Direction Control of Moving Vehicle using Dual RTK-GNSS and Kalman Filter

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Abstract

We have been investing a weeding robot. The robot estimates its position with Global Navigation Satellite System(GNSS) but includes errors, which are around a few meters, when it does single positioning. The direction of the robot deviates a lot as it is based on location information. Hence by using the more accurate Real Time Kinematic GNSS (RTK-GNSS), the positional accuracy improved. However, since the direction of the robot was estimated from the difference with the position of the previous robot, it was difficult to estimate the direction while posing. Therefore, we presumed self-position with two single frequency RTK-GNSS receivers which become to be available recently and are economically friendly. By setting the normal vector calculated from the left and right position information with two modules as the direction of the robot, it made it possible to estimate the direction not only while running but also posing. Moreover, we will tackle construction of position estimation system with Kalman filter.

1 Introduction

Our research group has been developed a small weeding robot[1]. This robot weeds automatically in paddy fields. It is important for the robot to know the self-position because it moves in a vast environment. To know the self-position, some researchers use camera[2] or beacon[3]. However, these devices easily affected by disturbance such as weather, so it is difficult to apply to our robot. Therefore, we adopt Global Navigation Satellite System(GNSS) to obtain self-position of the robot[4]. Conventionally, robots obtain self-position by single-positioning method. However, position errors and orientation errors are greatly increase. Therefore, we adopt Real Time Kinematic-GNSS (RTK-GNSS) for higher accuracy.

GNSS modules mainly receive two kinds of carries. Dual frequency receivers are expensive and large, so we can not mount our robot. On the other hand, the number of satellites has increased by multi-GNSS technology in recent years. As a result, cheap and compact modules that can acquire one frequency carrier have been on the market. Therefore, we adopt these modules. We installed two modules on the both side of the robot because it is difficult to estimate the orientation of the robot using only one module[5][6]. In this research, we propose a more accurate self-localization system by introducing the Kalman filter into our positioning system. We verify our proposed method by Matlab.

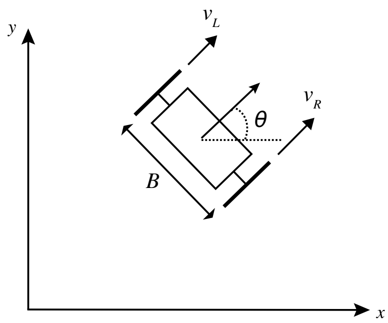

Fig. 1: Robot model

2 Kalman filter

In this chapter we will explain the Kalman filter. The aigamo robot moves on a two-dimensional plane. Let the center coordinates of the robot be (x, y) and θ be the angle formed by the traveling direction of the robot and the x axis. The state vector x of the robot is expressed as Equation 1.

$$\boldsymbol{x} = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} \tag{1}$$

The robot is controlled by the left and right speeds v_L and v_R, and the control vector u is expressed as Equation 2.

$$\boldsymbol{u} = \begin{bmatrix} v_L \\ v_R \end{bmatrix} \tag{2}$$

From the general equation of the Kalman filter, the estimated position of the robot is expressed as Equation 3.

$$\hat{\boldsymbol{x}}_t = F\hat{\boldsymbol{x}}_{t-1} + B\boldsymbol{u_t} + \boldsymbol{w_t} \tag{3}$$

where, $F = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$, $B = \begin{bmatrix} dt * cos\theta & 0 \\ dt * sin\theta & 0 \\ 0 & 1 \end{bmatrix}$, $\boldsymbol{w}$ is process noise.
Also, updating the error covariance matrix is expressed as Equation 4.

$$P_t = FP_{t-1}F^T + Q \tag{4}$$

However, P represents the error covariance matrix, Q represents the covariance matrix of the process, and

$Q = \begin{bmatrix} \sigma_{v_L}^2 & 0 \\ 0 & \sigma_{v_R}^2 \end{bmatrix}$

The position z of the robot by GPS is expressed as Equation 5.

$$\boldsymbol{z}_t = H\boldsymbol{x}_t + \boldsymbol{v}_t \tag{5}$$

where, $H = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$, $\boldsymbol{v}$ is observation noise.

In the update phase of the Kalman filter, update of the observation error covariance matrix S, correction of the Kalman gain K, and updating of the estimated state quantity $\hat{\boldsymbol{x}}$ are performed by the expression of Expression 6-10.

$$\boldsymbol{y}_t = \boldsymbol{z}_t - H\hat{\boldsymbol{x}}_t \tag{6}$$

$$S_t = R + HP_tH^T \tag{7}$$

$$K_t = P_tH^TS_t^{-1} \tag{8}$$

$$\hat{\boldsymbol{x}}_t = \hat{\boldsymbol{x}}_t + K_t\boldsymbol{y}_t \tag{9}$$

$$P_t = (I - K_tH^T)P_t(I - K_tH^T)^T + K_tRK_t^T \tag{10}$$

However, R is the observation covariance matrix,

$R = \begin{bmatrix} \sigma_{xx} & \sigma_{xy} & \sigma_{x\theta} \\ \sigma_{yx} & \sigma_y^2 & \sigma_{y\theta} \\ \sigma_{\theta x} & \sigma_{\theta y} & \sigma_\theta^2 \end{bmatrix}$

3 Pre experiments

We investigated the error distribution used for the Kalman filter in the previous study.

3.1 Experimental device

RTK-GNSS requires at least GNSS modules, base station and rover. In this experiment, we use one Reach RS[7] from Emlid as a base station and two Reach[8] from Emlid as a rover. As shown in Figure 2, the base station is installed at a position of 150 [cm] above the ground with a quaint triangle with a clear view. Rover uses an experimental device as shown in Figure 3. Under the antennas of the base station and the mobile station, an aluminum plate of 10 [cm] × 10 [cm] is laid down to prevent multipass from the ground.

Fig. 2: Base Environment

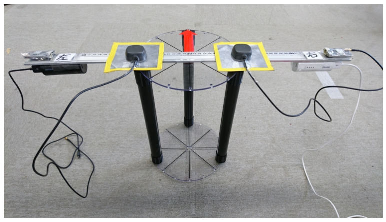

Fig. 3: Experimental device

3.2 Investigation method

In the previous study, the following data set was measured in order to investigate the position error, the orientation error, the influence of the module distance and orientation, when two modules were used for a rover. Each data set acquires 8 azimuths at a frequency of 5 Hz (100 data) in increments of 45 degrees.

(i) Ground height 30cm/Distance between modules 20cm

(ii) Ground height 30cm/Distance between modules 30cm

(iii) Ground height 30cm/Distance between modules 40cm

(iv) Ground height 150cm/Distance between modules 20cm

(v) Ground height 150cm/Distance between modules 30cm

(vi) Ground height 150cm/Distance between modules 40cm

3.3 Result

Figures 4 and 5 show the results of (ii) which is closest to our robot.

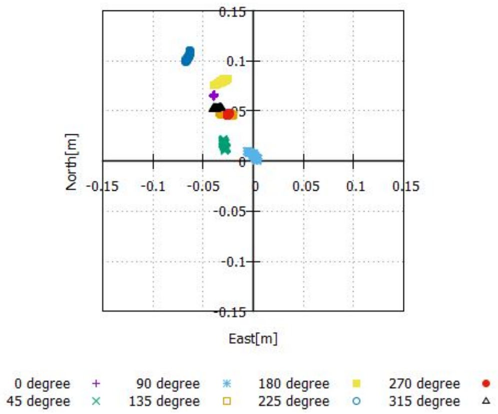

Fig. 4: Position error

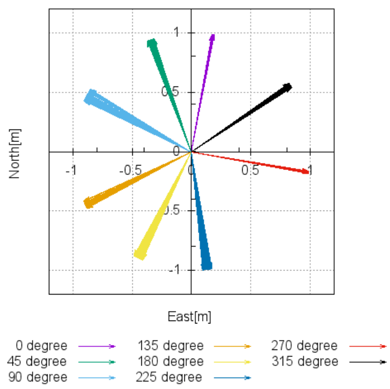

Fig. 5: Orientation variation

A variance covariance matrix is calculated from the error data obtained from this experiment. The multivariate normal distribution of only the position is shown in figure 6.

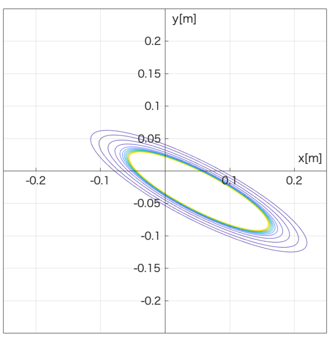

Fig. 6: Multivariate normal distribution

The mean and variance covariance matrix with the orientation of the robot also added are shown in equations 11 and 12.

$$\mu = \begin{bmatrix} \mu_x \\ \mu_y \\ \mu_\theta \end{bmatrix} = \begin{bmatrix} 0.0523096875 \\ -0.0315079375 \\ -0.0287904375 \end{bmatrix} \tag{11}$$

$$R = \begin{bmatrix} 0.0000041093 & -0.0000001684 & -0.0000053749 \\ -0.0000001684 & 0.0000058535 & 0.0000322863 \\ -0.0000053749 & 0.0000322863 & 0.0003444646 \end{bmatrix} \tag{12}$$

4 Simulation using Kalman filter

From the previous experiment, the variance covariance matrix of the position and orientation of our positioning system was calculated. We simulate the superiority of the Kalman filter in Dual RTK-GNSS by using equations 10 and 11. The parameters used in the simulation are shown in Table 1. The robot performs sequence control in the CCW direction. In consideration of the road surface condition, we give small, medium and large noise to the wheels. Since the road surface on which the Aigamo robot runs is an irregular rice field, it assumes a large noise.

Table 1: Parameters for simulation

Parameter	Value
Wheel distance B	$0.35[m]$
Left wheel speed v_L	$0.2[m/s]$
Right wheel speed v_R	$0.3[m/s]$
Robot control frequency	$100[Hz]$
Update frequency of GNSS	$5[Hz]$

Table 2: Wheel noise

Magnitude of noise	Convariance matrix
small	$Q = \begin{bmatrix} 0.1^2 & 0 \\ 0 & 0.1^2 \end{bmatrix}$
middle	$Q = \begin{bmatrix} 0.3^2 & 0 \\ 0 & 0.3^2 \end{bmatrix}$
large	$Q = \begin{bmatrix} 1^2 & 0 \\ 0 & 1^2 \end{bmatrix}$

4.1 Result and Discussion

The simulation results for small, medium and large wheels disturbance are shown in Figure 7-9.

When the noise is small and medium, the estimated self-position by the Kalman filter deviates largely while oscillating in the middle stage. The cause of this middle misalignment has not been elucidated. On the other hand, when the noise is large, the estimated self-position by the Kalman filter does not shift even in the middle stage. The precision of the observation value of GNSS at small, medium and large noise was quite high. Most of the observed values of GNSS deviate to the lower right of the position of the real robot. This is because the position error distribution in the previous experiment was biased toward the lower right. The Kalman filter was greatly affected by the observation value of GNSS. This is because the variance of the error in the preliminary experiment was rather small and the observation was more reliable.

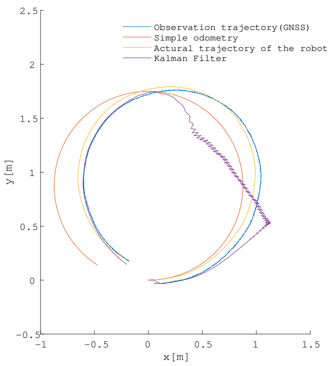

Fig. 7: Small process noise

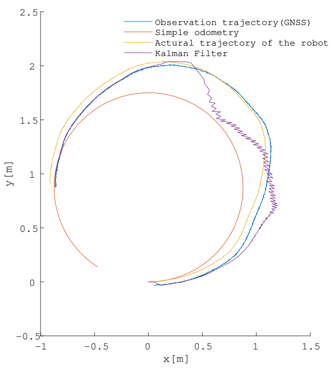

Fig. 8: Middle process noise

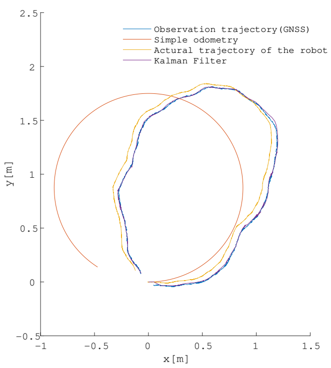

Fig. 9: Large process noise

5 Conclusions

In the simulation using error data acquired in previous experiments, the accuracy of the GNSS module was quiet high. Although the stationary body was used for the error data used in this study, it is expected that the accuracy of the observation value will decrease because the real robot is a moving object. If the error distribution varies depending on the date and time and location, we think that the accuracy of self position estimation will be further improved by setting the time for calibration and applying an offset to the observation value. In the case of small and medium noise, the future task is to elucidate the reason why the estimated self-position by the Kalman filter shifts while oscillating large in the middle stage.

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