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Full Research Paper

Greenhouse Mobile Robot Navigation Using Wheel Revolution Encoding and Learning Algorithm

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Abstract

Repetitive and dangerous tasks such as harvesting and spraying have made robots usable in the greenhouses. The mechanical structure and navigation algorithm are two important parameters in the design and fabrication of mobile greenhouse robots. In this study, a four- wheel differential steering mobile robot was designed and constructed to act as a greenhouse robot. Then, the navigation of the robot at different levels and actual greenhouses was evaluated. The robot navigation algorithm was based on the path learning, so that the route was stored in the robot memory using a remote control based on the pulses transmitted from the wheels encoders; then, the robot automatically traversed the path. Robot navigation accuracy was tested at different surfaces (ceramics, concrete, dense soil and loose soil) in a straight path 20 meters long and a square path, 4×4 m. Then, robot navigation accuracy was investigated in a greenhouse. Robot movement deviation value was calculated using root mean square error (RMSE) and standard deviation (SD). The results showed that the RMSE of deviation of autonomous method from manual control method in the straight path to the length of 20 meters in ceramic, concrete, dense soil and loose soil were 4.3, 2.8, 4.6 and 8 cm, and in the 4×4 m square route were 6.6, 5.5, 13.1 and 47.1 cm, respectively.

Keywords: Agricultural robot, Encoder sensor, Vehicle navigation, Wheeled mobile robot

Introduction

Productivity in agriculture is obtained by increasing the quality and yield of the product, for which technology plays a crucial role. Greenhouses are expanding in order to use soil and water and other agricultural inputs better, resulting in high production efficiency and better quality of agricultural products. Hard and harmful tasks such as harvesting, spraying and pruning are needed in the greenhouse environment. Working in such an environment reduces the usefulness and damages operator's health (Nuyttens *et al*., 2004). Working in such an environment with a high temperature and humidity is a tough task. In a closed environment with low air flow, it is harmful for workers to act especially when toxic chemicals are used (Sánchez-Hermosilla *et al*., 2013). In recent years, the advancements in robotics have made mobile robots be used in the greenhouse, which can reduce operator fatigue and heavy work, and also increase the operator's productivity and health. The application of a robot in a greenhouse is successful if two issues are considered: 1- Designing vehicles appropriate to the greenhouse structure, 2- Implementing navigation techniques that permit the vehicle to move through the corridors between the rows of plants (González *et al*., 2009). Designing suitable navigation techniques for autonomous vehicles that travel in closed construction environments such as greenhouses is an important issue (Kondo *et al*., 2011). Various navigation technologies have been used to apply robots in the greenhouse. Manipulator robots have been used successfully in the industry. Therefore, these types of robots were examined in the greenhouse environment, too. These robots, usually being controlled by vision systems, have had an acceptable performance in the

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greenhouse environment (Dario *et al*., 1994; Kondo and Ting, 1998; Sandini *et al*., 1990). Several researchers investigated automated guided vehicle (AGV) in the greenhouse. An automated guided vehicle or automatic guided vehicle is a portable robot that follows along marked long lines or wires on the floor, or uses radio waves, vision cameras, magnets, or lasers for navigation. They are most often used in industrial applications to transport heavy materials around a large industrial building, such as a factory or a warehouse. Sammons *et al*. (2005) describes an autonomous spraying robot whose navigation control relies on inductive sensors which detect metallic pipes buried in the soil. Van Henten *et al*. (2002) presents a robot for harvesting cucumbers in the greenhouse, and its guidance system was based on sensing heating steel pipes. Sulakhe and Karanjkar (2013) made and tested an autonomous robot for greenhouse spraying, and the navigation experiment was conducted by tracking a signal wire on the ground. Similarly, a rail type traveling robot was described by Rajendra *et al*. (2009) for strawberry harvesting with a vision algorithm in a table top culture greenhouse. Successful use of AGV in agricultural fields has been reported by Comba *et al*. (2012). One of disadvantages of using these devices in the greenhouse is necessity of installation of rails or metal tubes leading to a high cost for the use of these types of robots in the greenhouse. Sánchez-Hermosilla *et al*. (2013) reported the successful use of AGV in the greenhouse without any changes in the plant or greenhouse structure. Distance measuring sensors such as ultrasonic, laser, etc., have been tested by many researchers to robot navigation. Ultrasonic sensors have been used in many studies to identify the plant, as well as navigation in the greenhouse and agricultural environments because of the low cost and ease of use. In these types of sensors, the time interval between transmitting and receiving waves is measured, and according to the speed of sound in that environment, the distance to object is estimated. Singh *et al*. (2005) developed a robotic vehicle with the six-wheel differential steering for greenhouse spraying. It was tested on sand and concrete surfaces through simulated greenhouse corridors using ultrasonic sensors. Iida and Burks (2002) conducted the tractor autonomous navigation in horticulture using ultrasonic sensors. Mandow *et al*. (1996) applied ultrasonic sensors in greenhouse sprayer for navigation. Ultrasonic sensors were used to detect the plant to guide the robot across the row crops (Celen *et al*., 2015). Masoudi *et al*. (2012) developed an automatic guidance system for sprayer robot by using ultrasonic sensors. Ultrasonic sensors have been introduced in some studies for obstacle detection (Borenstein and Koren, 1989; Harper and McKerrow, 1999; Veelaert and Bogaerts, 1999). Borenstein and Koren (1989) listed three reasons why ultrasonic sensors are poor sensors when accuracy is required. These reasons are: (i) Poor directionality that limits accuracy in determining the spatial position of an obstacle to 10-50 cm, depending on the distance to the obstacle and the angle between the obstacles surface and the acoustic beam. (ii) Frequent misreading caused by either ultrasonic noise from external sources or stray reflections from neighboring sensors (crosstalk). Misreading cannot always be filtered out and they cause the algorithm to see nonexistent obstacles. (iii) Specular reflections that occur when the angles between the wave front and the normal to a smooth surface is too large. In this case, the surface reflects the incoming ultra sound waves away from the sensor, and the obstacle is either not detected at all, or (since only part of the surface is detected) is seen much smaller than it is in reality. However, despite all the limitations of ultrasonic sensors, the technique can still be put to good use as a safety net sensor. The use of optical sensors, especially, has been reported in open environments for plant detection and navigation. Machine vision is another method for greenhouse robot navigation. Mehta *et al*., (2008) used machine vision to guide the robot among the corridors. Xue *et al*. (2017) developed a vision-based algorithm for navigation and operations of row planting crops, taking operations of spraying water and weeding by machine as examples. Dario *et al*. (1994) developed an AGOBOT platform with stereo vision and a manipulator arm equipped with a gripper and six degrees freedom for greenhouse cultivation of tomatoes, whose vision system controlled the moving direction and kept the vehicle at the center of the free path. Vision systems are most commonly used in outdoor agricultural environments for navigation and obstacle avoidance. The disadvantage of this method includes the effects of ambient light conditions on vision sensors performance, especially in outdoor environments. Another method of navigation of mobile robots is odometry. This method, in addition to being easy to use, is inexpensive. Odometry uses motion sensor data to estimate position changes in time. Mobile robots are used to estimate the relative position to the starting location. The inequality of wheels, wheel slippage, bump and tracks are factors that cause errors in this method. Due to these limitations, many researchers have used this method along with other methods to navigate mobile robots (Cox, 1991; Byrne *et al*., 1992; Chenavier and Crowley; 1992). A number of researchers have used complementary sensors (for example accelerometers, magnetic compass, gyroscope, machine vision, etc.) with odometry to increase navigational accuracy (Borenstein *et al*., 1996; Younse and Burks, 2007; Cho and Ki, 1999; Kleeman, 1992; Tsai, 1998; Piedrahita and Guayacundo, 2006). Goli *et al.* (2014) in a research compared four different positioning methods in order to evaluate their accuracy, using a remotely controlled robot on a specific route. These methods included: using a single GPS module, combining the data from three GPS modules, using an Inertial Measurement Unit (IMU), and GPS/IMU data fusion. The comparison of these four methods showed that GPS/IMU data fusion along with a Kalman filter was the most precise method, having a root mean square error of 23.4 cm.

Considering that in previous researches, different navigation systems have been used for greenhouse robots that sometimes have disadvantages and advantages and are relatively complex mechanism with high cost. So, in this project, a new navigation mechanism using wheel rotation coding as well as learning algorithm was designed, which, in addition to its simplicity and low cost, has an acceptable performance in robot routing in known environments such as greenhouses.

Materials and Methods

Mechanical structure

The width and length of the robot are two important parameters in designing of a greenhouse robot. The width of the greenhouse corridor and corridor's end space to turn, as well as the devices which mount on the robot chassis (Including battery, engine, power transmission system and sprayer) are the basis for determining the length and width of the robot. Commercial greenhouse corridors in Iran have a width of 70 to 120 cm. There is also a length of 2 meters at the end of the corridor to turn. By considering these factors, the width and the length of the robot were considered 55 and 110 cm, respectively. A four-wheel drive system was designed for the robot to minimize wheel slippage and more stability (Figure 1). Two electrical motors (24 V, 200 W) were equipped with a snail gearbox that were mounted in left and right sides and were connected to driver wheels by chain and sprocket. The electrical power which was required for motors, as well as the electrical circuit, was supplied by two batteries (12V, 45 Ah). Due to low speed (0.35 m s^{-1}) and the path of the robot in the greenhouse corridors which was fairly uniform, a suspension system was not designed for the device.

Fig.1. Robot platform

Turning mechanism

Differential drive was used to drive the robot. Differential drive is the simplest mechanical drive since it does not need rotation of a driven axis. The robot included a four-wheel drive, with a two-wheel drive on the right and two wheels on the left side of the robot platform. In this case, the two sides of the vehicle are independently powered. The velocity of right and left wheels was equal. If the wheels rotate at the same speed, the robot moves straight forward or backward. If both wheels are rotating at the same velocity in opposite directions, the robot turns about the midpoint of the two driving wheels (Figure 2). This mechanism was used to steer the robot due to the similar speed of the right and left wheels.

Fig.2. Turning mechanism

Navigation algorithm and robot learning

This robot is able to operate in every environment such as greenhouses and the path can be taught to the robot (Figure 3). But, because of using 3 paths: straight, square shape and move through the greenhouse corridors in this study, training process was done in these paths. Therefore, the learning algorithm was used in this robot. At first, the robot traveled the path with the operator's guidance and was trained during the course of the journey. After learning, the robot traveled autonomously. The learning process was carried out with the help of an advanced electronic system. The block diagram of the advanced electronic circuit is presented in Figure 4.

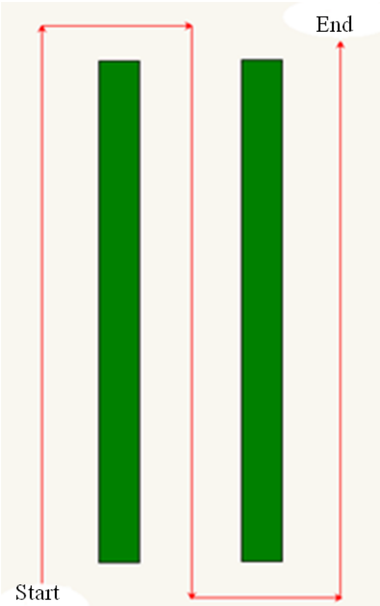

Fig.3. Rows of plants in a greenhouse and robot moving route

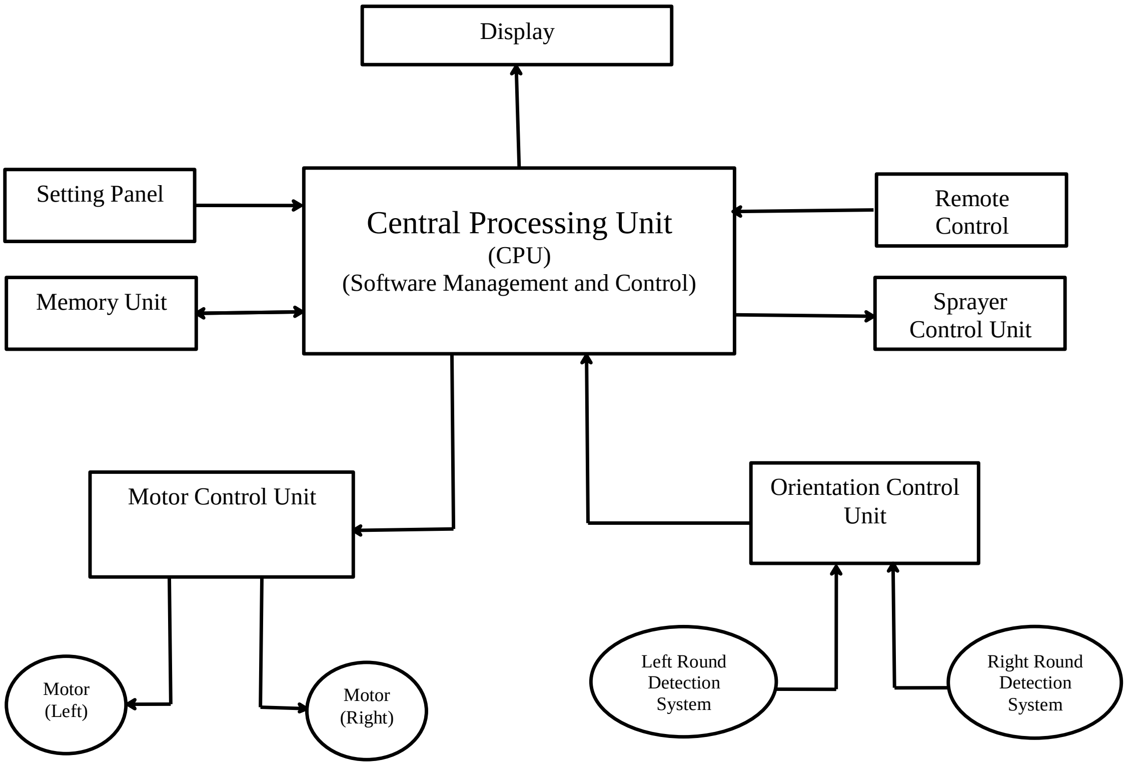

Fig.4. Flow Chart of the robot electronic circuit

Wheel revolution encoding

The motion control unit was designed to measure the angular rotation of the wheel. The two rotary encoders (E40H12-1024-3-T-24, Autonics, South Korea) with the specifications presented in Table 1 were mounted on the right and left rotating shafts to measure their position by converting axis rotation into electronics pulse (Figure 5).

Fig.5. Rotary encoder mounted on rotating shaft

Table 1- Encoder specifications

Sensor	Mark	Model	Resolution	Signal output	Power supply	Shaft type	Encoder diameter
Incremental	Autonics	E40H12-1024-3-T-24	1024	Pulse	12-24	Hallow shaft	40
			Pulse/rev		volt		mm

Software unit

Software program of the robot includes three main parts: 1) Learning unit, 2) Arithmetic logic unit (ALU) and 3) Algorithm execution unit.

The learning unit was designed to follow the path by the robot; by operator guidance appropriate pulses were sent to this unit and robot followed them into the specified path. In the ALU, the trained path was stored in the robot's memory after correction and reduction of noises. Finally, algorithm execution unit leads the robot to move into the preset path.

Robot navigation estimation

Considering that greenhouse corridors are usually earthy or concrete (Figure 6), robot navigation accuracy was tested on various surfaces including ceramics (in Lab), concrete, dense soil and loose soil (Figure 7) in straight path (20 m in length) (Fig. 8) and a square path 4×4 m (Borenstein *et al*., 1996) (Figure 9). A test with five replications was used. The test procedure was carried out using the following method:

At first by sending the appropriate pulses, the robot was traveling in the right direction and was learning the path from beginning to end. Then, the traveled path was stored in the robot memory unit by ALU. Learned path was traversed again exactly from the starting point independently by the robot and eventually stopped at pseudo-end point algorithm execution unit. The difference between this pseudo-end point and the end point of the real path was measured as the total deviation value.

To determine the robot's lateral deviation from the target line, the robot was tested in a straight line of 20 meters long. On the route at intervals of 4 meters (5 points), the horizontal distance of the robot was measured from the central line in two modes of manual and autonomous control (Figure 10).

(a) (b)

Fig.6. Greenhouse (a- Earthy surface; b- Concrete surface)


(a) (b) (c)

Fig.7. Various surfaces (a- Ceramic; b- Concrete; c- Soil)

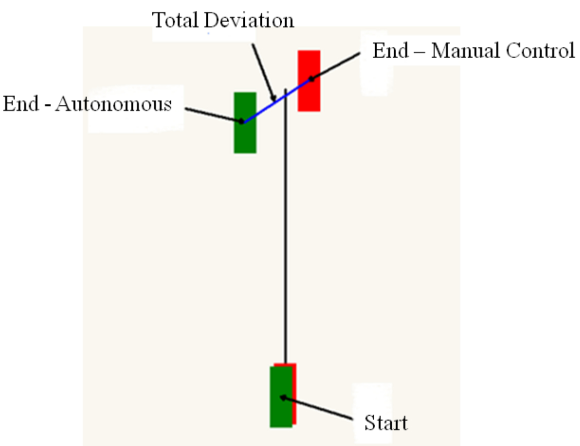

Fig.8. Robot testing in the straight line, 20 m long

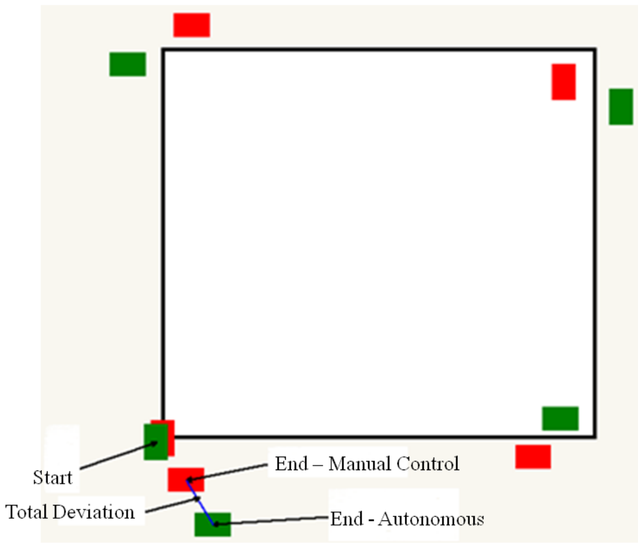

Fig.9. Robot testing in the 4×4 m square path

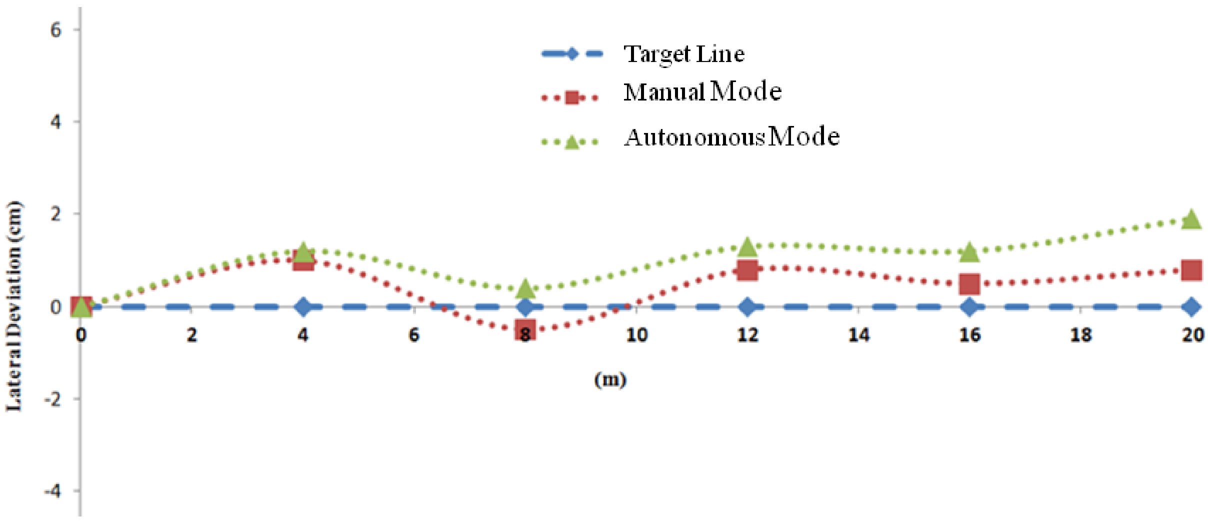

Fig.10. Determining the lateral deviation of the robot from the target line

Robot navigation accuracy tested in greenhouse environment

A sprayer have been installed on the robot chassis (Figure 11), and sprayer robot was tested in a greenhouse with a concrete surface. The area of the greenhouse was about 250 square meters. First, the robot was guided by manual control from the initial point to the end point (Figure 12). Then, the robot automatically traversed the path, and at the end the robot error rate was calculated. This experiment was repeated five times.

Fig.11. Sprayer robot

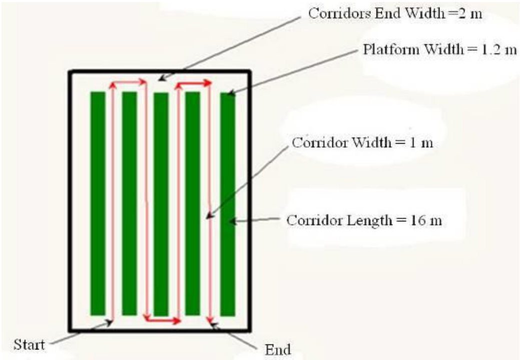

Fig.12. Greenhouse specifications

Data analysis

The statistical indices including RMSE and SD were used to measure the precision of the robot navigation (Wang *et al*., 2019). The following equations were used to calculate RMSE and SD.

$$\text{RMSE}=\sqrt{\frac{\sum e^2}{n}} \quad (1)$$

$$\text{SD}=\sqrt{\frac{\sum(e-\bar{e})^2}{n-1}} \quad (2)$$

Where e and $\bar{e}$ are total deviation (cm) and average deviation (cm), respectively and n is the number of collected data during the robot task.

Results and Discussion

Robot lateral deviation from central line in straight path

The average deviation of the robot from the center line in the direct path test in two manual and autonomous modes at different levels is presented in Table 2 and Figure 13. In both manual and autonomous states, the robot deviated from the central line. In manual control mode, if there are no systematic and non-systematic errors (Borenstein *et al*., 1996) and also no operator error, the robot must move in the straight line without any lateral deviation. However, in practice, due to systematic and non-systematic errors and operator error, there is always an error. But, in manual mode, this ability was available to allow the robot to move in a path with a minimum deviation of the target line. In an autonomous state, it was expected to follow the specified path with manual control by the robot but in practice, it did not happen, and there was always some errors, which was probably due to the wheel's slippage and probably due to a delay in the electric motors responding to commands issued by the central processing unit (It should be noted that two atmega8 microcontrollers were used to control the motors and increase the speed of execution of the commands in the control system). Also considering that the right and left sides of the robot have separate power systems (Includes motor and gearbox, wheel and chain system and wheels). As a result, there may be differences in the execution of the commands of the two systems in a fraction of the time, which can also affect the overall system error. Operator error can be in time to train the robot and also place the robot at the starting point in autonomous mode. During training, due to operator error, the robot's lateral deviation from target line is too high. As a result, lateral deviation from the target line also increases in autonomous mode. Any slight difference in the starting point in the autonomous state compared to training state causes an error in the autonomous state. As the results indicate, the robot deviations from the specified path decreased in loose soil, dense soil, ceramic and concrete, respectively. On the other words, the accuracy of the robot's navigation and compliance with the path specified in the rigid levels was higher. The least deviation was observed in the concrete surface, which is probably due to less slipping of the wheels. The reason for the increase in error at the ceramic surface relative to the concrete surface, despite its relatively uniform stiffness, may be due to the smoothness of the ceramic surface, which causes the wheels to slide. Celen *et al*. (2015) reported the precision of row guide using ultrasonic sensors is ±7cm at the velocity of 1 m s^{-1}. González *et al*. (2009) using sensors including of encoder, ultrasonic and magnetic compass reported the mean deviation of robot from the desired path (middle of the greenhouse aisles) was less than 15 cm. Xue *et al*. (2017), using the machine vision, showed that maximum deviation of the robot from the central lines of row crop was 4.7 cm. A study based on laid cable detection was carried out by Aghkhani and Abbaspoure-Fard (2009) for automatic off-road vehicle steering system. The system included a cable-spreading unit with a slim steel cable, a fifth or ground wheel with some cable-positioning sensors, a control unit and processor along with an electro-mechanical steering wheel driver. It was reported that, the overall offset deviation (error) on a longitudinal path from the desired path was 26 mm m^{-1} and 27.4 mm m^{-1}, on soil and asphalt surfaces, respectively.

Another factor that can affect the robot error is encoder resolution. Encoder resolution is commonly measured in pulses per revolution (PPR) for incremental encoders. Therefore, using a high-resolution encoder reduces the robot error. The use of high-resolution encoders can reduce the error of the robot, but it also increases costs.

Robot total deviation in straight and square paths

The values of mean deviation, SD and RMSE of autonomous mode from manual mode in a straight and a square path with 4×4 m dimensions on various surfaces are presented in Table 3. RMSE of autonomous mode from manual mode in a straight path (20 m long) on ceramic, concrete, dense soil and loose soil were 4.3, 2.8, 4.6 and 8 cm, respectively, whereas these values were 6.6, 5.5, 13.1 and 47.1 cm for the square path, respectively. Results show that robot deviation is smaller in straight path than the square-shaped path at various surfaces that was a predictable result because of increasing the error in the corners for turning. Also, it can be concluded that robot deviation is less on firm surfaces. The results are inconsistent with reports by Younse and Burks (2007). They used visual odometer for greenhouse robot navigation. The average robot error (difference in distance between the measured position and the position estimated by the visual odometer) in a straight path with a length of 154 cm on the concrete, sand, gravel and land laboratory surfaces have been 12.4, 4.75, 8.75, and 6.05 cm, respectively. The high robot error on concrete surfaces was due to the low efficiency of the camera in detecting these levels. Masoudi *et al*. (2012) applied ultrasonic sensors for robot navigation in a greenhouse which had been equipped with conductor lines. The root mean square errors (RMSE) of robot from the desired path at various velocities were 4.93 to 6.51cm. In a 60 cm wide corridor, the RMSE of robot from central line was 2.5 cm (Singh *et al*., 2005). Also, in the square path, especially in the loose soils, the amount of deviation was high. This amount of deviation has occurred in square corners to turn due to the sinking of the robot wheels into the soil; as a result, this parameter increases the slip of the wheels (Fig. 14). According to the results of the other studies, the robot navigation on concrete, ceramic and dense surfaces is acceptable. Therefore, it is suggested, to minimize the robot deviation from specified path in the greenhouse, especially those with a soil surface, the path of the robot movement should be compressed (Figure 15).

Table 2- The maximum deviation of the robot from central lines in two modes (manual and autonomous control) in the 20 meters long straight path test at different levels

Surface type	Maximum lateral deviation in manual control mode (cm)	Maximum lateral deviation in autonomous control mode (cm)
Ceramic	1.6	3.6
Concrete	1.4	2.1
Dense soil	2.2	5.2
Loose soil (Soft soil)	2.5	7.8

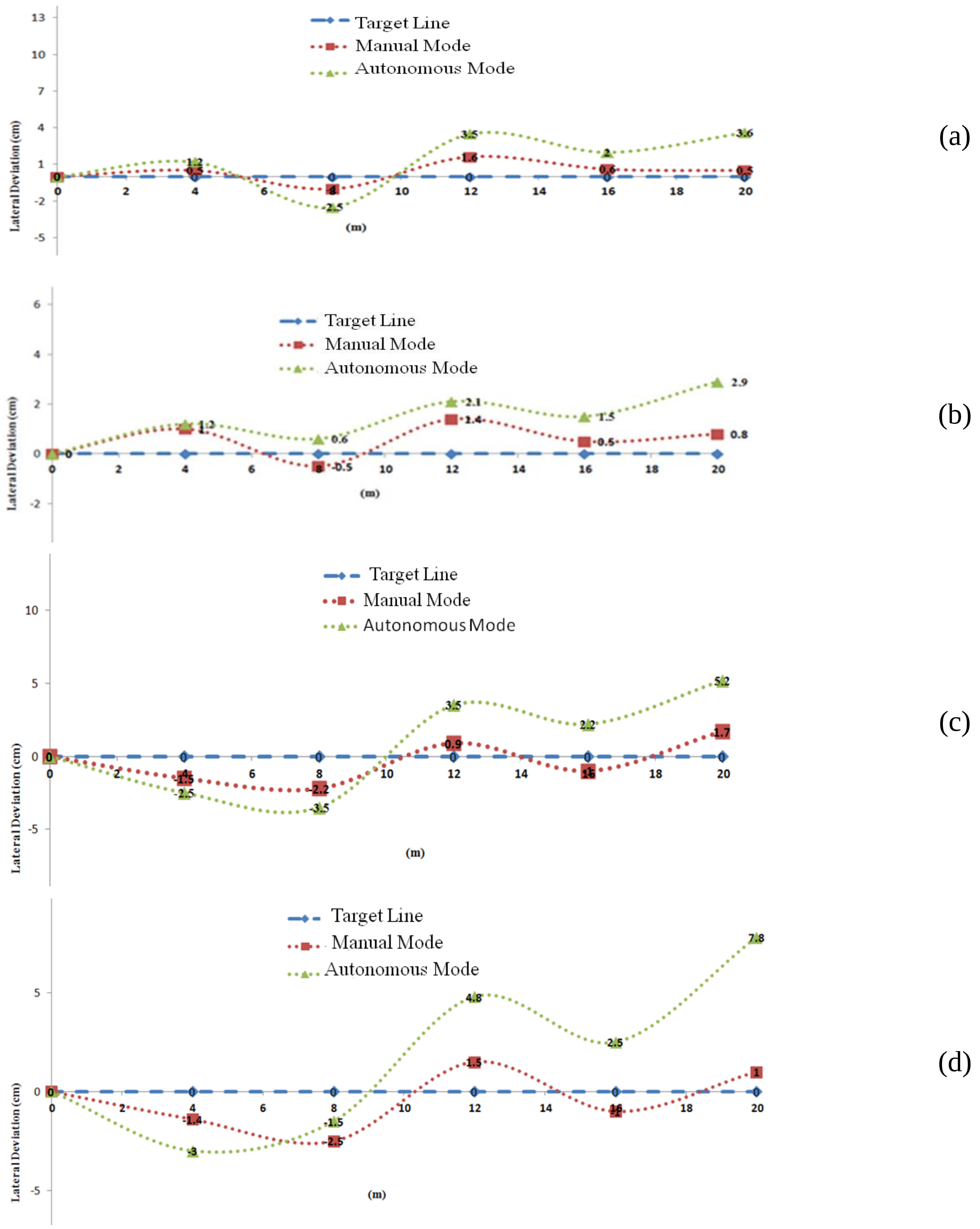

Fig.13. Robot lateral deviation from the central line in two modes (manual and autonomous control) at the different levels (a- Ceramic, b- Concrete, c- Dense soil and d- Soft soil)

Table 3- Comparison of automatic method error from manual control method at different levels and paths

Rep.	Error (cm) Straight path (20 meters long)				Error (cm) 4×4 m square path			
	Ceramic	Concrete	Dens soil	Loose soil	Ceramic	Concrete	Dens soil	Loose soil
1	3.5	2	5.4	8.4	8.2	4.9	13.8	46.5
2	6.4	2.5	4.5	7.5	7.4	5.2	14.1	42
3	4.5	3.4	4.8	8.8	7	5.8	11.5	50.4
4	3	2	5.7	7.9	6.8	6.1	12.2	47.8
5	3.2	2.7	5.2	7.3	8.4	5.4	13.5	48.4
Mean	4.1	2.8	5.1	8	7.6	5.5	13	47
RMSE	4.3	2.8	4.6	8	6.6	5.5	13.1	47.1
SD	1.4	0.58	0.47	0.62	0.71	0.47	1.1	3.1

Fig.14. Turning in loose soil

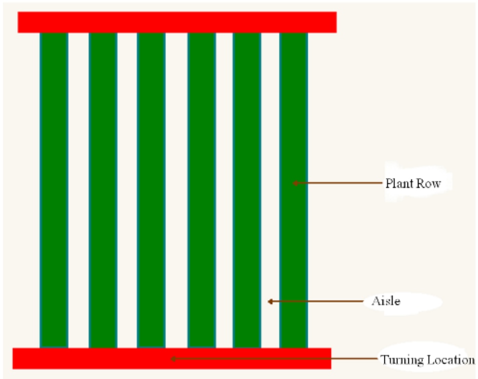

Fig.15. Plan view of the greenhouse

Accurate robot navigation in the greenhouse

Values of mean deviation, RMSE and SD of autonomous mode from manual mode in actual greenhouse are presented in Table 4. Mean deviation, RMSE and SD of autonomous mode from manual mode were 15.8, 15.85 and 1.75 cm, respectively. It can be concluded that robot efficiency in small greenhouses is acceptable. In large greenhouses, it is suggested that the greenhouse be divided into smaller parts or using complementary sensors along with this mechanism to enhance robot navigation accuracy.

Table 4- Total deviation of autonomous mode from manual mode at greenhouse

Rep.	Total deviation(cm)
1	15.5
2	13.8
3	16.8
4	18.2
5	14.6
Mean	15.8
RMSE	15.85
SD	1.75

Conclusions

In this study, the design and fabrication of an appropriate mobile wheel robot for the greenhouse environment were described. This robot has two important characteristics: 1) Simple mechanism, 2) Low cost of construction. Then, robot navigation accuracy was studied at different levels in a straight path and a square path. Robot navigation performance was acceptable at rigid surfaces such as concrete and compacted soil. In greenhouses with a soft soil, it is recommended to increase the accuracy of the robot's navigation, the path of the robot movement should be compressed. It is also suggested the robot navigation be investigated at various velocities.

References

1. Aghkhani, M. H., and M. H. Abbaspour-Fard. 2009. Automatic off-road vehicle steering system with a surface laid cable: Concept and preliminary tests. Biosystems Engineering 103: 265-270.
2. Borenstein, J., H. Everett, and L. Feng. 1996. Navigating mobile robots: Systems and techniques: AK Peters Wellesley, MA.
3. Borenstein, J., H. R. Everett, L. Feng, and D. Wehe. 1997. Mobile robot positioning: Sensors and techniques. Journal of Robotic Systems 14 (4): 231-249.
4. Borenstein, J., and Y. Koren. 1989. Real-time obstacle avoidance for fast mobile robots. IEEE Transactions on systems, Man, and Cybernetics 19 (5): 1179-1187.
5. Byrne, R., P. Klarer, and J. Pletta. 1992. Techniques for autonomous navigation. Sandia Report SAND92-0457, Sandia National Laboratories, Albuquerque, NM, March.
6. Celen, I., E. Onler, and E. Kilic. 2015. A Design of an Autonomous Agricultural Robot to Navigate between Rows. Paper presented at the 2015 International Conference on Electrical, Automation and Mechanical Engineering; Atlantis Press: Phuket, Thailand.
7. Chenavier, F., and J. L. Crowley. 1992. Position estimation for a mobile robot using vision and odometry. Paper presented at the Robotics and Automation, 1992. Proceedings., 1992 IEEE International Conference on.
8. Cho, S., and N. Ki. 1999. Autonomous speed sprayer guidance using machine vision and fuzzy logic. Transactions of the ASAE 42 (4): 1137-1143.
9. Comba, L., S. Martínez, P. Gay, and D. Aimonino. 2012. Reliable low cost sensors and systems for the navigation of autonomous robots in pot crop nurseries. Paper presented at the Proceedings of the First International Conference on Robotics and Associated High-technologies and Equipment for Agriculture. Applications of automated systems and robotics for crop protection in sustainable precision agriculture, (RHEA-2012) Pisa, Italy-September 19-21, 2012.
10. Cox, I. J. 1991. Blanche-an experiment in guidance and navigation of an autonomous robot vehicle. IEEE transactions on Robotics and Automation 7 (2): 193-204.
11. Dario, P., G. Sandini, B. Allotta, A. Bucci, F. Buemi, M. Massa, F. Ferrari, M. Magrassi, L. Bosio, R. Valleggi, E. Gallo, A. Bologna, F. Cantatore, G. Torrielli, and A. Mannucci. 1994. The Agrobot project for greenhouse automation. Acta Horticulturae 361: 85-92. DOI: 10.17660/ActaHortic.1994.361.7
12. González, R., F. Rodríguez, J. Sánchez-Hermosilla, and J. Donaire.2009. Navigation techniques for mobile robots in greenhouses. Applied Engineering in Agriculture 25 (2): 153-165.
13. Harper, N., and P. McKerrow. 1999. Detecting plants for landmarks with ultrasonic sensing. Paper presented at the Proceedings of the International Conference on Field and Service Robotics.
14. Iida, M., and T. Burks. 2002. Ultrasonic sensor development for automatic steering control of orchard tractor, Proceedings of the Automation Technology for Off-Road Equipment Chicago, Illinois, p. 221- 229.
15. Kleeman, L. 1992. Optimal estimation of position and heading for mobile robots using ultrasonic beacons and dead-reckoning. Paper presented at the Robotics and Automation, 1992.

Proceedings., 1992 IEEE International Conference on Robotics and Automation.12-24 May. Nice. France.

16. Kondo, N., M. Monta, and N. Noguchi. 2011. Agricultural Robots: Mechanisms and Practice: Apollo Books.
17. Kondo, N., and K. Ting. 1998. Robotics for plant production. artificial intelligence Review 12 (1-3): 227-243.
18. Mandow, A., J. Gomez-de-Gabriel, J. L. Martinez, V. F. Munoz, A. Ollero, and A. Garcia-Cerezo. 1996. The autonomous mobile robot AURORA for greenhouse operation. IEEE Robotics & Automation Magazine 3 (4): 18-28.
19. Masoudi, H., R. Alimardani, M. Omid, S. S. Mohtasebi, and N. Noguchi.2012. Determination of ultrasonic sensor ability for use as guidance sensors of mobile robots. Sensors and Materials 24 (3): 115-126.
20. Mehta, S., T. Burks, and W. Dixon. 2008. Vision-based localization of a wheeled mobile robot for greenhouse applications: A daisy-chaining approach. Computers and Electronics in Agriculture 63 (1): 28-37.
21. Goli, H., S. Minaee, A. Jafari, A. R. Keyhani, A. Hajiahmad, H. Abdolmaleki, and A. M. Borghaei. 2014. Comparision of foure different methods for agricultural positioning using GPS and IMU. Journal of Agicultural Machinery 4 (2): 285-295. (In Farsi).
22. Nuyttens, D., S. Windey, and B. Sonck. 2004. Comparison of operator exposure for five different greenhouse spraying applications. Journal of Agricultural Safety and Health 10 (3): 187.
23. Piedrahita, G. A., and D. M. Guayacundo. 2006. Evaluation of accelerometers as inertial navigation system for mobile robots. Paper presented at the IEEE 3rd Latin American Robotics Symposium. Santiago. Chile.
24. Rajendra, P., N. Kondo, K. Ninomiya, J. Kamata, M. Kurita, T. Shiigi, and Y. Kohno. 2009. Machine vision algorithm for robots to harvest strawberries in tabletop culture greenhouses. Engineering in Agriculture, Environment and Food 2 (1): 24-30.
25. Sammons, P. J., T. Furukawa, and A. Bulgin. 2005. Autonomous pesticide spraying robot for use in a greenhouse. Paper presented at the Australian Conference on Robotics and Automation. Canberra Australia.
26. Sánchez-Hermosilla, J., R. González, F. Rodríguez, and J. G. Donaire. 2013. Mechatronic description of a laser autoguided vehicle for greenhouse operations. Sensors 13 (1): 769-784.
27. Sandini, G., F. Buemi, M. Massa, and M. Zucchini. 1990. Visually guided operations in green-houses. Paper presented at the IEEE International Workshop on Intelligent Robots and Systems. Towards a New Frontier of Application. Ibaraki. Japan.
28. Singh, S., T. Burks, and W. Lee. 2005. Autonomous robotic vehicle development for greenhouse spraying. Transactions of the ASAE 48 (6): 2355-2361.
29. Sulakhe, A., and M. N. Karanjkar. 2013. Design and operation of agricultural based pesticide spraying robot. International Journal of Science and Research 4: 1286-1289.
30. Tsai, C. C. 1998. A localization system of a mobile robot by fusing dead-reckoning and ultrasonic measurements. IEEE Transactions on Instrumentation and Measurement, 47 (5): 1399-1404.
31. Van Henten, E. J., J. Hemming, B. Van Tuijl, J. Kornet, J. Meuleman, J. Bontsema, and E. Van Os. 2002. An autonomous robot for harvesting cucumbers in greenhouses. Autonomous Robots 13 (3): 241-258.
32. Veelaert, P., and W. Bogaerts. 1999. Ultrasonic potential field sensor for obstacle avoidance. IEEE transactions on Robotics and Automation 15 (4): 774-779.
33. Wang, H., J. Li, W. Cui, X. Lu, Z. Zhange, C. Sheng, and Q. Liu. 2019. Mobile robot indoor positioning system base on K-ELM. Journal of Sensors.http:\\doi.org\10.1155\2019\7547648.

34. Xue, J. l., B. W. Fan, X. X. Zhang, and F. Yong. 2017. An Agricultural Robot for Multipurpose Operations in a Greenhouse. DEStech Transactions on Engineering and Technology Research (icmme).
35. Younse, P., and T. Burks. 2007. Greenhouse robot navigation using KLT feature tracking for visual odometry. Agricultural Engineering International: CIGR Journal.

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مقاله علمی-پژوهشی

ناوبری ربات متحرک گلخانه با استفاده از کدگذاری چرخش چرخ و الگوریتم یادگیری

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چکیده

وجود کارهای تکراری، سخت و طاقت‌فرسا و بعضاً خطرناک در محیط گلخانه هم‌چون سم‌پاشی و برداشت، استفاده از ربات را در گلخانه ضروری نموده است. ساختار مکانیکی و الگوریتم ناوبری دو فاکتور مهم در طراحی و ساخت ربات‌های گلخانه می‌باشند. در این پروژه یک ربات متحرک گلخانه چهار چرخ محرک با فرمان‌گیری دیفرانسیلی طراحی و ساخته شد. سپس ناوبری ربات در سطوح با جنس‌های مختلف و نیز محیط گلخانه واقعی مورد ارزیابی قرار گرفت. الگوریتم ناوبری ربات بر اساس یادگیری مسیر بود بدین صورت که ابتدا مسیر مورد نظر با استفاده از کنترل راه دور بر اساس پالس ارسالی از اینکودرهای چرخ، در حافظه ربات ذخیره می‌شد سپس ربات به‌صورت خودکار این مسیر را طی می‌کرد. دقت ناوبری ربات در سطوح با جنس‌های مختلف (سرامیک، بتون، خاک متراکم و خاک نرم) در مسیر مستقیم به طول ۲۰ متر و مسیر مربع شکل ۴×۴ متر مورد آزمایش قرار گرفت. هم‌چنین دقت ناوبری ربات در محیط گلخانه ارزیابی شد. مقدار انحراف ربات با استفاده از شاخص‌های آماری ریشه میانگین مربعات خطا (RMSE) و انحراف معیار (SD) محاسبه شدند. نتایج نشان داد که ریشه میانگین مربعات خطای انحراف ربات در حالت خودکار نسبت به روش دستی در مسیر مستقیم به طول ۲۰ متر در سطوح سرامیکی، سیمانی، خاک متراکم و خاک نرم به‌ترتیب ۴/۳، ۲/۸، ۴/۶ و ۸ سانتی‌متر و در مسیر مربع شکل۴×۴ متر، ۶/۶، ۵/۵، ۱۳/۱ و ۴۷/۱ سانتی‌متر به‌دست آمد.

واژه‌های کلیدی: حسگر اینکودر، ربات کشاورزی، ربات متحرک چرخ‌دار، ناوبری

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