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Variable field-of-view machine vision based row guidance of an agricultural robot

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ABSTRACT

A novel variable field-of-view machine vision method was developed allowing an agricultural robot to navigate between rows in cornfields. The machine vision hardware consisted of a camera with pitch and yaw motion control. Guidance lines were detected using an image-processing algorithm, employing morphological features in a far, near and lateral field of view, and the robot was guided along these lines using fuzzy logic control.

The method was tested while the vehicle successfully traveled through a distance of 30 m towards the end of a crop row in three replications. To evaluate the guidance performance, RTK-GPS data were collected, showing a maximum guidance error of 15.8 mm and stable navigational behavior.

1. Introduction

The development of robotics in agriculture in general is slow, but persistent. Ample robotics research has taken place in controlled environments such as in the development of greenhouse grafting robots (Kondo and Ting, 1998), harvesting robots for cucumber (Van Henten et al., 2003), strawberry (Shiigi et al., 2008), and tomato (Kondo et al., 2008). In addition, autonomous vehicles are in development for orchards (Hamner et al., 2011; Singh et al., 2010). In field crops, the focus has been primarily on robotic weed control and for good reasons: Worldwide, 201 weed species were found to carry at least one form of resistance to one of the 19 major herbicide groups (Heap et al., 2011) and robotic (mechanical) weed control could play a role in solving this problem. Scouting for abiotic (drought, nutritional deficiencies) and biotic (diseases, insects, weeds) stress factors is also an important activity in agricultural fields but, due to time constraints, often overlooked: "Ask any yield contest winner what the most critical thing they did to win and they almost unanimously tell you, 'walk your fields often.'" (Advanced Ag Solutions, 2011). Although scouting is often used as a justification for field robotics research, no papers were found in the literature where pertinent data was collected from crop and/or soil in a robotic manner.

Machine vision applications in agriculture can be categorized into three main areas being nondestructive measurement, visual navigation, and behavioral surveillance (Chen et al., 2002; Ji et al., 2009). Machine vision based navigation of agricultural vehicles has had ample coverage in the literature in recent decades, since it allows the development of future autonomous vehicles (Åstrand and Baerveldt, 2005). For instance, Subramanian et al. (2006) and Han et al. (2004) developed a method to steer tractors in citrus groves and crop fields automatically. The same approach was used in a weeding cultivator and a grain harvester (Okamoto et al., 2002; Benson et al., 2003). In addition, Chen et al. (2003), Bak and Jakobsen (2004) and Xue and Xu (2010) applied a camera in the development of autonomous robots for field applications. The common denominator among these examples is the use of a fixed forward field of view ("far FOV") camera arrangement, which works adequately, in the case of tall, mature plants, but has its limitations when the plants are small, and is inadequate when used for turning at the end of the row. For this purpose two FOV modes were added to the far FOV being the "near FOV" for short plants, and the "lateral FOV" used in turning the robot.

The objective of this research was to design and test a variable FOV machine vision system, allowing accurate guidance of agricultural robots.

2. Variable field of view arrangement and robot platform

Classical, fixed, forward-looking cameras have a constant pose, which limits their perspective. However, the blind spot areas outside the FOV often contain useful information, especially when the machine travels towards the end of a row, where no plants are present. A variable FOV arrangement can adapt to the crop type, missing plants in rows, as well as its growth stage. For example, a near FOV arrangement is capable of segmenting smaller corn

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plants, but a far FOV arrangement is suitable for guidance among taller corn plants.

2.1. Variable field of view arrangement

A low cost digital camera (Logitech® QuickCam) with a resolution of 640 ∗ 480 pixels and a maximum frame rate of 30 per second was connected to a laptop computer with an AMD Turion 64 X2 TL-50 dual-core processor through a High-Speed USB 2.0 cable. MatLab® was used to acquire and process images and after processing, commands were sent to the microcontroller in the robot through a serial RS232 link. The variable FOV camera arrangement was implemented by mounting the camera on a fixture that allowed both yaw and pitch motion of the camera, driven by two DC motors (GWS Standard S03N STD Servo Motor). The angles of the camera were referenced to a "straight ahead" pose where the pitch and yaw angle were defined as zero. The pitch angle was defined as α_{up} when the camera is looking up and α_{down} when the camera is looking down, as shown in Fig. 1(a). The maximum value of α_{up} was 36°, owing to mechanical constraints, and the maximum value of α_{down} was 125°. The yaw angles were defined as β_{left} when the camera yawed to the left and β_{right} when the camera yawed to the right, both with a maximum value of 125° as shown in Fig. 1(b).

2.2. Robot platform

The variable FOV camera arrangement was employed to guide an agricultural robotic platform named "AgTracker", developed by Department of Agricultural and Biological Engineering at University of Illinois (Fig. 2(a)). AgTracker is controlled by a single BasicAtom® micro-controller that serves to relay steering information from a laptop computer to the drive wheels. The drive system of the robot consisted of two DC brushless motors (Astroflight 940P Geared Motor) with a maximum power output of 750 W. These motors were geared down to obtain a maximum speed of approximately 1 m/s (Fig. 2(b)).

3. Guidance line detection and row guidance control

The purpose of machine vision based row guidance is to enable stable navigation of a machine by identifying crop plants using a camera, and subsequently calculate a guidance line for the machine to follow. An algorithm calculated the error between the desired heading and the instantaneous heading, as well as the instantaneous offset from the guidance line, and generates a control signal as a function of the discrepancy (error) between desired and instantaneous values. In the research as presented here, this classical control scheme was adopted with the added complexity associated with employing a variable FOV camera arrangement.

3.1. Row guidance method

When the robot was traveling deep inside a cornfield, the far FOV was used which allowed for clear and swift segmentation of corn plants against a high contrasting soil background. When the number of pixels in the far FOV imagery decreased below a preset threshold, the machine switched to a near FOV state by pitching the camera downward. Subsequently, when the number of pixels in the near FOV imagery decreased below another preset threshold, indicating the proximity of the row end, the machine was switched to a lateral FOV state by yawing the camera in the lateral direction. The method of calculating the instantaneous offset and heading in the far and near FOV case as shown in Fig. 3(a) and in the lateral FOV case in Fig. 3(b). In Fig. 3(a), the lines R_1R_2 and L_1L_2 represent the right and left crop rows, respectively. Based on these, the center (guidance) line C_1C_2 was calculated. To obtain the offset and heading of the robot, two points Q_1 and Q_2 were projected onto the soil surface in software. These points are a function of the geometry of the robot and camera pose, and determined using calibration prior to field-testing. Subsequently, the line Q_1Q_2 in combination with a chosen fixed point G on this line, were used to measure the offset and heading angle of the robot platform relative to the center guidance line C_1C_2. In the lateral FOV case as shown in Fig. 3(b), the offset and heading were calculated based on the distance error between the guidance line L_1L_2 and the same fixed point G on the baseline Q_1Q_2.

3.2. Guidance line determination

To calculate the left and right crop lines as well as the guidance line in the center, images acquired in the far FOV mode (Fig. 4), were processed. Fig. 4(a) shows an image of a cornrow under sunny conditions. The first step in the guidance line determination process was to distinguish the green corn plants from the soil background, which was achieved using color segmentation, yielding a binary image (Fig. 4(b)). Subsequently, a morphological "opening" operation was applied to determine left and right crop row delineation lines as well as the guidance line in the center (Fig. 4(c)). The opening operation also allowed for removal of small noisy objects in the image while preserving the shape and size of larger

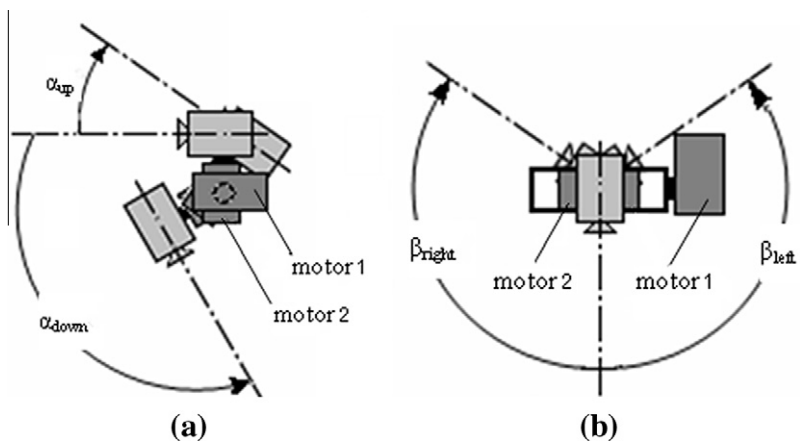
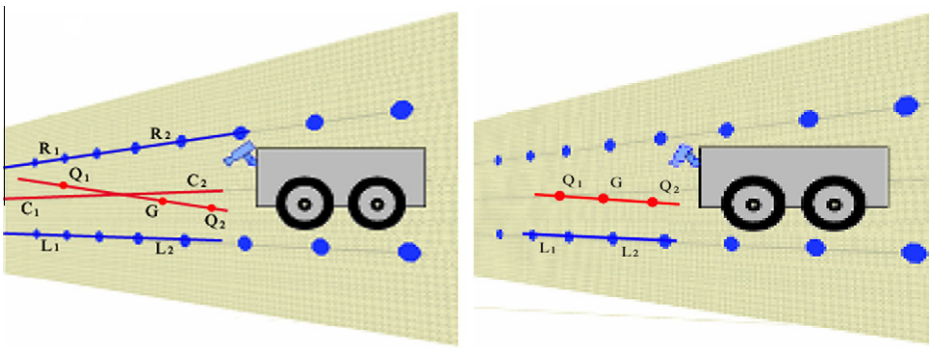


Fig. 1. Diagrams of the variable FOV arrangements. (a) Pitch motion of the camera; (b) yaw motion of the camera. Motor 1 and motor 2 control the pitch and yaw motion of the camera, respectively. Angles α_{up} and α_{down} represent pitch angles when the camera looks up and down (a), respectively. Angles β_{left} and β_{right} represent yaw angles when the camera turns to the left and the right (b), respectively.

(a) (b)

Fig. 2. Robot platform (a) and drive train (b).



(a) (b)

Fig. 3. Measurement principle of offset and heading angle in the forward FOV (a) and lateral FOV (b).

objects. In the far FOV case, the processing time per image was 0.3 s due to a strong contrast between crop and soil.

When the number of pixels representing the crop decreased below a preset threshold, the arrangement was switched to the near FOV state (Fig. 5(a)). In this case, the crop related objects in the images were mainly stalks and therefore morphological operations with a rectangular structuring element were used to identify and segment the stalks (Fig. 5(b)). As in the far FOV case, the guidance line was obtained based on the left and right crop row delineation lines (Fig. 5(c)). In the near FOV case, the processing time per image increased to 0.6–0.8 s.

When the robot reached a distance of about 1.5 m from the end of the row, no more stalks were visible in the images, and therefore the camera arrangement was switched to the lateral FOV state, yielding imagery as shown in Fig. 6(a). The algorithm that was used to determine the crop edge was identical to that used in the near FOV case, although significantly fewer stalks were present, which extended the processing time to 0.7–0.9 s (Fig. 6(b)). In the lateral FOV case, the crop row line was calculated according to the principle shown in Fig. 3(b) and used as the guidance line (Fig. 6(c)).

3.3. Row guidance control

As mentioned, the robot platform was driven by two DC motors that controlled the speeds of the left and right wheels. Both wheels on either side of the robot where mechanically linked together, which allowed for "skid steering", a robust steering method used in tracked off-road vehicles. Skid steering implies that when the speeds of the left wheel set and the right wheel set are equal, but with inverse rotational direction, the vehicle is traveling forward or backward along a straight line. If the left wheel set speed is lower than the right wheel set with inverse rotational direction, the vehicle will veer to the left and *vice versa*. In addition, a spin turn can be implemented by rotating the left and right wheel sets at equal speeds and equal rotational direction.

After calculating the offset and heading of the robot relative to the guidance line, the speeds of left and right wheel sets were adjusted to steer the robot towards the guidance line. The control method used to accomplish this was based on fuzzy logic, with two input signals being the offset and heading of the robot. In the fuzzy guidance control, a triangular membership function using a uniform distribution, Max–Min fuzzy inference algorithm and decoupling sentencing law with a center of gravity method were applied. The discourse domain of the fuzzy subset of input and output were set to five levels as {NG, NS, ZE, PS, PG}. Regarding the discourse domain of the fuzzy subset of output, ZE indicates that the robot maintains the last state, PS represents a small shift to the left, PG a large shift to the left, NG a small shift to the right and NS a large shift to the right. Indoor simulation was used to establish the relationship between the instantaneous position of the robot and guidance information from the imagery (Fig. 7). In Fig. 7, the right and left lines represent cornrows and the centerline represents the guidance line. During the simulation, the robot was placed in various positions yielding varying offsets and heading an-

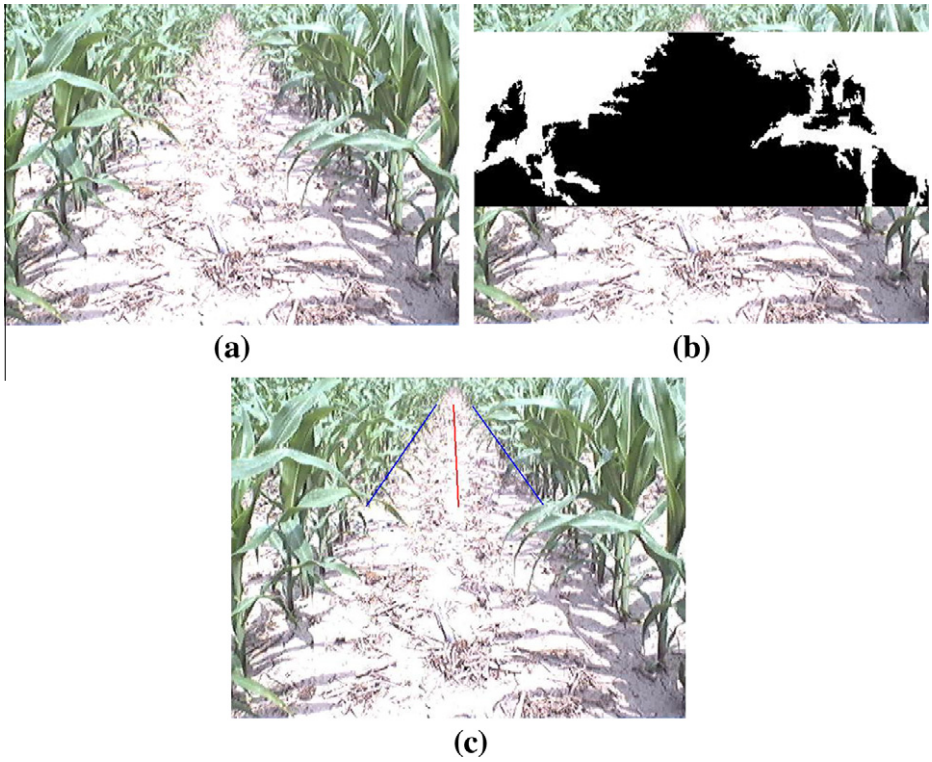


Fig. 4. Far FOV results for 70 cm tall corn. (a) Raw image; (b) binary image; (c) processed image.

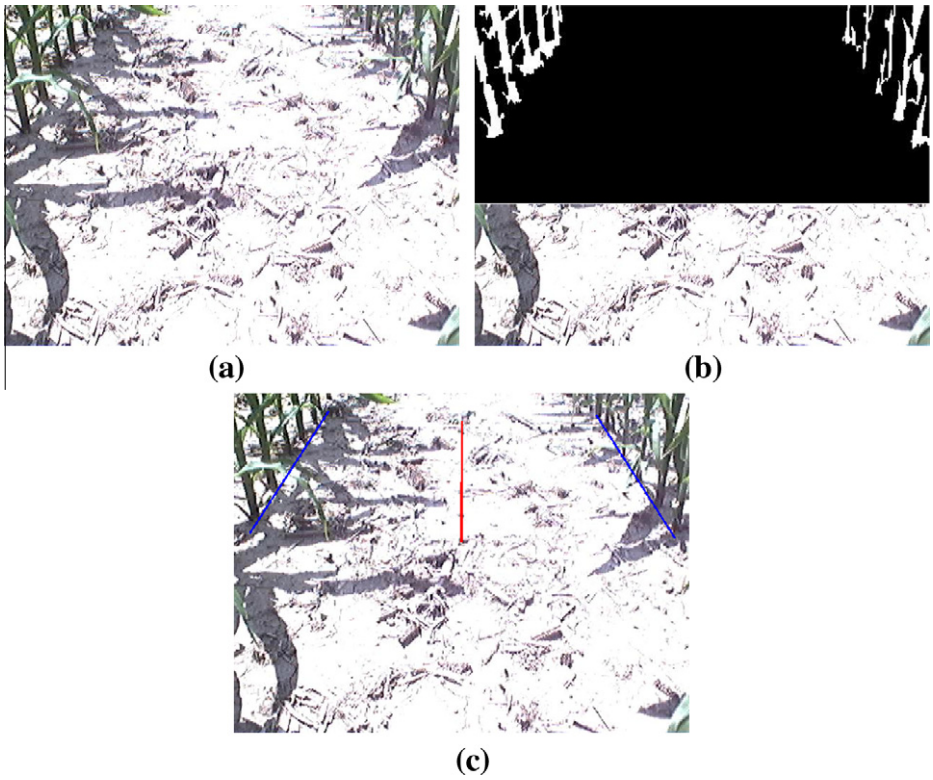


Fig. 5. Near FOV results for 70 cm tall corn. (a) Raw image; (b) binary image; (c) processed image.

gles to obtain the relationship between the offset and heading angle from the actual state and from the images. For the near, far and lateral FOV arrangements, the same simulation approach was adopted.

4. Experiments and results

To verify performance of the guidance system, tests were conducted in a cornfield located at the Agricultural Engineering Farm

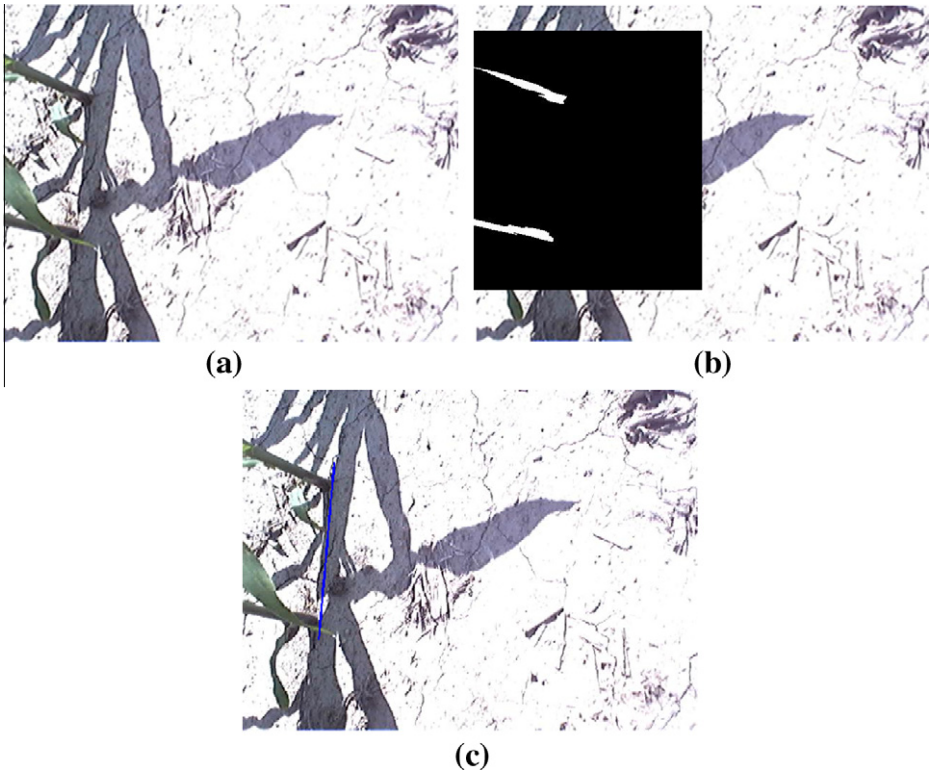


Fig. 6. Lateral FOV results for 70 cm tall corn. (a) Raw image; (b) binary image; (c) processed image.

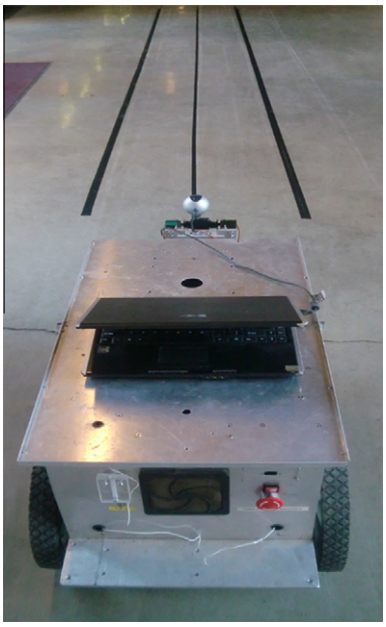


Fig. 7. Indoor simulation of the variable FOV arrangement.

Fig. 8. Experimental corn field.

of the University of Illinois (Fig. 8). The rows in the field were over 100 m in length with a row spacing of 75 cm, and a plant spacing of 15 cm. The width of the robot was approximately 60 cm, leaving a total of 15 cm of combined navigation room on the left and right side. At the time of the experiments, the corn plants were approximately 70 cm tall, and the initial speed of the robot was 0.2 m/s. The starting point of each experiment was chosen at a distance of 30 m from the end of the row. The soil surface of the field was kept intact, no leveling or compaction was applied before experiments.

At the beginning of each tests, a far FOV ($\alpha_{down} = 10°$, $\beta_{left} = 0°$) arrangement was used. As the first pixel threshold was encountered, the robot was stopped and the FOV of camera was adjusted automatically to a near FOV ($\alpha_{down} = 34°$, $\beta_{left} = 0°$). As the second threshold was encountered, indicating that the end of the row was near, the robot was stopped again and the lateral FOV ($\alpha_{down} = 80°$, $\beta_{left} = 30°$) of the camera was applied.

The tests were repeated three times with the same starting position, to ensure a consistent point of reference. An RTK-GPS receiver (Trimble 5800 GPS) was mounted on the robot to determine its path in intervals of one second, and to evaluate the row guidance accuracy. The GPS receiver was also used to determine the centerline in the 30 m long section of the experimental cornrow. The trajectory error was set to zero at the starting position, and subsequently, the robot was started under autonomous control and stopped automatically. Figure 9 shows the offset between

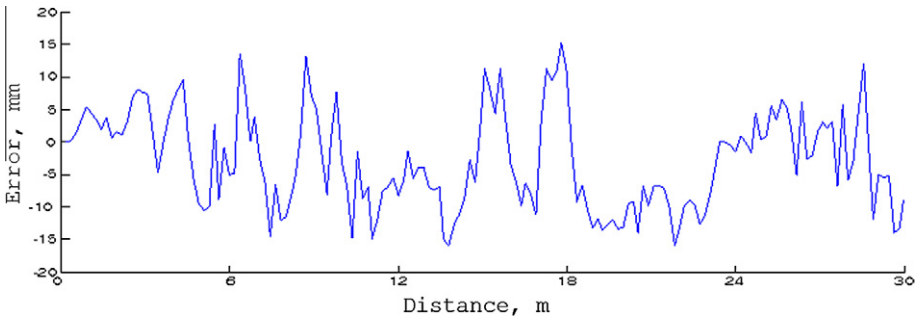


Fig. 9. Trajectory of row guidance.

Table 1
Performance measures of the robot's guidance system. A negative sign indicates that the error is biased to the right.

FOV arrangement	Maximum error (mm)	Average error (mm)	RMS error (mm)	Standard deviation
Far	−14.9	−1.0	56.8	7.1
Near	−15.8	−3.9	78.1	7.5
Lateral	−13.9	−3.5	31.2	7.5
Total stage	−15.8	−2.7	67	7.4

the robot location (from GPS) and the exact centerline of the 30 m row section.

Table 1 shows the overall performance, averaged among three runs, in the three FOV states, where a negative sign indicates that the error is biased to the right. The average error and standard deviation were lower than 2.7 mm and 7.4 mm, respectively, as indicated in Table 1, implying that the fuzzy control method was successful in driving the error to zero and yield stable navigational behavior. From Table 1, it is clear that the navigational accuracy of the far FOV was superior compared to the near and lateral FOV arrangement, since its errors were consistently the lowest. In contrast, the near FOV arrangement consistently had the poorest accuracy: Here the maximum RMS error was 78.1 mm, which can be contributed to an uneven cornfield caused by residual roots and hard soil clods. Although the images in the lateral FOV arrangement contained the least crop related information, it exhibited the smallest maximum error, which may be contributed to the short test distance of 2 m and the flatter soil surface in this stage.

5. Conclusions

A variable field of view (FOV) machine vision based guidance system was developed to navigate a robot through cornrows. Three FOV arrangements were tested being (1) near FOV, (2) far FOV and (3) lateral FOV. Morphological operations were used to calculate guidance lines in the field, and a fuzzy logic control scheme was used to guide the robot. RTK-GPS data were used to evaluate the guidance performance.

The results showed that the far FOV guidance method had the best performance with an average error of 1 mm and a standard deviation of 7.1 mm. The near FOV guidance had the poorest performance with an average absolute error of 3.9 mm and a standard deviation of 7.5 mm. Overall, the three methods had acceptable accuracy since the worst-case guidance error was 15.8 mm, and no plants were touched or run over during the tests. The results show that the method as developed is capable of guiding a robot through a cornfield, with acceptable accuracy and stability and without damaging the crop.

Although in the prototype as discussed in this paper, the camera was moved to accommodate the three FOVs, once the methodology is established, using three cameras for the individual FOVs may become preferable.

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