UGV) navigation system (Fig. 1) has three main components: the

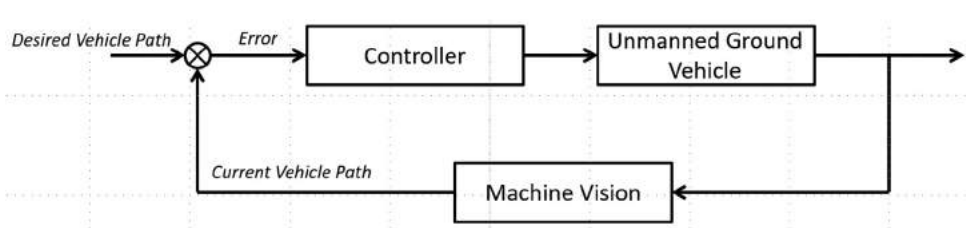

Fig. 1. Unmanned Vehicle Navigation System.

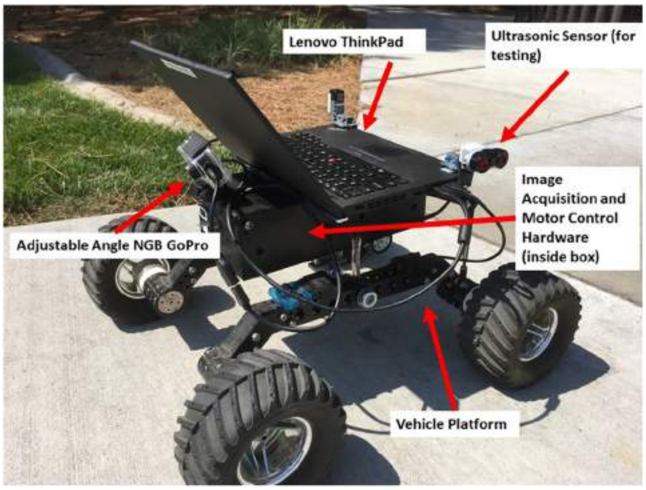

Fig. 2. Unmanned Ground Vehicle Platform.

unmanned ground vehicle platform, the visual feedback system, and the controller. The input to the system is the desired vehicle position, and the visual feedback system is used to estimate the current vehicle position. The controller to correct the position of the vehicle as it moves along the tree rows uses the difference between the desired position and the current position.

2.1. Unmanned ground vehicle platform: robotic platform

A GEARs Surface Mobility Platform (SMP) was selected as the UGV platform due to its more robust design, a larger box for stowing electronics and mounting the guidance system. This platform was driven by four twelve-volt motors connected directly to each of the four wheels. A differential arm attached to the left and right side of the chassis and the control box of the SMP allowed for a good articulation of the chassis over objects while maintaining stability at the control box, where the guidance system and the image acquisition system would be located. Fig. 2 shows the UGV platform with its components.

2.2. Motor controller and actuators

The UGV platform was steered as a differentially steered vehicle, where steering is accomplished through the difference between the velocity of the motors on the left side and the motors on the right side. A difference in left and right motor speeds results in a change of direction of the vehicle. If the velocity of the two left motors is equal to the velocity of the two right motors, no directional change happens, and the UGV platform continues in a straight line. The motor control system (Fig. 3) used the Lego Mindstorms EV3 in conjunction with a Tetrix Motor controller. The use of the Lego EV3 controller allowed for rapid application development and experimentation of unmanned vehicle navigation system. Fig. 3 shows the block diagram of the motor control system. The inputs to the Tetrix motor controller were a twelve-volt battery input and a Lego Mindstorms control signal input. The outputs of the controller were two twelve-volt motor outputs, which were used to power four twelve-volt motors, two on the left side of the chassis and two on the right side of the chassis. When programming, values between −100 and +100 were sent to the motor controller, indicating a percentage of the max voltage to send to the motors, with +100 being 100 percent of 12 V and −100 being −100 percent of 12 V or −12 V, driving the motor in reverse. This is similar to a pulse-width-modulation control of DC motors.

2.3. Visual feedback system

The visual feedback system is composed of image acquisition unit and image processing. The image acquisition unit consisted of a camera mounted on the front of the UGV platform and connected to a portable Lenovo ThinkPad with a Windows 10 operating system. For rapid application development, the navigation control system was developed using LabView, which has the module for the Lego Mindstorms EV3 controller and the National Instruments (NI) Vision module. The NI Vision module was used to develop the image acquisition and image processing. This set-up simplified the evaluation of the navigation control, which is the goal of this paper.

The camera used for image acquisition was a modified GoPro Hero 3+. The original filter of GoPro camera was replaced with a filter that allows near infrared centered at 750 nm, the green band, and the blue band. The modification was made to enhance the reflection of the leaves, which had a high near-infrared reflectance due to the presence of chlorophyll. A video capture card was used to connect the GoPro camera to the computer for image acquisition. The GoPro camera was mounted on the front of the Ground Vehicle Platform, and the camera angle was adjusted so that from one end of the row, the sky at the far end was at the bottom of the image. This ensured that the sky would always be in the image.

2.4. Image processing

The desired path of the UGV is a straight line between tree rows of an orchard. There are several methods of using a vision-based system for straight-line navigation along the row. One of the approaches is a ground-based method where features of the ground such as the orchard floor grass and the trunks of the trees. As mentioned, the major challenges for this approach are the

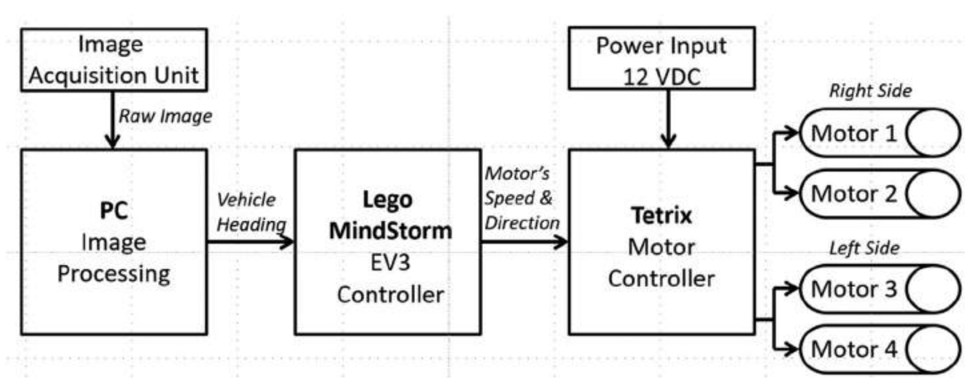

Fig. 3. Motor Control System.

Fig. 4. Comparison between ground and sky-based guidance.

shadows presented by the canopy, the color similarity of the canopy and orchard floor, the solar angle, and the tree trunks from adjacent rows. To eliminate the effects of these challenges, this paper presents a unique method of using a sky-based approach. Upon inspection of the images from the ground vehicles field-of-view (FOV), both the sky and the ground outline a similar path. Fig. 4 compares the similarities between the shape of the sky within the orchard row image and the shape of the ground constrained by the tree trunks.

Fig. 5 shows the image processing for the sky-based approach. After an image was acquired, the image was cropped to remove the portion of the sky in the field of view that was closest to the camera. This was done to produce a more sensitive control system. Slight changes in the direction of the vehicle were magnified when using the centroid of a point that was further away from the camera. Also, the cropped image contained less data needing to be processed, resulting in faster processing time and more rapid response of the ground vehicle platform. The next step was to extract the green color plane from the image. The green color plane provided the higher contrast between the sky and the tree canopy. Due to this high contrast between sky and canopy, a simple thresholding approach was employed to extract the path plane of the vehicle. Next, the thresholded image was filtered to remove the 'salt-and-pepper' noise. Then, the centroid of the path plane was determined to calculate the vehicle's heading.

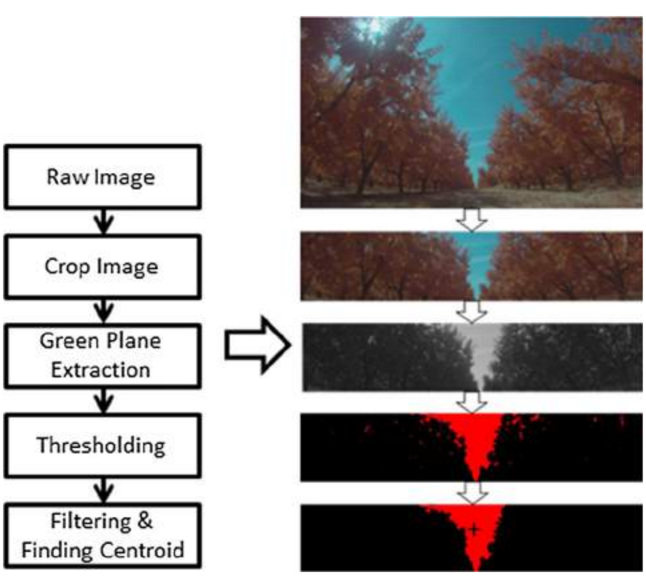

Fig. 5. Image processing algorithm for autonomous navigation.

2.5. Control system

The control system (Fig. 6) for the UGV platform was an image-based position servoing system, where features of the image were used as control variables to estimate vehicle's heading. The next figure demonstrates the calculation of the vehicle's heading. After the path plane was extracted, the path plane was inverted and used the position of the difference between the centroid and the set point to find the vehicle's heading and used it to drive the motor actuators. The Proportional-plus-Integral (PI) controller was used to handle the position difference and used it differentially steer the vehicle. To determine gains, KP and KI, of the PI controller, several test runs were conducted and the integral gain was initially set to zero and adjusting the proportional gain until the system's response was slightly overdamped. Then the integral gain was adjusted to remove the steady-state error. Once the PI controller had been tuned, a forward speed adjusted to 30% of the maximum value was used as the forward control signal.

2.6. Tree row navigation

An initial testing was done to determine the performance of the control system. A straight sidewalk was selected for the initial testing and we had the UGV following down a straight sidewalk. An ultrasonic sensor was attached to the UGV, and a cardboard box was placed at the edge of the sidewalk. The ultrasonic sensor read the distance from the vehicle to the box, or edge of the sidewalk, as the vehicle tracked along the sidewalk.

After determining the gains of the control system from the straight sidewalk test, the straight-line navigation control system was evaluated using a commercial peach orchard located in Caldwell, Idaho, USA. The orchard is well maintained, and one of the rows was randomly selected as a test row. A cardboard box was held at a fixed distance of 2.4 m from one row of trees, and the vehicle traveled down the row, measuring the distance from the cardboard via the ultrasonic sensor. This test was conducted over 27 m. Also, the vehicle's performance down the whole length of the row was observed, however, no ultrasonic data was taken for this test as it was a general observation of the machine vision system to guide the UGV down an entire row.

3. Results

3.1. Lab test results

As mentioned above, the image processing algorithm and vision control system was first tested on a straight sidewalk. Regarding the image processing, testing would be very similar to an orchard

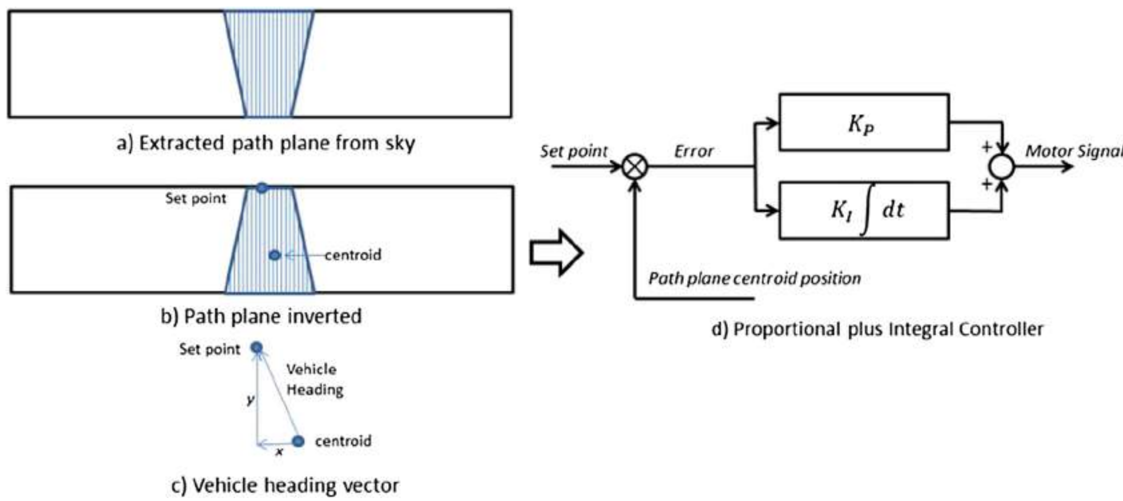

Fig. 6. Calculation of vehicle heading vector and PI controller of feedback system.

and a sidewalk with the only differences being the camera angle-pointing towards the ground for the sidewalk tests and towards the sky for orchard tests. The basic image processing algorithm was identical except the path plane was not inverted, locating the centroid of the binary image and using it as the process variable for the PI controller. The test was evaluated by fixing an ultrasonic sensor on the UGV that would measure the distance from the vehicle to the edge of the sidewalk using a piece of cardboard placed vertically at the edge of the sidewalk. The test was conducted over a portion of the path 23 m in length. The vehicle traveled at an approximate speed of 0.20 m per second. The sidewalk was 1.5 m wide. Fig. 7 shows the deviation of the UGV from its starting point. The UGV had a maximum deviation of 5.5 cm from its starting point with a root mean square (RMS) error of 2.35 cm. It can be observed from Fig. 7 that the UGV was able to correct itself after the maximum error occured which demonstrated that the visual feedback system was effective.

3.2. Field test results

In addition to the controlled sidewalk test, a test of the performance in the orchard was conducted. The conditions for testing were less controlled, but the purpose of the test was to observe the general performance of the UGV in field applications. The setup for the test consisted of a line placed 2.44 m from the tree trunks toward the center of the row. The distance between the two rows of trees on each side of the row was approximately 6.4 m. The distance from the UGV to the line was measured using an ultrasonic sensor as the UGV traveled 27 m. Fig. 8 shows the UGV's deviation from the starting point similar to the controlled sidewalk test. The maximum deviation from the starting point was 3.5 cm with an RMS error of 2.13 cm.

4. Discussion

Based on the test results, it was determined that the image-processing algorithm for the vehicle guidance system was adequate for guiding the vehicle down the orchard row. The difficulties such as inconsistent lighting, shadows, and color similarities in features were eliminated by using the sky-based approach where the image was reduced to canopy plus sky, thus simplifying the segmentation process. Feature detection using machine vision is facilitated if the segmentation process is effective. In addition to the tests in which ultrasonic data was taken over a controlled distance, a general performance test was conducted to observe the performance of the UGV down the entire length of an orchard row. During this test, the UGV completed the entire row with very little deviation from the center. However, it was observed that there were larger deviations from the center of the row when the UGV approached sections where there was a

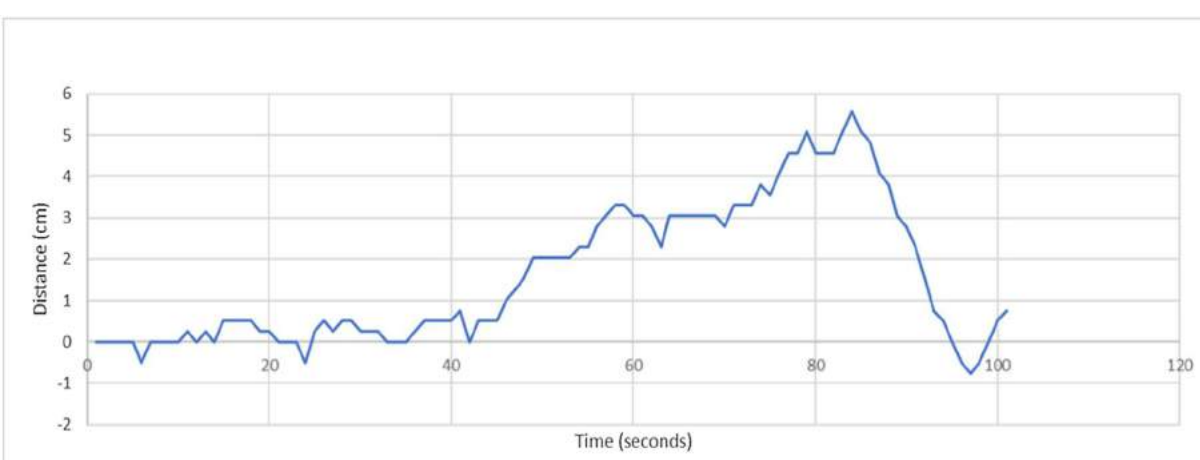

Fig. 7. Deviation from start for sidewalk test.

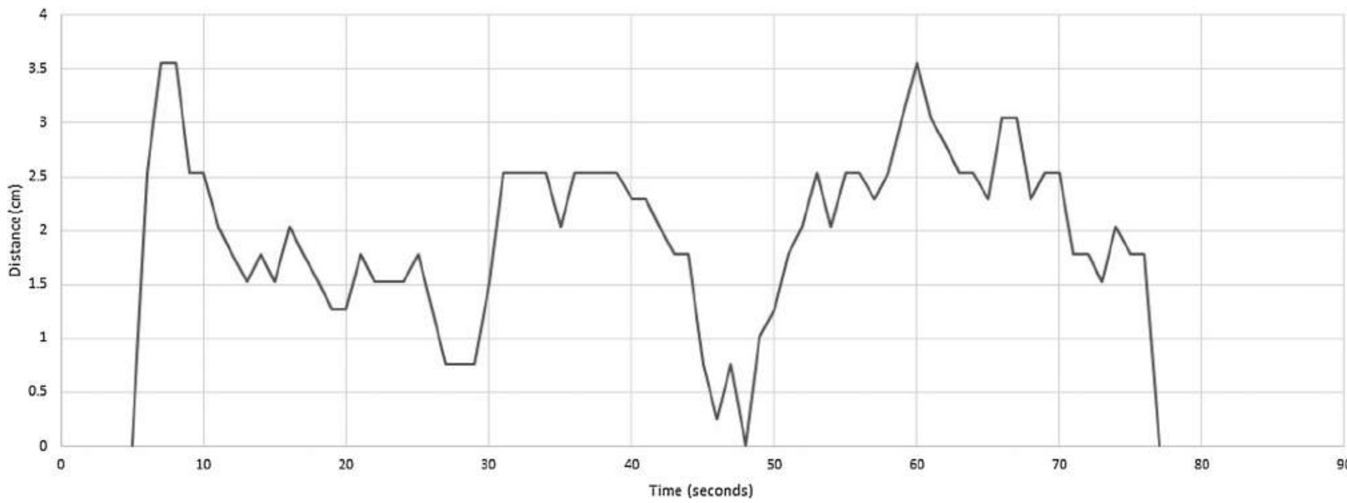

Fig. 8. Deviation from starting point for orchard test.

break in the canopy due to either a missing tree or a tree with limited leaf growth. These breaks in the canopy caused the UGV to move away from the center of the row, but when the UGV would move past that section, it would correct itself and return to the center. The result of a missing tree changes the shape of the path plane. This means that the shape of the path plane could be used to determine a missing tree or end of the row conditions.

The data showing the deviation of the UGV from its starting point indicated that the control system was effective in guiding the UGV in the center of the row or sidewalk. For the sidewalk test, the maximum error of deviation from the starting point was only 5.5 cm in a width of 1.52 m with an RMS error of 2.35 cm. For the orchard row test, the UGV had a maximum deviation of 3.5 cm from the starting point where the width of the whole row was 6.4 m, and the RMS error was 2.13 cm. It can be seen that the relative error of the width of the row was very small. The response of the system could be improved by tuning the gains of the controller. The current gains were tuned such that the system was overdamped to avoid oscillation as it travels along the row. This result was deemed satisfactory for the project. The result of the test run in the field showed that the sky-based approach in combination with the PI controller was able to guide the UGV down the row.

The proposed sky-based machine vision for orchard navigation demonstrated the potential of guiding a UGV in a straight-line motion. However, there are obvious limitations to the proposed approach. The first is the proposed approach is only useful when the trees have fully developed canopies. This will be useful for orchards that will have canopies year-round such as citrus. On the other hand, fruit trees that lose their leaves in the winter and remain dormant until the spring season has no canopy. In this case, a ground-based image processing would be effective since the problems with shadows when the canopy is present is eliminated. Therefore, for orchards that have deciduous trees, an adaptive image processing approach could be implemented to deal with the changing environmental condition. For example, a sky-based image processing will be used when canopies are present, and a ground-based approach will be employed when there are no leaves. Another thing to consider is the sensor's field of view, mounting configuration, and the row width. These factors affect the shape of the path plane which dictates the gains of the controller. The other limitation of the proposed approach is it only tackles the straight-line motion down the row but not the end of the row condition. The end of the row condition could be handled in several ways. An ultrasonic sensor could be used to detect the absence of a series of trees. Another approach would be to observe the path plane of the sky-based approach. The shape of the path plane will be different at the end of the row, and this can be used to trigger the vehicle that it is at the end of the row. Future research would include dealing with a changing environment such as with canopy and without canopy conditions, detecting the end of the row condition, and translating to the next row.

5. Conclusion

A machine vision system to guide a small-unmanned ground vehicle system in an orchard was developed. The vehicle is differentially steered by four DC motors. The navigation is based on a visual servo system using machine vision system, which is composed of a multispectral camera to acquire images and a personal computer to process the images. The camera was positioned to focus on the tree canopies and the sky, which is a sky-based approach. The image processing segmented the sky from the tree canopy background, and the centroid features of the segmented object were used as the process variable to guide the unmanned ground vehicle through the tree rows. A proportional and integral controller was used in the visual feedback system. Laboratory field tests showed that the autonomous navigation using the developed algorithm had an RMS error of 2.35 cm. The actual field test in a commercial peach orchard showed that the autonomous navigation had an RMS error of 2.13 cm. These results showed that the unique approach of using the sky and canopy as features have the potential to guide small utility vehicles in the orchard.

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Glossary

Autonomous navigation: Operation of a vehicle system without human intervention
Machine vision: A sensor system that uses an image acquisition system like a camera and image processing to extract features for process control
Precision agriculture: A site-specific technology of observing field variability and responding to this variability to optimize crop production