Localization and controlling the mobile robot by sensory data fusion

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Abstract: Localization of a mobile robot with any structure, work space and task is one of the most fundamental issues in the field of robotics and the prerequisite for moving any mobile robot that has always been a challenge for researchers. In this paper, Dempster-Shafer (D.S.) and Kalman filter (K.F.) methods are used as the two main tools for the integration and processing of sensor data in robot localization to achieve the best estimate of positioning according to the unsteady environmental conditions and a framework for Global Positioning System (GPS) and Inertial Measurement Unit (IMU) sensor data fusion. Also, by providing a new method, the initial weighing on each of these GPS sensors and wheel encoders is done based on the reliability of each one. The methods were compared with the simulation model and the best method was chosen in each situation. In addition to obtaining the geometric equations governing the robot, a Proportional Integral Derivative (PID) controller was used for the kinematic control of the robot and implemented in the MATLAB Simulink. Also, using these two Mean Absolute Deviation (MAD) and Mean Square Error (MSE) criteria, the localization error was compared in both K.F. and D.S. methods. In normal Gaussian noise, the K.F. with a mean error of 2.59% performed better than the D.S. method with a 3.12% error. However, in terms of non-Gaussian noise exposure, which we are faced with in real condition, K.F. information was associated with a moderate error of 1.4, while the D.S. behavior in the face of these conditions was not significantly changed.

Keywords: sensory data fusion, mobile robot, localization, Dempster-Shafer method, Kalman filter

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1 Introduction

Currently, agricultural automation is inevitable in order to save on costs and produce more per unit area. Robotics can also meet the goals of automation in agriculture, by minimizing the tough, risky, deadly and long working conditions, along with precise monitoring and control. Between 1750 and 1900, a revolution in the agricultural industry was formed at the same time as fundamental changes in American agriculture. The basis of this revolution was the entry of machines in the industry. The idea of self-driving agricultural vehicles is not very new, and the prototype of a non-driver agricultural tractor, controlled through a cable, dates back to the 1960s (Roberts et al., 1998). In the 1980s, with the development of computer science and the ability to use sight sensors, they created new situations for self-contained robots, which were first used by researchers at the University of Michigan and the University of Texas. In the decade for the first time, an orange harvesting robot was designed and developed by researchers at the University of Florida (Edan, 1995). With the development of research in this field and the development of tools used to guide robots, including optical, ultrasound and radio sensors, the problem of increasing the accuracy and speed of the robots was considered (Murakami et al., 2006). Data fusion is a method for combining the data from several sources of information used to obtain a brighter picture of the problem being investigated and measured. Data fusion systems are currently being used in a variety of fields, including sensor networks, robotics, photo and video processing, and smart system design. A lot of researches, especially in recent years, has been done in the field of data fusion, but there is still a long gap between

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intelligent systems in this area with the ability of organisms, especially the ability of the human brain (Hall and Llinas, 1997). Klein (1993) provided a definition of the integration of sensor data, which combines sensor data, from one type to different sources of data. Both definitions provide a general form in the use of sensors and can be used in a variety of applications, including remote sensing. The authors have reviewed many of the methods of data fusion and discussed each one. Based on the strengths and weaknesses of previous work, a basic definition of information integration is presented as follows: information integration is an effective way to automatically or semi-automatic conversion of information from different sources or at different time points into an effective output that in the decision-making process, acts automatically or supports human decision-making. In their research, the neural network tool is used in data fusion and describes different levels of data fusion. Ghahroudi and Fasih (2007) have used the fusion of sensor data by using fuzzy logic utilization at the decision level in the driver assistance system. Subramanian et al.(2009) used a combination of optical and visual sensors via a fuzzy system to auto routing agricultural vehicles in specific routes of citrus orchards, where the routing error improved in comparison with the use of separate sensors. In this research, the results of the data fusion prior to the decision were refined by the Kalman filter. Akhoundi and Valavi (2010) used fuzzy systems to integrate sensor data and showed that aggregation of sensor data by this method is more efficient than the sum of sensor data separately. This fuzzy system included a fuzzy rule base based on sensors that were complementary in accuracy and bandwidth. In studies for localization, the combination of the global positioning system and other sensors such as inertial measurement sensors, position detection sensors (digital compass), camera, radar and laser sensors, have shown more accurate results than the use of only the global positioning system (GPS) (Keicher and Seufert, 2000; Subramanian et al., 2006; Li et al., 2010). In numerous studies, differential global positioning system (DGPS) has been used to determine the position with a precision of a few centimeters in agricultural conditions. The combination of GPS speed with the inertial navigation systems (INS) sensor was used to measure the slip angle of the vehicle and the tire when it was turned (Bevly et al., 2001). In other research, Zhang et al. (2002) equipped an agricultural tractor with an intelligent navigation system with machine vision sensors and optical fiber gyroscope. The results of this assessment showed that the intelligent navigation system, combined with several navigation sensors, could drive agricultural machinery in the field of row crop without crossing the product. Also, Nagasaka et al. (2004) used this navigation system for automatic transplantation in rice fields. Their experiments showed that the precision of folding with this method was favorable, but it was not sufficiently accurate for spraying and mechanical weeding operations because of the movement among the rows. In a research conducted by Mizushima et al. (2011) positioning sensors were combined with three vibrational gyroscopes and two inclinometers. Park (2016) for safe and comfortable mobile robot navigation in dynamic and uncertain environments, extended the state of the art in analytic control of mobile robots, sampling based optimal path planning, and stochastic model predictive control. Self locating method was used based on fuzzy three dimensional grid by Shi et al. (2017), in which, with reduced computing, accuracy was increased.

Shafer (1976) introduced the theory of evidence, later known as the Dempster-Shefer theory. The basis of this approach is to integrate data into evidence or beliefs that can manage information deficiencies. This was a reinterpretation of Arthur Dempster's research in the 1960s, which, according to Dempster, has been largely modified by Shafer (Shafer et al., 2003).

The Dempster-Shafer theory is a generalization of Bayesian theory, widely used in computer science and artificial intelligence, and resembles fuzzy sets (Rakowsky, 2007). These three aforementioned theories and the capabilities of each one are compared widely in the sensor data fusion, and in some applications, the Dempster-Shafer theory is used to link other data fusion methods (Betz et al., 1989; Boston, 2000; Fenton et al., 1998; Murphy, 1998; Pagac et al., 1998). Denoeux et al. (2018), provided two new division methods, along with simulation of some applications in the Dempster method. Liu et al. (2018), in their research, proposed a new weighting method in Dempster-Shafer theory by a fuzzy algorithm that could use the evidence obtained from different methods to classify the target.

Despite extensive research in the field of robotics and control, the implementation of plans and methods of localization in the agricultural industry have been less studied due to the fundamental difference in the laboratory environment with real conditions. Because highly accurate sensors such as DGPS, in addition to the high cost, have access restrictions, In this paper, various methods of integrating global positioning unit and inertia measurement unit are utilized by Dempster-Shafer theory as well as Kalman filtering, and the results were compared to select an accurate method for localization at an appropriate cost. Also, by introducing a new method, initial weighting has been made on the information of each of the GPS sensors and wheel encoders, based on the reliability of each one. In addition to obtaining the geometric equations governing the robot, a Proportional Integral Derivative (PID) controller was implemented in the MATLAB Simulink for kinematic control and evaluation of the robot localization algorithms.

The rest of the paper is organized as follows: the kinematic modeling of the agricultural robot, the simulation of the robot in the MATLAB SimMechanic, the control of the robot with its results and localization by Dempster- Shafer (D.S.) and Kalman filter (K.F.) are given in Materials and method section. Comparing of these two methods and the results is presented in Result and discussions. Finally, some conclusions are highlighted.

2 Materials and methods

2.1 Modeling

In this section, a model will be created for a robot that is a car-like robot. The typical model for the four-wheel robots is the bicycle model shown in Figure 1. The two-wheel drive model has a rear wheel mounted on its body, and the front wheel plate rotates around a vertical axis for steering. The position of the robot is represented by a moving coordinate system whose x-axis is in the direction of moving forward of the robot and its center corresponds to the center of the rear axle of the robot. The configuration of the robot is also defined by general coordinates $q=(x,y,\theta)\in C$ in which, C, is an Euclidean two-dimensional space. In this coordinate system, the speed of the robot is along the x-axis, because the robot cannot slip sideways. Because of the low speed, longitudinal slip and centrifugal force can be ignored.

$$v_x = v,\ v_y = 0 \tag{1}$$

The wheels cannot move in the direction of the dashes, and these two dashes cut off at one point, which is called the instantaneous center of rotation. This point is the center of the circle the robot tracks and the angular velocity of the robot is obtained from the following equation.

$$\dot{\theta} = \frac{v}{R_1} \tag{2}$$

In which R_1=L/tanγ and L is equal to the length of the robot.

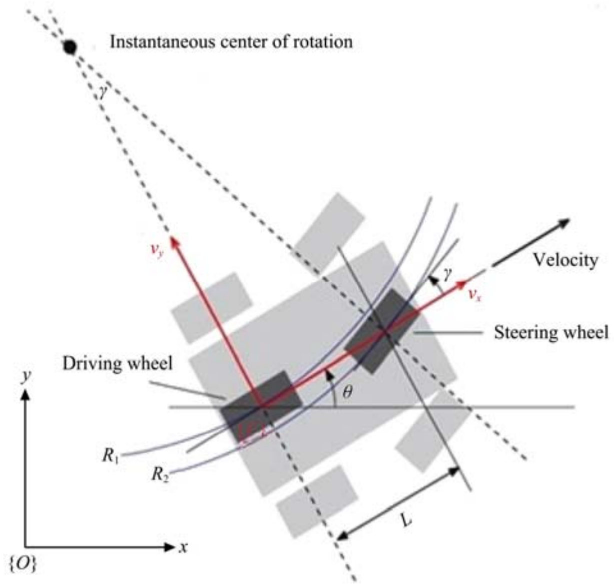


Figure 1 Bicycle model of four wheeled robot

As can be imagined, the radius of the robot's circular path increases with increasing the length of the robot. On the other hand, the steering angle has a mechanical limit and its maximum value specifies the minimum R_1 value. Thus, if the steering angle is constant, the robot runs a circular arc.

According to Figure 1, R_2>R_1, which means that the front wheel must travel longer and therefore have a higher speed than the rear wheel. Also, in a four-wheel robot, the outer wheels are rotational with different radials from the inner wheels. Therefore, there is very little difference between the steering angle of the steering wheels, and this difference can be made using Ackerman steering mechanism on the steering wheels. Similarly, in moving wheels, the speed of rotation varies. The speed of the robot is equal to ($v\cos\theta$, $v\sin\theta$) in the reference coordinate system. By combining it with Equation (2), the equations of motion are obtained as follows.

$$\dot{x} = v\cos\theta \tag{3}$$

$$\dot{y} = v\sin\theta \tag{4}$$

$$\dot{\theta} = \frac{v}{L}\tan\gamma \tag{5}$$

This model is a kinematic model of the robot, because it is described by the speed of the robot, not the force and torque that speeds up. In the global or reference coordinate system:

$$\dot{y}\cos\theta - \dot{x}\sin\theta = 0 \tag{6}$$

This is a non-holonomic motion control. Another important feature of this model is that when the robot speed is zero, then $\dot{\theta} = 0$. This means that the robot direction cannot be changed without moving. It comes from Equation (5). Because, $\dot{\theta}$ is the instantaneous velocity of rotation. Also the robot command is always less than $\pi/2$.

2.2 Simulation

In this section, according to the kinematic model of the robot, a simulation of the robot in the MATLAB software has been addressed. Figure 2 shows the implementation of Equations (3) to (5) in the Simulink environment. Linear speed and steering angle as input, and position and angle of the robot are considered as output of this model.

In order to have a dynamic environment and visual representation of the robot's motion, the robot model is interconnected individually in the SimMechanics of Matlab software to allow the robot's behavior in dealing with various control algorithms observed by combining it with Simulink environment. In Figure 3, a plan is visible from this environment.

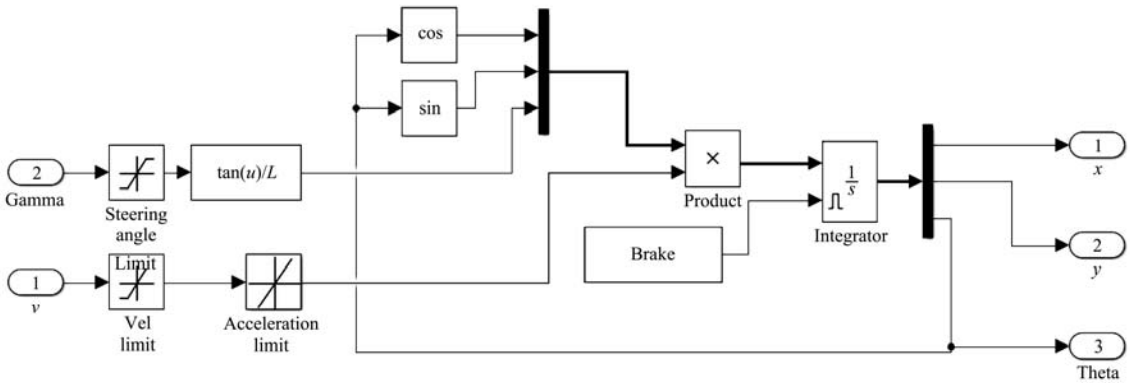


Figure 2 Simulation of the kinematics model of robot

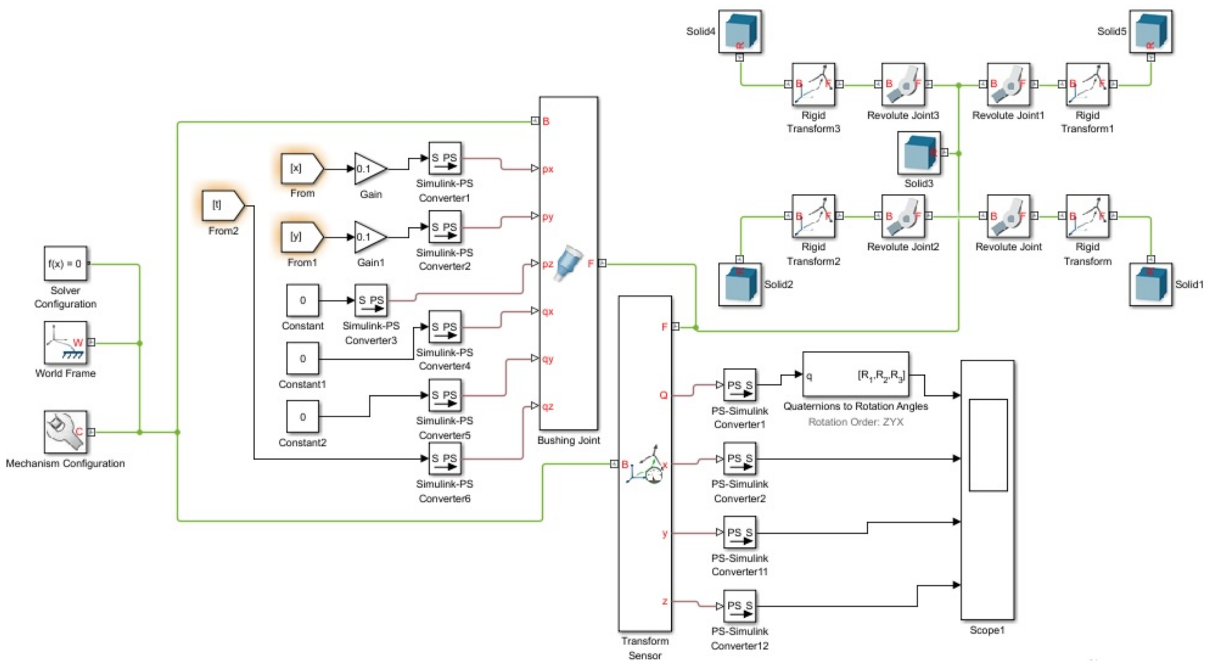


Figure 3 Mobile robot simulation in the SimMechanics

In this simulation model, at first, different parts of the robot, which are designed in SolidWorks software, are brought to the SimMechanics environment by Solid blocks. Blocks are assembled in this environment by appropriate joints to show how well the robot behaves. By placing a sensor on a robot, in order to report its position and angles (such as the gyroscope sensor), these robot features are available throughout the path. The robot moves with constant velocity and the steering angle is the only control variable.

The control commands to the simulated model have been implemented from controllers written in the Simulink. In addition, by reporting the amount of rotation of each joint, in fact, will be an encoder on the each wheel which produces output in radians per second. In Figure 4, simulation of the robot and the transfer of various parts of SolidWorks to the SimMechanics, along with an explanation of each part, are presented.

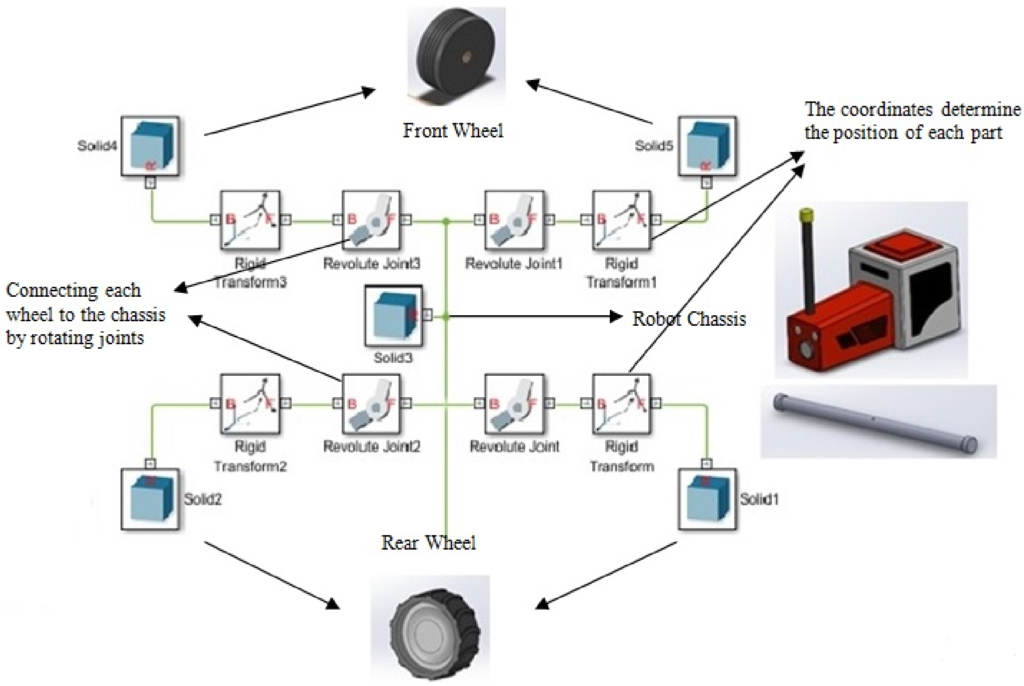


Figure 4 Simulate a robot and transfer parts to the simulator SimMechanics

2.3 Control

This section firstly examined the robot movement from an initial point to a target point (x^*, y^*). A proportional controller has been used to apply the input to the kinematic model of the robot. To control the robot speed, the following equation was used (Corke, 2011):

$$v = K_V \sqrt{(x^* - x)^2 + (y^* - y)^2} \tag{7}$$

Equation (7) calculates the velocity applied to the model of robot by the controller. Also, the angle of the robot at the target point and steering angle is also obtained from the following equations.

$$\theta^* = \tan^{-1} \frac{y^* - y}{x^* - x} \tag{8}$$

$$\gamma = K_s(\theta^* - \theta) \tag{9}$$

Also, tracking errors are obtained from reducing the current position of the robot from the optimal input value at any given moment and by the PID controller, these errors are pushed to zero. Another important task for robots is to move to a specific line and follow it. Consider the hypothetical $ax+by+c=0$ line. We need two controllers to control the steering. The first controller is designed to control the steering in tracking the line, and the second controller is designed to match the direction of the robot with the hypothetical line (Corke, 2011):

$$d = \frac{(a,b,c)\cdot(x,y,1)}{\sqrt{a^2+b^2}} \quad \alpha_d = K_d d \quad K_d > 0 \tag{10}$$

$$\theta^* = \tan^{-1}\frac{-a}{b} \quad \alpha_h = K_h > 0(\theta^* - \theta) \quad K_h > 0 \tag{11}$$

The above equations are the mathematical relations of steering controllers for this maneuver. Finally, the steering angle is obtained according to the equation as follow:

$$\gamma = K_d d + K_h(\theta^* - \theta) \tag{12}$$

Finally, the robot tracks the path that is generally defined on the x-y plane. This path can be obtained by sequencing the coordinates of the points that the robot should go through. The robot's motion control in this case is very similar to the one in which the robot moves to a target point, With the difference that in this case the target point changes (Corke, 2011):

The robot is always at a short distance (d^*) from the target point. Therefore, the error is calculated as follow:

$$e = \sqrt{(x^* - x)^2 + (y^* - y)^2} - d^* \tag{13}$$

To control the speed at points where the error is zero, we use a PID controller.

$$v^* = -K_v e + K_i \int e dt + K_d \frac{de}{dt} \tag{14}$$

To control the steering angle, as before, we use a proportional controller.

$$\theta^* = \tan^{-1} \frac{y^* - y}{x^* - x} \tag{15}$$

In Figure 5, tracking the path by the robot is simulated from a primitive point in the plane. In this block, Equations (18)-(21) are implemented in the Simulink toolbox of MATLAB, and the robot follows it after applying the optimal path. In Figure 6, the path of the robot from the red center point is shown in order to track the desired path.

In Figure 7, the agricultural robot simulated in the MATLAB mechanical simulator is tracking the path.

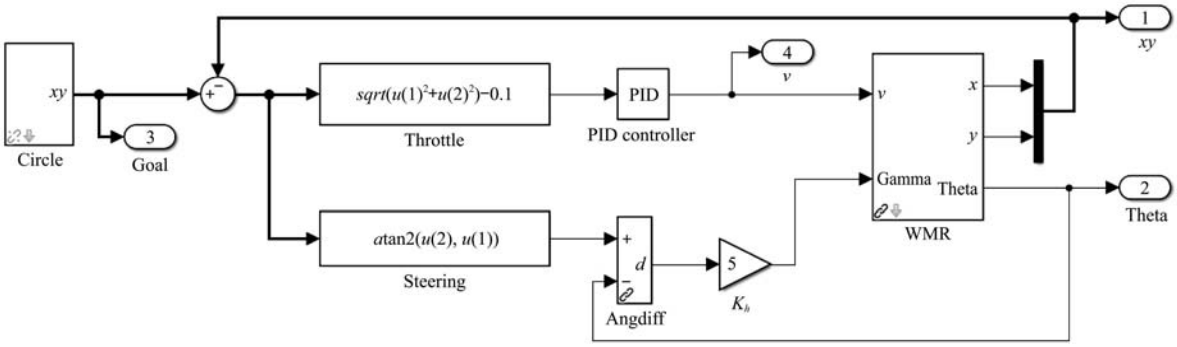


Figure 5 Simulate motion in a desired path

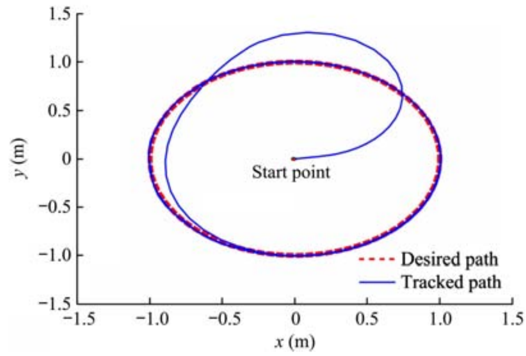


Figure 6 Simulated path of robot movement

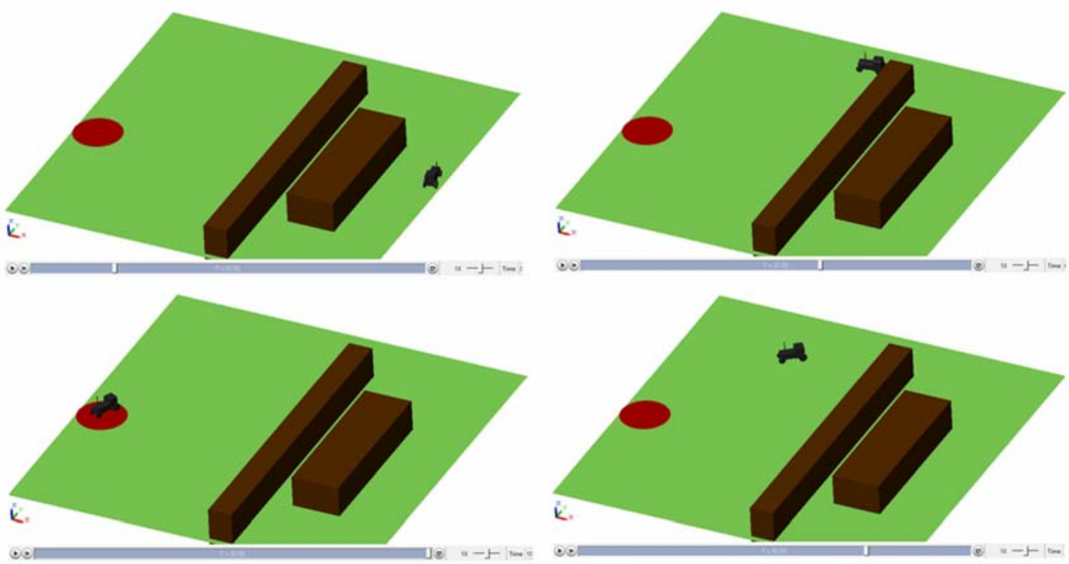


Figure 7 Move the robot in the simulated path

2.4 Localization

Now, the robot positioning in the simulation environment is performed using two methods, K.F. and D.S. Also, the initial weighing to the sensors' results will be explained and applied.

2.4.1 Dempster – Shafer's Theory

Dempster-Shafer's Theory of Evidence according to many credible references, is the most powerful method in data fusion. In fact, this method merges data at the decision level. This method has the ability to integrate any numerical, signal, and multi-dimensional data. One of the areas that this tool and its features are underused is the localization. In this paper, how D.S. Theory of Evidence can be used in precise positioning of moving objects was firstly shown, and then the performance of this method in localization was compared with K.F. method. D.S. theory is a generalization of the Bayesian method that can handle sensor information defects. In the event that all necessary information is available, all data fusion methods provide a comprehensive and acceptable approach. But in the face of lack of sensitivity and sensitivity data, they are not reliable. Because in this case, these methods should make assumptions about sensor data which may not match on real data. Consequently, conflicting results may be obtained. But D.S. theory is not limited by model defects or previous information defects. In this way, the evidence is determined solely on the basis of the data obtained, and not with the assumed data. Thus, this method is a quick and accurate tool for combining incomplete data. For sensory data fusion using the D.S. method, a given weight must be assigned to each data source at any given time. For this purpose, firstly, by the standard deviation of data, for the N last produced data, the amount of data validation for each sensor is determined. If the standard deviation of the N last data is smaller than the specified value α, there are fewer jumps and more confidence in that sensor, and if the standard deviation is greater than that value, reliability will be less. α and N values are empirically determined based on the behavior of sensor data or expert opinion. Initially, the variance of each sensor's data is calculated:

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2 \tag{16}$$

$$\begin{aligned}&\text{Highly reliable level } (c_1 = 1) \quad \sigma^2 \le \alpha \\ &\text{Poorly reliable level } (c_2 = 2) \quad \sigma^2 > \alpha\end{aligned} \tag{17}$$

With each new data, the variance of the N last data is updated and the upper and lower levels of confidence are specified. These levels are used in Shannon entropy relations as follows: (Lu et al., 2016)

$$P_{1t}^{c} = \frac{\int c_{1t}}{\int c_{1t} + \int c_{2t}}, \quad P_{2t}^{c} = \frac{\int c_{2t}}{\int c_{1t} + \int c_{2t}} \tag{18}$$

And the entropy criterion for each of the sensors is obtained as follows (Lu et al, 2016):

$$H_{it} = \sum_{c=1}^{2} P_{it}^{c} \log_2 P_{it}^{c} \tag{19}$$

Finally, by the entropy obtained for each sensor, and using the formula below, its weight will be determined (Lu et al, 2016):

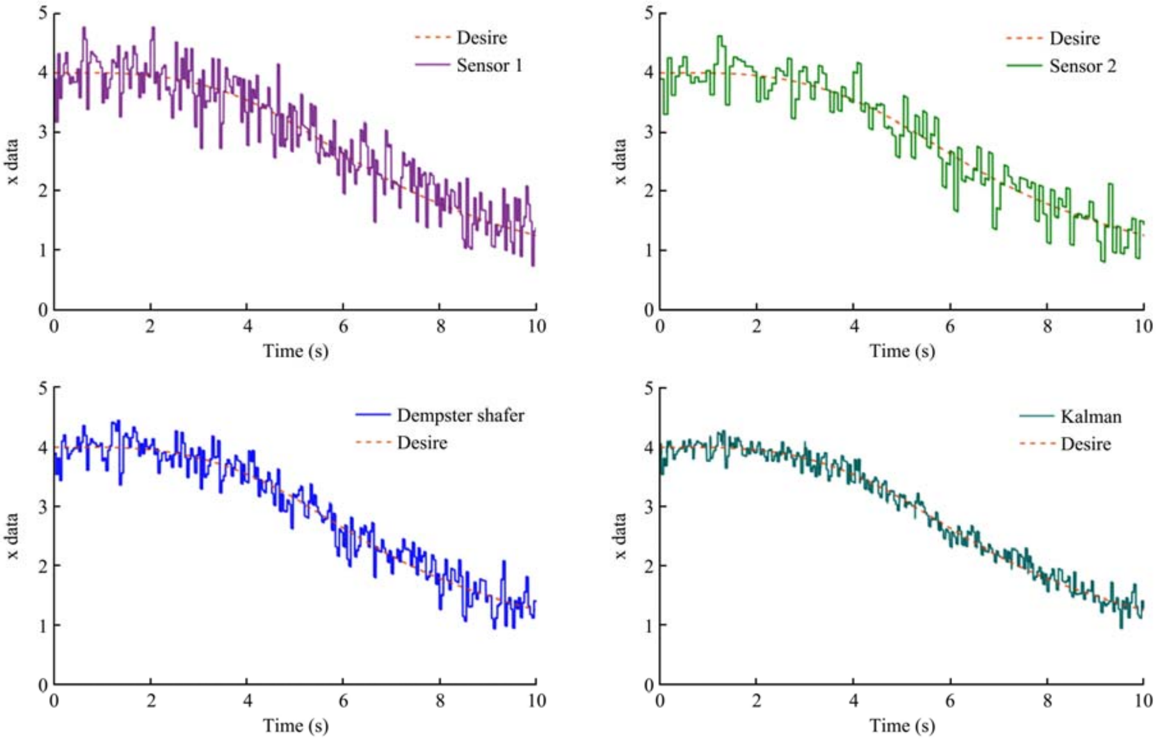
$$W_{it} = \frac{1}{(H_{it})^2 \sum_{i=1}^{I}(H_{it})^{-2}} \tag{20}$$

The greater the entropy of a sensor's data, the lower the confidence level, and consequently the lower the weight assigned.

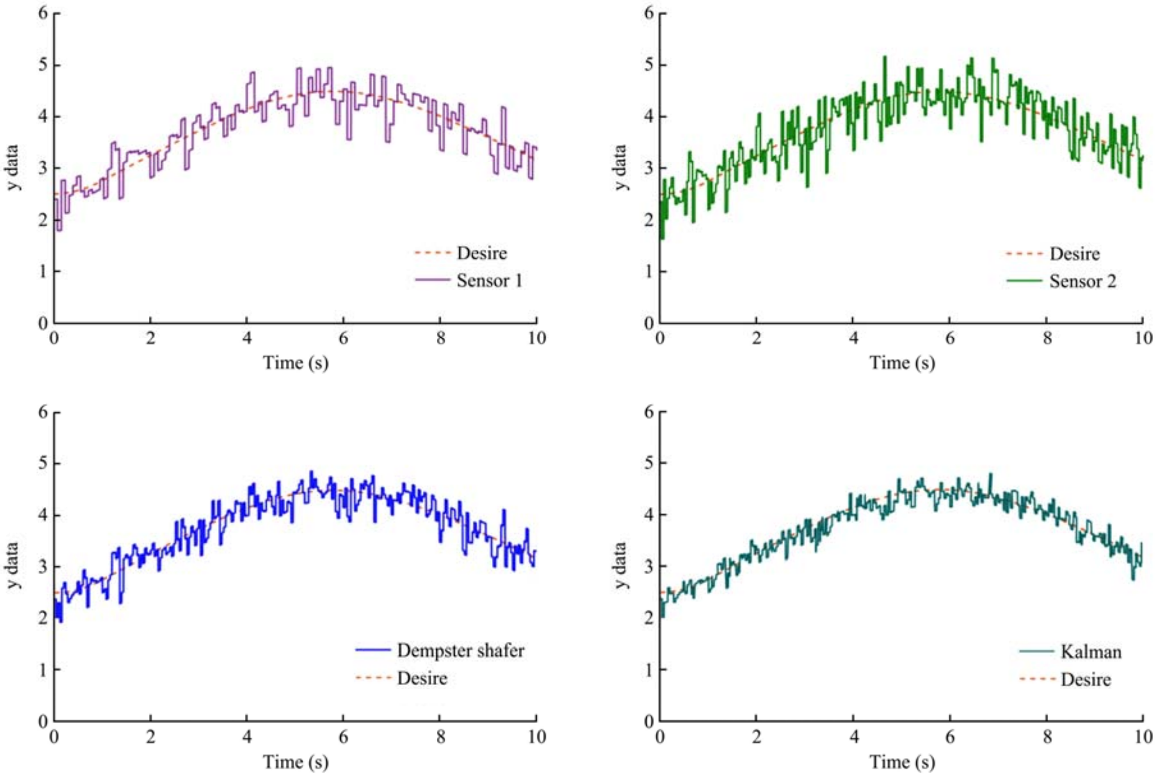
2.4.2 Sensor Noise Simulation and Performance Analysis of fusion Tools

Firstly, the positioning data of two sensor data sources- Sensor 1: the GPS data and Sensor 2: the total of inertial measurement unit (IMU) data and the rear wheel encoders- is received from sensor blocks in the Simulink toolbox, and re-simulated after adding noise and bias up to 10% of the turmoil to those. Then, in the first step, for a specific semicircular path, the sensor values are combined by K.F. and D.S. separately. There are three series of diagrams, each showing one of the robot position parameters. In each series of charts, the output of the simulated blocks of two sensor sources that are coupled with noise, and the results of applying two data fusion tools are shown. In Figure 8(a), the parameter x, in the Figure 8(b), the parameter y and in the Figure 8(c), the parameter θ are analyzed in MATLAB simulation toolbox. The performance of these two data fusion tools is shown in a given time period and path. As indicated in these diagrams, the red-dashed paths are the real robot motions in the simulation environment, which is expected to show by the ideal sensors. Purple and pale green colors are shown simulated sensor data after the noise respectively for the first and second sensor sources. Also the blue color shows the fusion of two noisy sensor data by D.S. method and the dark green color shows the fusion by the K.F. method. It is clear that the Kalman method shows better performance in Gaussian noise.

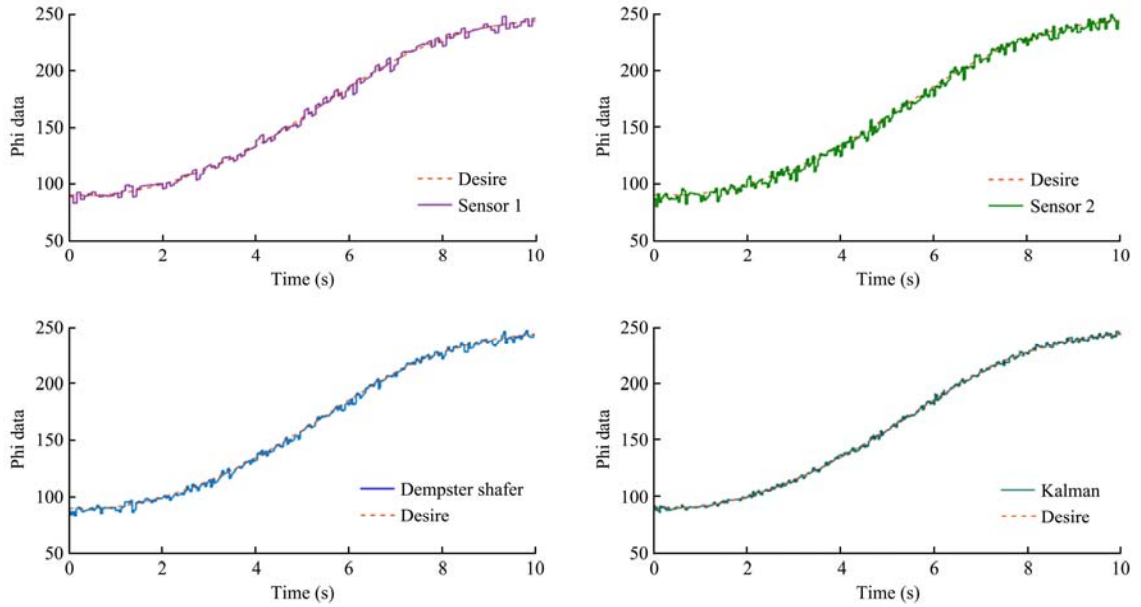
Figure 9(a) is the entropy graph of the two sensor sources, and Figure 9(b) is the obtained weight graph based on sensor data. As shown in these charts, the entropy of the Sensor 1 is greater than the Sensor 2, which indicates more disorder in GPS data than the encoder plus IMU data and so, the reliability of the data is less and the weight allocated to that sensor will be less.



(a)

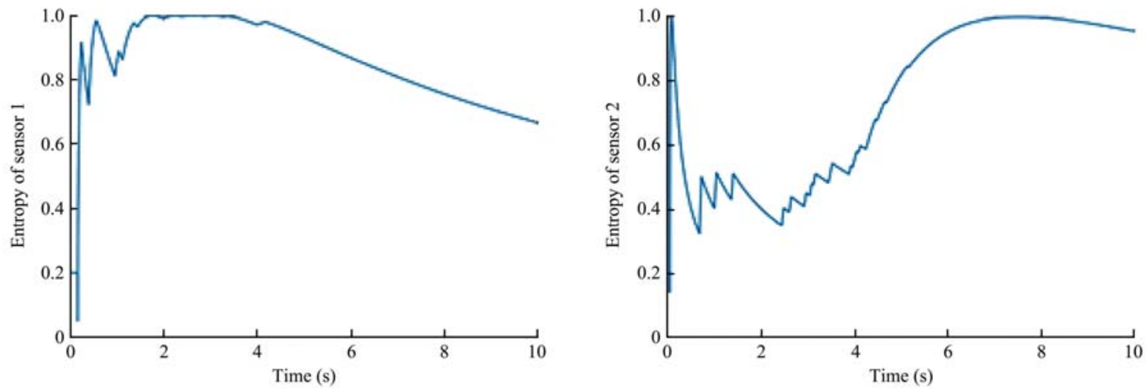


(b)

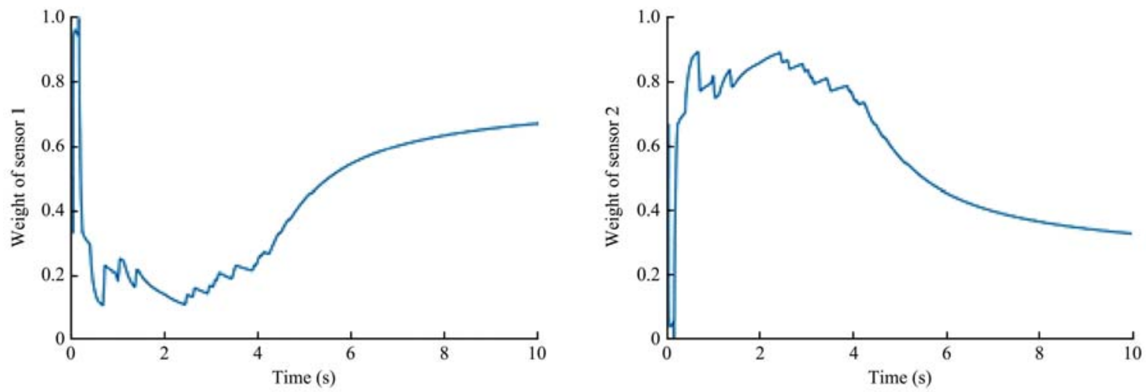


(c)

Figure 8 Noise simulation diagrams and the results of applying the fusion tool to the robot position parameters



(a)



(b)

Figure 9 Entropy graph of sensor data and weight assigned to sensor sources

3 Results and discussions

As shown in Figure 8, K.F. seems to have a better performance than D.S., but according to Figure 9, the need to provide a benchmark for comparing the performance of these two data fusion tools seems to be necessary. For this reason, the mean absolute deviation (MAD) and mean square error (MSE) criteria have been used.

The MAD, also referred to as the ‘mean deviation’ or sometimes ‘average absolute deviation’, is the mean of the data’s absolute deviations around the data's mean: the average (absolute) distance from the mean. ‘Average absolute deviation’ can refer to either this usage, or to the general form with respect to a specified central point. The mean absolute deviation of a set $\{x_1, x_2, x_3, \ldots, x_n\}$ is

$$MAD = \frac{1}{n}\sum\nolimits_{i=1}^{n} | x_i - m(x) | \qquad (21)$$

Which n is the number of values and $m(x)$ is the mean. MAD has been proposed to be used in place of standard deviation since it corresponds better to real life. Because the MAD is a simpler measure of variability than the standard deviation. This method's forecast accuracy is very closely related to the MSE method which is just the average squared error of the forecasts. Although these methods are very closely related, MAD is more commonly used because it is both easier to compute (avoiding the need for squaring) and easier to understand.

$$MSE = \frac{1}{n}\sum\nolimits_{i=1}^{n} (x_i - \hat{x}_l)^2 \qquad (22)$$

Which $\hat{x}_l$ is predicted value.

The numbers in the table below belong to the x variable in each simulation test and for each evaluation criterion.

The simulation reported in the previous section has been carried out six times for two different paths (a linear path and a circular path). In the fifth and sixth tests, the noise level applied to the Sensors is non-Gaussian noise. Typical IMU/GPS integration approaches usually adopt the Gaussian error assumption. However, in practice, especially during off-road navigation and when several sources of GPS interference are present, this assumption does not hold. To this end, the best non-Gaussian noise model is the Huber estimator using a robust estimator algorithm, which is able to handle multipath GPS signals as well as intentional and unintentional interferences. Gaussian mixture models are based on the representation of any non-Gaussian distribution as the sum of multiple Gaussian densities with different weights (Karlgaard and Schaubt, 2007).

For the IMU/GPS algorithm discussed here, the noise is assumed to be composed of two Gaussian components.

The results presented in Table 1 showed that the performance of the D.S. method in sensor data fusion associated with non-Gaussian noise was better than the K.F. Since in real life the noise behavior was more non-Gaussian, it seemed that the Dempster method would perform better in dealing with real issues.

Table 1 Comparison of the performance of two data fusion tools

Test number	Benchmarking	Dempestre - Shaffer (percentage error)	Kalman filter (percentage error)
1	MAD	1.99	1.45
	MSE	4.76	2.59
2	MAD	2.23	1.59
	MSE	6.02	3.22
3	MAD	1.94	1.42
	MSE	4.76	2.62
4	MAD	1.77	1.49
	MSE	4.01	2.85
5	MAD	1.78	2.03
	MSE	3.45	5.23
6	MAD	1.43	1.59
	MSE	2.77	3.22

4 Conclusion

In this paper, tried to simulate controlling of an agricultural tractor robot and it's localization in real condition using Dempster-Shafer and Kalman filter algorithms, as data fusion tools, in the MATLAB software. In the control part of the robot, various control scenarios were be carried out on the robot, including tracking, moving toward the target point and moving to a given line, and they are simulated in the mechanical simulator of MATLAB (SimMechanics). In the field of localization, the use of D.S. evidence theory as a tool for data fusion and exploiting the strengths of this method and comparing it with the K.F. for the best possible implementation of collecting and processing sensory data is one of the innovations of this paper. In this way, the evidence is determined solely on the basis of real data. This is a quick and accurate tool for incomplete data fusion. Also, the initial weighting of sensors by entropy method is one of the other innovations in this paper to determine the confidence coefficient of each sensor and to determine its weight. To apply the weight of each of the sensors in this method as evidence theory, at the decision level, entropy of sensor data is used. After the implementation of data fusion methods and in order to provide a scientific standard for comparing the above methods, the simulation was repeated with the application of Gaussian and non-Gaussian noise in different paths and the localization information of these two methods in these simulations was examined by two MAD and MSE criteria. The results showed a better performance of the

D.S. method when applying non-Gaussian noise which is the reliability validation of the D.S. method in conditions close to real conditions. The upcoming process is the practical implementation of the localization and control algorithms examined in this paper and use of the results obtained from it.

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