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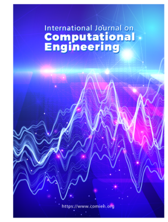

Tracking System on Autonomous Vehicle using Radiolink M8N SE100 with Kalman Filter Method Based on Rasberry PI

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***Abstract*—An autonomous vehicle is a robot that can move automatically toward the destination. This technology has the potential to change people's lifestyles, making future transportation systems safer, and can also be implemented for logistics delivery to areas that are difficult to reach. This final project aims to drive an autonomous vehicle to a specified destination using the Global Positioning System (GPS) and a compass sensor. Data from the compass sensor was used to determine the heading and bearing to determine the direction of motion of the autonomous vehicle. When testing the M8030 GPS in silent conditions for five minutes, the problems had an average measurement error of 4.78 meters. The Kalman Filter method was applied to minimize these inaccuracies, which is ideal for dynamic systems. The test results using the Kalman Filter with R=10 showed an average difference between the stop point and the target point of 7,285 meters, while the test results without the Kalman Filter showed a difference of more than 10 meters in each test. These results indicated that the Kalman Filter tracking system works well to reduce noise Then testing on the Compass QMC5883L sensor showed a small percentage of error with an average of 0.36%. In future research, it can use other GPS modules with more robust signal locking because autonomous vehicles need accuracy and precision. It is possible to increase the performance of the autonomous vehicle by adding a controller to the system.**

***Keywords*—Autonomous vehicle; global positioning system; compass sensor; Kalman Filter.**

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I. INTRODUCTION

An autonomous vehicle is a robot that can operate without human intervention and move toward a predetermined destination. This technology has the potential to reduce the number of accidents caused by human [1]-[15], change people's lifestyles, making future transportation systems safer, and can also be implemented for logistics delivery to areas that are difficult to reach. For the autonomous vehicle can operate, it needs the ability to detect surrounding conditions. After knowing the surrounding environment, it's time for the autonomous vehicle to be able to see or read the path to the target point. This process requires a GPS or Global Positioning System that can find the route to arrive at the destination. In addition, GPS can also provide robot location information. For the system to work optimally, the GPS tracking system must obtain a signal originating from a satellite, resulting in its application not being carried out outdoors. It is because obstructions will hamper the satellite signal. Real-time data processing, machine learning, and artificial intelligence enable autonomous vehicles to make intelligent decisions and navigate complex driving scenarios [6]. Some researchers have researched tracking systems in autonomous vehicles using GPS sensors on robots [5], [7], [8]. Ginting et al. (2020) used GPS to direct the robot automatically using the Fuzzy Logic Control method. GPS is used to define the coordinates of the initial reference point as a starting point through the calculation of latitude and longitude coordinates. Next, the robot carries out the initialization of the destination coordinates. Two coordinates data points can be calculated on the distance and angle error where the processing is done by Fuzzy Logic. From the results of this study, it was found that the output of the control is relatively stable when the robot is in a stationary condition. When measurements are made along an imaginary straight line between two coordinates, the robot tends to move on the right side of the imaginary path [1]. Furthermore, there is also research that has been conducted by Rizky et al. using GPS to instruct the robot boat to move from the start position to the finish position automatically using a waypoint navigation system with research results showing an error of up to 10.8 meters [2].

One of the most common navigation methods in developing autonomous vehicles is waypoint navigation. Waypoint navigation is a method for controlling the movement of an autonomous vehicle from a starting point to a destination point by assuming each position it passes in its movement to be a point in a coordinate system based on the earth's coordinate system [1]. In addition to requiring GPS, a waypoint navigation system also needs directions on the compass to control the autonomous vehicle's motion. Referring to research on tracking systems using GPS that is applied to robots that have been carried out, the problem that is often encountered is the need for more accuracy in sensor readings which will affect positioning and navigation. It is also known that the GPS is less accurate for measuring short distances due to the distance between the satellite and the receiving antenna. In addition to this, the obstruction of the GPS signal when indoors or in tall buildings and trees can affect the accuracy of distance measurements. This results in the GPS signal being lost frequently and resulting in a jump in receiving coordinate data [2]-[4].

Therefore, researchers used the Kalman Filter method because this method has efficient computation to estimate the conditions of a process and can reduce noise in the system under dynamic conditions [9], [11], [12]-[25]. In this study, the tracking system used the GPS and compass contained in the Radiolink SE100 [20]. The type of GPS used is the GPS u-blox UBX-M8030 (M8) [18], which determines the starting position, destination position, and path to be traversed. Furthermore, the type of compass sensor used is QMC5883L which determines the direction that will move the wheels [16]. From the two sensors, data is obtained the Raspberry Pi will process that with the help of the haversine formula, which will produce the calculation of the shortest distance between two coordinate points. This tracking system is designed for outdoor movements, especially inland areas with positions determined by the operator. The researcher's contribution to this Final Project is to design a tracking system using the Kalman Filter which is applied to the coordinates obtained from the GPS. This aims to direct the autonomous vehicle to move with a lower deviation. Every autonomous vehicle movement will be recorded in .txt format, which will be displayed on an HTML-shaped website integrated with Google Maps.

II. Material and Method

The research method consists of four main stages: navigation system design, Kalman filter design, hardware design consisting of Motor Driver Component Design and Radiolink SE100 M8N Design, and software design.

A. Navigation System Design

The design of the navigation system is carried out with the aim that autonomous vehicles can recognize positions based on the coordinate system and make corrections to the direction of motion to encourage increased accuracy to reach predetermined destination points [13], [14]. In this study, the destination coordinates were entered into the program. After determining the coordinates, then read the GPS sensor and compass sensor. If the data from the two sensors are read, then the latitude and longitude coordinate data will be obtained, accompanied by an LED that is constantly flashing and heading data. The compass sensor is used to determine the value of the heading angle ranging from 0 to 359 degrees. The autonomous vehicle will receive latitude and longitude data every second when it moves forward. Every five-second coordinate data received will be filtered with Kalman Filter to get the results of data filtering. The filtered data is used as a reference point that will be passed by the autonomous vehicle. When the autonomous vehicle moves automatically toward the destination point, it calculates the direction and the value of the shortest distance to the destination point. If the distance of the autonomous vehicle is less than ten meters from the target point, the autonomous vehicle will stop, or it can be assumed has reached its destination point.

B. Kalman Filter Design

In this study, the Kalman Filter acts as an algorithm for position calculations on coordinate data. The initial state variables that are processed consist of four variables, namely x is the position in the latitude direction, $\dot{x}$ is the speed in the latitude direction, y is the position in the longitude direction, $\dot{y}$ is the velocity in the longitude direction. This process is carried out because the position data obtained from the GPS has a measurement error. This shows that the value obtained from the measurement is not the true value, but contains a number of inaccuracies. In retrieving data from GPS, it is necessary to form a data model that will be included in the general equation form used in the Kalman Filter prediction process. In the initial Kalman Filter process, there is an initial estimate with a number of errors. The initial estimate can be defined into two values, consisting of xt is the current estimated value and xt-1 is the previous estimated value. The initial state matrix contains latitude coordinates, speed in latitude, longitude coordinates, and speed in longitude. That initial state becomes the previous state and when iterated through the process, the current state becomes the previous state. In equation (1) the values of A and B are the matrices used to help convert the input into a new state matrix.

$$x_k = Ax_{k-1} + Bu_k \tag{1}$$

In the correction section, the Kalman Gain calculation is used to find out how much the difference is between the measured value and the previous estimate as a new value that will be used for calculating the next estimate. In addition, this calculation is used to provide a weight factor between two things, namely the estimated value and measurement. If the measured value has a very small error, then the measured value should be given more weight. However, if the measurement value has a large error and results in a relatively small estimation error, then the value weight is assigned to the estimated value. If the measurement error value tends to zero and causes the Kalman Gain value to be one, then there is an adjustment to the measurement, if the measurement error value tends to be large, and causes the Kalman Gain value to be zero, then there is an adjustment to the estimate, and if the value tends to be zero, then the update measurement values as large will be ignored because the predicted value is assumed to be accurate. In the calculation of the Kalman Filter, an R value (measurement noise) is required, the P value is the prediction of the error covariance, which is referred to as the estimation uncertainty and the Q value, which is process noise.

In equation (1) x_k consists of two variables, namely longitude and latitude. The U value is omitted due to unknown external factors affecting the system. In this study, the equation is simplified to:

$$x_k = Ax_{k-1} \tag{2}$$

$$Z_k = Hx_k \tag{3}$$

Variable x_k consist of:

$$x_k = \begin{bmatrix} x_{k-1} \\ \dot{x}_{k-1} \\ y_{k-1} \\ \dot{y}_{k-1} \end{bmatrix} \tag{4}$$

Where x and y are positions, ẋ and ẏ are velocities. The estimated vehicle position for time n+1 can be calculated using the following system of equations:

$$x_k = x_{k-1} + \dot{x}_{k-1}\Delta t$$

$$\dot{x}_k = \dot{x}_{k-1} \tag{5}$$

$$y_k = y_{k-1} + \dot{y}_{k-1}\Delta t$$

$$\dot{y}_k = \dot{y}_{k-1}$$

Then the equation is converted into matrix form:

$$\begin{bmatrix} x_k \\ \dot{x}_k \\ y_k \\ \dot{y}_k \end{bmatrix} = \begin{bmatrix} 1 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \Delta t \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_{k-1} \\ \dot{x}_{k-1} \\ y_{k-1} \\ \dot{y}_{k-1} \end{bmatrix} \tag{6}$$

In this study GPS data reception is carried out every second, so the value of Δt=1. After determining the state predictions, the error covariance prediction calculation is performed in the form:

$$P_k = AP_{k-1} A^T \tag{7}$$

Where P_k is the prediction of the error covariance at time k, A is the transition matrix model, P_{k-1} is the prediction of the error covariance at time k-1, and Q is the process noise. The Q matrix can be determined in equation (8).

$$Q = \begin{bmatrix} \sigma_x^2 & \sigma_{x\dot{x}}^2 & 0 & 0 \\ \sigma_{\dot{x}x}^2 & \sigma_{\dot{x}}^2 & 0 & 0 \\ 0 & 0 & \sigma_y^2 & \sigma_{y\dot{y}}^2 \\ 0 & 0 & \sigma_{\dot{y}y}^2 & \sigma_{\dot{y}}^2 \end{bmatrix} \tag{8}$$

The P and Q matrices used in the Kalman Filter are matrices that function to determine the level of variation in GPS data. The P matrix stores information about how much the estimated current position will differ from the previous estimated position. A smaller value in the P matrix indicates that the estimated current position is expected to be more stable than previous estimates. Meanwhile, the Q matrix stores information about how much the GPS measurement will differ from the estimated current position. The two matrix values are initialized based on the value corresponding to the GPS measurement error rate.

In calculating the correction, the first step is to calculate the Kalman Gain value. The Kalman Gain function is to determine the number of predictive parts and measurement data that will be used to update values. Calculation of Kalman Gain can be done using equation (9).

$$K = \frac{P_k H^T}{(HP_k H^T + R)} \tag{9}$$

The K value is the Kalman Gain value. The P value is the predicted covariance error, H is the transition matrix, and R is the measurement error. The form of the H matrix can be shown in equation (10). Where z_k dimension is 2x1 and x_n dimension is 4x1. Therefore the dimension of the H observation matrix is 2x4

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tag{10}$$

After calculating the Kalman Gain value, an estimation update process is performed using the measurement value (z_k). This calculation includes data from predicted values and measurements that have been updated with the calculation results in equation (9). The calculation on the estimation update is shown in equation (11).

$$x_k = x_{k-1} + k(z_k - Hx_{k-1}) \tag{11}$$

The final calculation stage of the correction process is calculating the error covariance update or what is called the estimation uncertainty update process. This process will usually produce a smaller value in each iteration. If the uncertainty in the measurement value has a small value, then the Kalman Gain value will produce a high value and the uncertainty will go to a zero value.

C. *Hardware Design*

1) *Motor Driver Component Design*

The system circuit is shown in Figure 1. The motor driver regulates the DC motor's rotation, and the DC motor functions to move the wheels. GPS and compass are directly connected to the Raspberry Pi pins. The Ground pin of the two drivers is connected to the header pin, which is connected to pin 39. The VCC pin of the two drivers is connected to the header pin, which is connected to 5 volts found on pin 4. The first motor driver functions to set the direction of rotation of the front DC motor and the motor driver. The second function is to adjust the direction of rotation of the rear DC motor. The pins of the two drivers will be attached to Table 1.

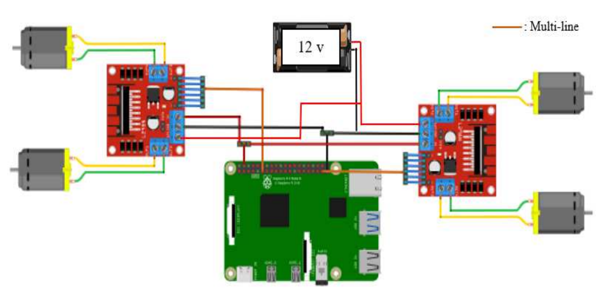

Fig. 1 Motor Driver Component Design

To be able to set Driver conditions when you want to move, steps are needed to make input and output programs on the Raspberry Pi. Here is the sequence of steps required:

- Activate the GPIO pin on the Raspberry Pi by importing the RPi.GPIO as GPIO library to set the port to be used as input or output.
- Define the GPIO pin on the Raspberry Pi as Broadcom with the GPIO.setmode(GPIO.BCM) command.
- Set the pin connected to the driver as output.

TABLE I
MOTOR DRIVER PINS WITH RASPBERRY PI PINS

Motor Driver	Motor Driver Pins	Raspberry Pi Pins
Front	Enable A	17
	IN 1	27
	IN 2	22
	IN 3	24
	IN 4	25
	Enable B	23
	OUT 1, OUT 2, OUT 3, OUT 4	2 pieces motor DC
Back	Enable A	26
	IN 1	19
	IN 2	6
	IN 3	20
	IN 4	21
	Enable B	16
	OUT 1, OUT 2, OUT 3, OUT 4	2 pieces motor DC

2) Radiolink SE100 M8N Design

At the component assembly stage, it is done by disconnecting the connector found on the Radiolink SE100 M8N, and this aims to connect the Radiolink SE100 with the Raspberry Pi pin. The cable on the Radiolink SE100 M8N is connected to a cross-connection model where the Rx on the Radiolink SE100 M8N is connected to the Tx Raspberry Pi, and the Tx on Radiolink SE100 is connected to the Rx Raspberry Pi. Then, to use the compass sensor contained in it, the SCA cable is connected to pin 3 on the Raspberry Pi, and the SDA cable is connected to pin 5 on the Raspberry Pi. The GPS contained in Radiolink SE100 is used as a sensor to get coordinates and calculate distances, and the compass sensor is used to determine the direction of motion and to determine the direction of the autonomous vehicle.

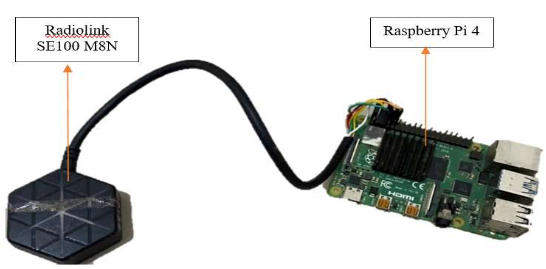

Fig. 2 Radiolink SE100 M8N Design

TABLE I
RADIOLINK SE100 M8N PINS WITH RASPBERRY PI PINS

Radiolink SE100 M8N Pins	Raspberry Pi Pins
VCC	2
Ground	6
TX	10
RX	8
SDA	3
CLK	5

D. Software design

1) Tracking System Flowchart

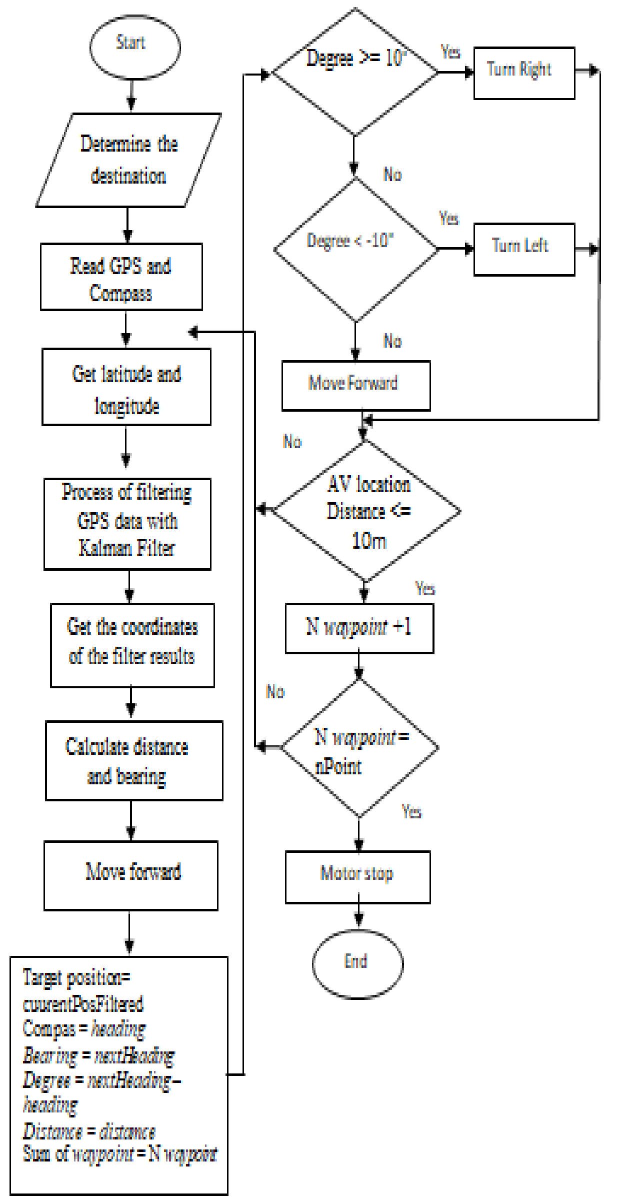

Fig. 3 The Autonomous Vehicle workflow

The Autonomous Vehicle workflow in Figure 3 is as follows:

- The program will determine the target point by giving a value (latitude and longitude) with a maximum limit of three.
- Then the program starts reading the coordinate data values from the GPS and the heading from the compass.
- Every time an autonomous vehicle makes a movement, coordinate point data will be received every second. Every GPS data received will be filtered using the Kalman Filter. Increasing the number of coordinates received will eliminate the coordinates that were received earlier. The result of this process will produce the latest reference coordinates.
- When the latest coordinates have been obtained, the Raspberry Pi will calculate the distance between the current position and the destination position and the angle from the current position to the destination point.
- The data resulting from the filter process and the compass data will become a reference for the autonomous vehicle movement route.
- If the calculation of the angle from the destination position and the current position results in a degree value of >= 10, then the autonomous vehicle will turn right. However, if the degree value is < -10, then the autonomous vehicle will turn left. If the degree value is between -9 to 9, then the autonomous vehicle will move forward.
- The autonomous vehicle will continue to move until the distance calculation based on the coordinates obtained is less than 10 meters from each waypoint. Then the autonomous vehicle will move towards the next waypoint. Next, it will be checked whether the number of waypoints = nPoint, nPoint is a constant. If the robot is within the third waypoint radius entered in the program, then the autonomous vehicle will stop. If not, then the autonomous vehicle will return to the GPS and compass reading process.

III. Results and Discussions

In this study, testing was carried out with several different target points with different number of waypoints. To find out the distance and direction from the autonomous vehicle's starting point to the target point, the haversine calculation is performed as well as the angle calculation of the heading obtained from the compass sensor. Testing is carried out with a starting point and a target point with several different locations. This test was carried out with and without the Kalman Filter. The starting point comes from the data received by the GPS and the target point is the coordinate point entered manually in the program.

From the bearing and heading calculations obtained from the compass sensor, the degree value is obtained which is the control to move the DC motor to turn right, left or forward. As shown in Figure 4 in Chapter III, if the degree value is >= 10, then the autonomous vehicle will turn right. However, if the degree value is < -10, then the autonomous vehicle will turn left. If the degree value is between -9 to 9, then the autonomous vehicle will move forward. In Figure 5 you can see an example of the calculation results attached to the terminal, the direction of the autonomous vehicle obtained from the compass is 145∘ and the direction of the destination point from the current position is 259∘, then the calculation is carried out by subtracting the nextHeading value from the heading and obtaining a degree value of 114 ∘ which means the autonomous vehicle must turn right to go to the destination point. Then in Figure 6 you can see an example of the calculation results attached to the terminal, the direction of the autonomous vehicle obtained from the compass is 95∘ and the direction of the destination point from the current position is 44.9∘. Then a calculation is performed by subtracting the nextHeading value from the heading and a degree value of -50.05∘ is obtained, which means that the autonomous vehicle must turn left to go to the destination point.

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Heading:  145
Next Heading:  259.0439087505786
Degree:  114.04390875057862
```

Fig. 4 The calculation result is positive

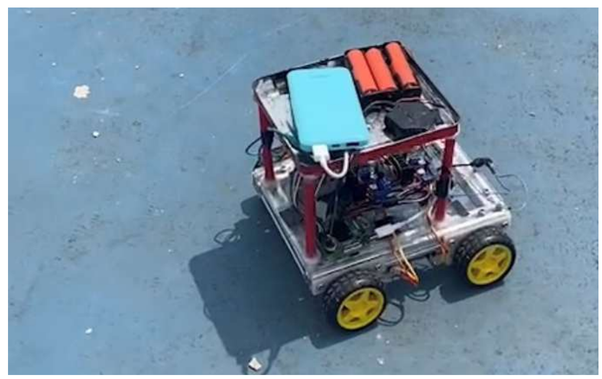

Fig. 5 Autonomous vehicle turns right

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Heading:  95
Next Heading:  44.94911683201326
Degree:  -50.05088316798674
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Fig. 6 The calculation result is negative

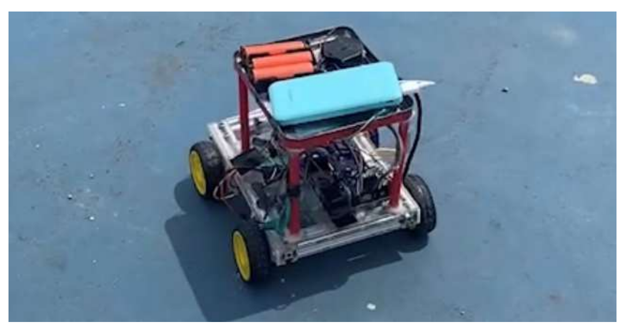

Fig. 7 Autonomous vehicle turns left

A. Analysis and Trial of Kalman Filter

The Kalman filter used for position calculations gets input in the form of coordinate readings from the GPS. Position data from GPS will be estimated to provide position calculation results which result in reduced noise that is prone to appear during data processing so that it can provide results close to real conditions. In calculating the Kalman Filter, there are several parameters that must be defined first, namely the Q matrix which is the process noise, which will affect the system response and the R matrix, which is the measurement noise. setting the value of the process noise covariance matrix and measurement noise must be adjusted correctly because the performance of the Kalman Filter is greatly influenced by Q and R. The comparison of the two can be seen through the Kalman Gain value, if the Kalman Gain value is high then the weight of the measurement results is higher. However, if the Q value is large, the Kalman Filter will make more corrections to the calculation results, in this condition the x_k value will be corrected with the z_k measurement results. The determination of the large R parameter indicates the amount of noise contained in the measurement value. This will make the Kalman Filter give greater weight to the estimates. Based on the measurement error, during dynamic conditions the Kalman Filter must give greater weight to the prediction process. This resulted in the R value having to be varied using a trial-and-error method approach to get the appropriate results. The Q matrix model is specified in the form:

$$Q = \begin{bmatrix} \frac{1}{4} & \frac{1}{2} & 0 & 0 \\ \frac{1}{2} & 1 & 0 & 0 \\ 0 & 0 & \frac{1}{4} & \frac{1}{2} \\ 0 & 0 & \frac{1}{2} & 1 \end{bmatrix} \tag{12}$$

The correct form of the P matrix will depend on the conditions and configuration of the system used. In this study, if the GPS measurement error is assumed to be 4.78 meters, then the P matrix must reflect this assumption. If the expected level of uncertainty in the system is a GPS measurement error of 4.78 meters, then the P matrix must reflect this variance value. In this case, if the GPS measurement error is 4.78 meters, then it is assumed that the estimated current position has the same variance as 4.78 squared. The matrix model P is initialized in the form:

$$P = \begin{bmatrix} 22.8 & 0 & 0 & 0 \\ 0 & 22.8 & 0 & 0 \\ 0 & 0 & 22.3 & 0 \\ 0 & 0 & 0 & 22.8 \end{bmatrix} \tag{13}$$

This matrix is used to store information about the variance of the estimated current position. In this case the P matrix is initialized with a value of 4.78 squared on the main diagonal and a value of 0 on the other elements. This indicates that the current estimated position is expected to differ from the previous estimate of 4.78 meters. This value is used to take the overall received GPS measurement and correct it by taking the previous estimated position. Values on the main diagonal represent the expected variance from the current position. Meanwhile, a value of 0 for the other elements indicates that there is no significant difference in speed. In this study, only the value of R was varied by trying various values, including 1, 5, 10, and 15. With this experiment, the number that produces optimal results will be taken.

1) Experiment 1

The experiment was carried out with a starting point on the south side of the field and the target point was in the north of the field with the robot position leading to the target point. This test aims to determine the amount of accuracy obtained using the Kalman Filter with a value of R of 1 and without using the Kalman Filter. The results of the mapping of the GPS reading coordinates with the help of Google Maps are shown in Figure 8. In experiment 1 the difference in stopping point with a target point as far as 7,457 meters. The actual distance is calculated manually there is a difference of 5.2 meters with a target point. While the experiment without using the Kalman Filter showed a rotating robot and did not approach the target point.

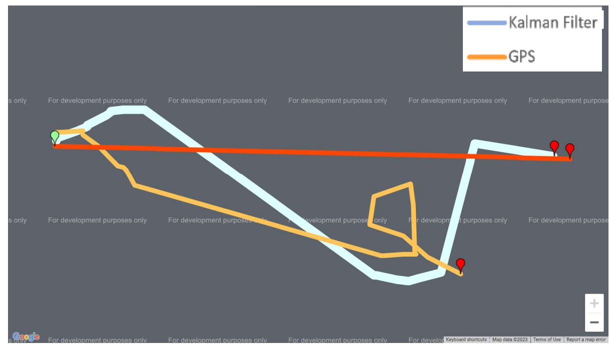

Fig. 8 Plot of the results of experiment 1 on the map

2) Experiment 2

The experiment was carried out with a starting point on the south side of the field and the target point was in the north of the field with the robot position leading to the target point. This test aims to determine the amount of accuracy obtained using the Kalman Filter with a R value of 5 and without using the Kalman Filter. The results of the mapping of GPS reading coordinates with the help of Google Maps are shown in Figure 9. In experiment 2 the difference in stop point with a target point as far as 9,759 meters. The actual distance is calculated manually there is a difference of 6.4 meters with a target point. While the experiment without using the Kalman Filter showed a rotating robot and did not approach the target point.

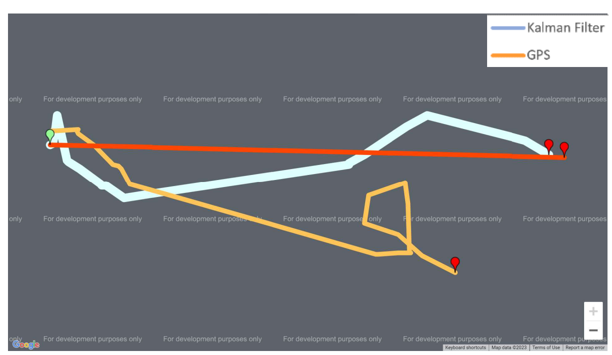

Fig. 9 Plot of the results of experiment 2 on the map

3) Experiment 3

The experiment was carried out with a starting point on the south side of the field and the target point was in the north of the field with the robot position leading to the target point. This test aims to determine the amount of accuracy obtained using the Kalman Filter with a R value of 10 and without using the Kalman Filter. The results of the mapping of the GPS reading coordinates with the help of Google Maps are shown in Figure 10. In experiment 3 the difference in stop point with the target point as far as 7,651 meters. The actual distance is calculated manually there is a difference of 2.2 meters with a target point. While the experiment without using the Kalman Filter showed a rotating robot and did not approach the target point.

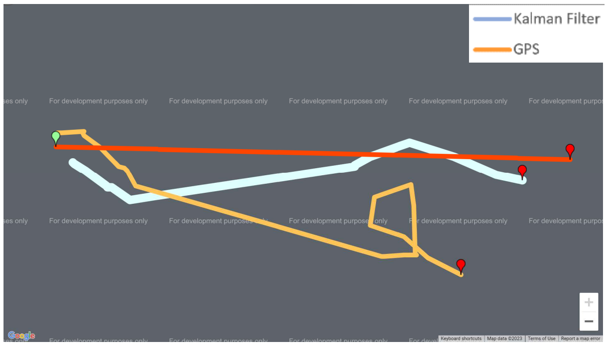

Fig. 10 Plot of the results of experiment 3 on the map

4) Experiment 4

The experiment was carried out with a starting point on the south side of the field and the target point was in the north of the field with the robot position leading to the target point. This test aims to determine the amount of accuracy obtained using the Kalman Filter with a value of R of 15 and without using the Kalman Filter. The results of the mapping of GPS reading coordinates with the help of Google Maps are shown in Figure 11. In experiment 4 the difference in stopping point with a target point as far as 2,551 meters. The actual distance is calculated manually there is a difference of 1.5 meters with a target point. While the experiment without using the Kalman Filter showed a rotating robot and did not approach the target point.

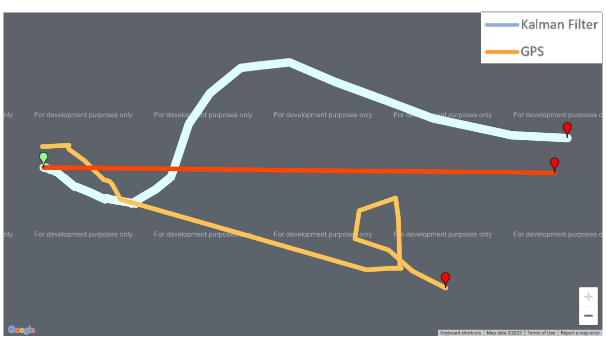

Fig. 11 Plot of the results of experiment 4 on the map

Where from experiments one to four is a test of the route traveled by the Autonomous Vehicle to test the system that has been designed as a whole. The travel route inputted is the same final destination in each test. Based on the results of testing the autonomous vehicle tracking system without the Kalman Filter, from the attached image, it appears that the path traversed by Autonomous Vehicle has a problem that is the existence of a deviant state shown by the robot movement does not lead to the target point. Then for the calculation of the distance in the program that is run is regulated less than 10 meters based on the calculation of haversine is considered up to. This is caused by a lack of GPS accuracy, this can be proven in Figure 12, where at the time of testing when the distance has been counted 12,617 meters from the destination point, with an inappropriate GPS accuracy, the point that is read is jumping away again to 13,214 meters with autonomous vehicle conditions which is close to the target point. Calculation of distances that only rely on data from GPS and then calculated by the Haversine equation greatly affects the movement of autonomous vehicles, because if the GPS is not appropriate to map the point, then the vehicle will be difficult to reach the target point with the distance that often jumps. In Figure 12, the test results containing the latitude and longitude obtained from GPS, bearing, heading, and distance between the current position and the next destination or nPoint position.

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-6.372217,106.900426,-125.87713501859412,171,17.50097794975007
-6.372263,106.900456,-149.04785834644554,194,13.467445542793232
-6.372264,106.900458,-88.03505655452875,133,13.461218407091692
-6.372273,106.900451,-158.03109062273813,203,12.226370081814297
-6.372266,106.900443,-239.0310372867542,284,12.617193628287309
-6.372257,106.900431,9.970004852239697,35,13.21476349092664
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Fig. 12 Distance read away when the vehicle approaches the target

Experiments that have been carried out with the aim of obtaining comparison data of the accuracy of Latitude and Longitude values from the reading of the UBLOX M8030 GPS sensor before applying the Kalman Filter with the results obtained by applying the Kalman Filter with a different R value. Determination of the value of R that has been carried out in the above experiment has an effect on the movement of autonomous vehicles. The specified R value illustrates the amount of noise on the GPS. When the value of R is worth 1 result of the Kalman Filter output more trusting the coordinate data received by GPS. When the value of R is worth 5 results of the output of Kalman Filter is still similar to GPS data but is better than the value of R worth 1. When R is worth 10 the results of the Kalaman Filter output produces a fairly good result. When the R value is raised higher, the system response is longer to reach stability. Furthermore, experiments were conducted from different directions, robots that turned their backs on target points, target points changed, and three destination points with a value of R = 10.

5) Experiment 5

The experiment was carried out with a starting point on the west side of the field and the target point was in the north of the field with the robot position leading to the target point. This test aims to determine the amount of accuracy obtained using the Kalman Filter with a R value of 10 with a different direction from the previous experiment. The results of the mapping of GPS reading coordinates with the help of Google Maps are shown in Figure 13. In experiment 5 the difference in stop point with a target point as far as 7,986 meters. The actual distance is calculated manually there is a difference of 5.45 meters with a target point. While the experiment without using the Kalman Filter showed that the robot initially moved towards the target point but after that away from the target point.

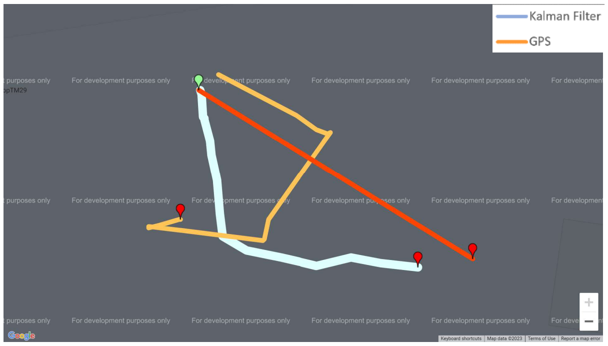

Fig. 13 Plot of the results of experiment 5 on the map

6) *Experiment 6*

The test was carried out with a starting point on the south side of the field and the target point was in the north of the field with the robot position back to the target point. This test aims to determine the amount of accuracy obtained using the Kalman Filter with a R value of 10 with a different direction from the previous experiment. The results of the mapping of the GPS reading coordinates with the help of Google Maps are shown in Figure 14. In experiment 6 the difference in stop point with a target point as far as 9,308 meters. The actual distance is calculated manually there is a difference of 9 meters with a target point.

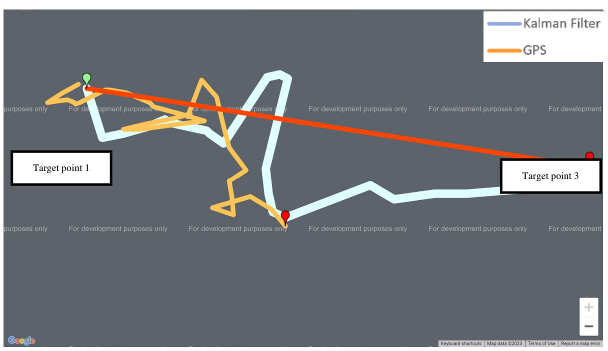

Fig. 14 Plot of the results of experiment 5 on the map

7) *Experiment 7*

The experiment was carried out with a starting point on the north side of the field and the target point was in the south of the field with the robot position facing the target point. This test aims to determine the amount of accuracy obtained using the Kalman Filter with a R value of 10 with a different target point from the previous experiment. The results of the mapping of the GPS reading coordinates with the help of Google Maps are shown in Figure 15. In experimental 7 the difference in stop point with a target point as far as 5,882 meters. The actual distance is calculated manually there is a difference of 4.4 meters with a target point.

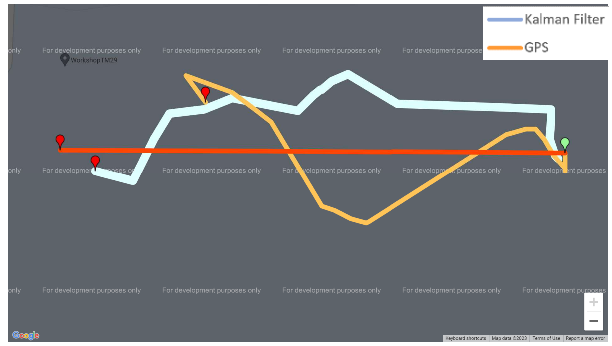

Fig. 15 Plot of the results of experiment 5 on the map

8) *Experiment 8*

The experiment was carried out with a starting point on the middle side of the field and the target point was in the south of the field, east of the field, and north of the field with the robot position facing the target point. This test aims to determine the amount of accuracy obtained using the Kalman Filter with a R value of 10 with a different target point from the previous experiment. The results of the mapping of the GPS reading coordinates with the help of Google Maps are shown in Figure 16. In the experiment 8 the difference in stopping point with the first target point as far as 9,136 meters while the actual distance is calculated manually there is a difference of 8.5 meters with a target point. The difference in stopping point with the second target point as far as 2,854 meters while the actual distance is calculated manually there is a difference of 1 meter with a target point. The difference in stopping point with the third target point as far as 9,748 meters while the actual distance is calculated manually there is a difference of 8 meters with a target point.

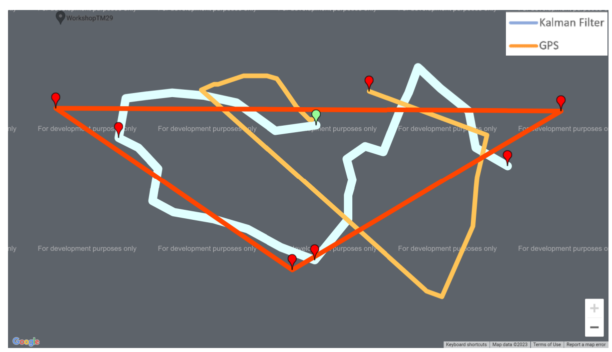

Fig. 16 Plot of the results of experiment 5 on the map

From the results of the experiment using the Kalman Filter that had been displayed above, showed the results obtained after applying the Kalman Filter reduced the instability obtained when compared to the receipt of data from GPS which was directly processed on the Raspberry Pi. In testing one to eight, it can be seen that the travel route that is traversed does not deviate from the point of the road being traversed, in this case the motion of Autonomous Vehicle is more stable. Although there is still an instability due to the lack of accuracy of GPS, this can be minimized after applying the Kalman Filter. The value of R changed affects the value of Kalman Gain, a small R value makes Kalman Gain will give weight to the measurement and vice versa the greater R value makes the Kalman Gain will give weight to the estimation. This arrangement is needed so that Kalman Gain does not really believe in both, because if Kalman Gain gives more weight from one of them, this causes the output results of the filter process will not be optimal. The parameter R was tried to be 1, 5, 10, and 15. In experiment 1 with a value of R = 1, Autonomous Vehicle runs far to the right of the field first which is similar to an experiment that only relies on GPS data even though the autonomous vehicle remains directed and successfully reached the destination point. But the hope is that the results given are better, therefore the R value will be increased because experiment 1 is too trusting GPS data. In experimental 2 with a value of r = 5, the autonomous vehicle slightly deviated to the right and after in the middle of the field strayed slightly to the left and then pointed to the destination point. Although there is an error in the movement, but this result is better than in experiment 1. In experiment 3 with a value of r = 10, autonomous vehicles are slightly deviated to the right and after in the middle of the autonomous vehicle leads to the destination point. This shows the estimated Kalaman Filter output, Kalman Filter does not really trust GPS or estimation. Although it takes a longer time to reach the destination point when compared to the value of R = 10 due to the response of the system that will be longer with the raised R value. In experimenting 4 with a value of r = 15, the autonomous vehicle deviated to the left first and then leads to the destination point. Of the four values, it can be seen that the value of R = 10 shows more optimal results. Therefore, for testing 5, 6, 7, and 8, an experiment was carried out using the value of R = 10. Then to overcome the instability and inaccuracies that often occur in distance calculation, reset is carried out to restore the system conditions such as the initial conditions which means the process will be repeated, This is enough to overcome the problem of the distance calculation. The test results with the Kalman Filter give the difference in distance difference still within the radius limit of success which in this case is 10 meters, this is evidenced by the results of the distance testing in testing 1 there is a difference of 7,457 meters with the destination point inputted in the program. In experiment 2 there was a difference of 9,759 meters with the destination point entered in the program. In experiment 3 there was a difference of 7,651 meters with the destination point entered in the program. In experiment 4 there was a difference of 2,551 meters with the destination point entered in the program. In testing 5 there was a difference of 7,986 meters with the destination point entered in the program. In testing 6 there is a difference of 9,308 meters with the destination point entered in the program. In testing 7 there is a difference of 5,882 meters with the destination point entered in the program. In the experiment 8 difference difference with the first target point as far as 9,136 meters, the difference in stopping point with the second target point as far as 2,854 meters, the difference in stopping point with the third target point as far as 9,748 meters. These results indicate that the tracking system using the Kalman Filter is better than not using the Kalman Filter looking at the GPS testing at the stationary condition there is an average measurement error of 4.78 meters.

IV. CONCLUSIONS

The conclusions from the research on Tracking Systems on Autonomous Vehicles using Radiolink SE100 M8N with the Raspberry Pi-Based Kalman Filter Method are as follows: Based on the results of the study that has been conducted using Radiolink SE100 M8N consisting of GPS and Kompas, when the condition is silent for five minutes, there is a measurement error in GPS as evidenced by the Latitude and Longitude data received at the first and last is as far as 4.78 Meter. Although there is a measurement error, the GPS M8030 has a high speed in receiving coordinate data in conditions without obstacles. Furthermore, from the research results of the Kompas QMC5883L sensor accuracy, there is a percentage of small errors with an average of 0.36%. The largest error is at an angle of 0◦ with a percentage of 1%.

Based on the results of testing without using the Kalman Filter showing Autonomous Vehicle does not directly move towards the target point but tends to spin and does not stop at the target point. While the test results using the Kalman Filter show that the autonomous vehicle moves towards the target point in the radius of success that shows the results are more accurate but not precise.

In experiment 1 there was a difference of 7,457 meters with the destination point entered in the program. In experiment 2 there was a difference of 9,759 meters with the destination point entered in the program. In experiment 3 there was a difference of 7,651 meters with the destination point entered in the program. In experiment 4 there was a difference of 2,551 meters with the destination point entered in the program. In testing 5 there was a difference of 7,986 meters with the destination point entered in the program. In testing 6 there is a difference of 9,308 meters with the destination point entered in the program. In testing 7 there is a difference of 5,882 meters with the destination point entered in the program. In the experiment 8 difference difference with the first target point as far as 9,136 meters, the difference in stopping point with the second target point as far as 2,854 meters, the difference in stopping point with the third target point as far as 9,748 meters.

Calculations to determine the direction and coordinates that are intended can use the bearing calculation and formula haveersine. Based on the test results, autonomous vehicles are able to move according to the coordinates inputted in the program with a radius of 10 meters of success based on the calculation of the Haversine distance.

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