확장 칼만 필터를 이용한 메카넘휠 기반 이동 로봇 위치 추정

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Mecanum-wheeled mobile robot localization using extended Kalman filter

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Abstract – This paper provides a localization technique for a mecanum-wheeled omnidirectional mobile robot (MWOMR) to obtain an accurate position of the robot. To this end, the correct MWOMR localization is estimated by an extended Kalman filter (EKF) from the fused data of wheel odometry and IMU sensors. This paper evaluates the accuracy of possible sensor combinations in a circular trajectory and compares it with the true position obtained from Gazebo simulator. The results show that the encoder and IMU fused data with EKF acts as a better option rather than dead reckoning relying on wheel odometry alone.

1. Introduction

Localization plays a vital role in robotics fields such as a mecanum wheel mobile robot to obtain the correct position of the robot. Poor localization might produce poor tracking performance that may lead to accidents in the real world such as autonomous mobile robots crashing into things or even humans. However, relying only on wheel odometry for localization in a mobile robot is not sufficient to retrieve the accurate position of a mobile robot as it suffers from cumulative error. It motivates the research of fusing multiple sensors to correct the displacement that might arise from one sensor.

Previous research has shown that Kalman filter gives exceptional performance for localization problems. [1] and [2] have demonstrated that multiple sensor fusion using the Kalman filter yields satisfying results. Another massive solution is [3] as it estimates 12 states by an extended Kalman filter that enables the algorithm to fuse from an unlimited number of inputs from multiple sensor types. The latter method uses a standard 3D kinematic model derived from Newtonian mechanics.

This paper focuses on delivering a localization technique for a mecanum-wheeled mobile robot using wheel odometry fused with an IMU sensor. Since the IMU sensor could generate data much faster, it will lead to asynchronous data fusion. Therefore, an algorithm to synchronize and fuse both sensors is presented and applied to a mecanum-wheeled mobile robot in a circular path. Furthermore, the results are compared to the ground truth data obtained from the Gazebo simulator and the dead reckoning localization to see the improvement from the proposed method.

2. Sensor Fusion With Extended Kalman Filter

2.1 Dynamic of mecanum-wheeled mobile robot

To incorporate the sensor data and work in a discrete-time manner, consider the dynamic of the mobile robot as

$$\begin{pmatrix} x_{k+1} \\ y_{k+1} \\ \theta_{k+1} \\ v_{x,k+1} \\ v_{y,k+1} \\ \omega_{r,k+1} \end{pmatrix} = \begin{pmatrix} x_k + (v_{x,k}\cos(\theta_k) - v_{y,k}\sin(\theta_k))\Delta t \\ y_k + (v_{x,k}\sin(\theta_k) + v_{y,k}\cos(\theta_k))\Delta t \\ \theta + \omega_{r,k}\Delta t \\ v_{x,k} \\ v_{y,k} \\ \omega_{r,k} \end{pmatrix} \tag{1}$$

where the x (m) and y (m) are the position in cartesian coordinate and θ (rad) is the heading angle. $[v_x, v_y, \omega_r]^T$ are the linear speed (m/s), the lateral speed (m/s), and the angular speed (rad/s) of the mobile robot, respectively.

2.2 Sensor Fusion

Let us consider $\omega_{fl}, \omega_{flr}, \omega_{rl}, \omega_{rr}$ are the angular velocity of the front left wheel, front right wheel, rear left wheel, and rear right wheel, respectively. The configuration of all mecanum wheels determines the combination of mecanum-wheeled mobile robot movement. Suppose the angular velocity of each wheel is obtained from the encoder of each wheel, then the velocity of the mobile robot is

$$\begin{pmatrix} v_x \\ v_y \\ \omega_r \end{pmatrix} = \frac{r}{4}\begin{pmatrix} 1 & 1 & 1 & 1 \\ -1 & 1 & 1 & -1 \\ -\frac{1}{a+b} & \frac{1}{a+b} & -\frac{1}{a+b} & \frac{1}{a+b} \end{pmatrix}\begin{pmatrix} \omega_{fl} \\ \omega_{fr} \\ \omega_{rl} \\ \omega_{rr} \end{pmatrix} \tag{2}$$

where r (m) is the radius of the wheel, a (m) is the half of wheel base, b (m) the half of robot's wheel track, and $\omega_{(.,.)}$ (rad/s) describes the angular speed of each motor.

In this paper, the raw IMU data, which consists of angular rate and linear acceleration data, is processed using the algorithm presented in [4]. The data used from the IMU sensor reading are yaw for the heading of the mobile robot and angular velocity on the z-axis.

From this setup, the angular speed of the robot is obtained from 2 sensors. An algorithm from [5] is employed to synchronize the different rate data. The fused measurement of similar data and its error covariance are given by [5]

$$\omega_r^{fused} = \left(\frac{\omega_r^{IMU}}{R^{IMU}} + \frac{\omega_r^{wheel}}{R^{wheel}}\right) R^{fused} \tag{3}$$

$$R^{fused} = \left(\frac{1}{R^{IMU}} + \frac{1}{R^{wheel}}\right)^{-1} \tag{4}$$

The resulted data obtained from the combined sensor are $y = [\theta, v_x, v_y, \omega_r]^T$.

2.3 Extended Kalman Filter

Since the measured data does not have the information about the position of the robot, extended Kalman filter is used in this paper to estimate the position for the nonlinear dynamic in (1). In general, extended Kalman filter is summarized as

$$
\begin{aligned}
&\hat{x}_{k|k-1} = f(\hat{x}_{k-1|k-1}, u_k) \\
&P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k \\
&K_k = P_{k|k-1} H_k^T \left(H_k P_{k|k-1} H_k^T + R_k \right)^{-1} \\
&\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \left(y_k - h(\hat{x}_{k|k-1}) \right) \\
&P_{k|k} = (I - K_k H_k) P_{k|k-1}
\end{aligned}
$$

where the state transition and observation matrices are defined to Jacobians of state and output functions. From (1) and the fused sensor data $y = [\theta, v_x, v_y, \omega_r]^T$, then the state transition and observation matrices for mecanum-wheeled mobile robot are

$$
F_k = \begin{pmatrix}
1 & 0 & (-v_{x,k}\sin(\theta_k) - v_{y,k}\cos(\theta_k))\Delta t & \cos(\theta_k)\Delta t & -\sin(\theta_k)\Delta t & 0 \\
0 & 1 & (v_{x,k}\cos(\theta_k) - v_{y,k}\sin(\theta_k))\Delta t & \sin(\theta_k)\Delta t & \cos(\theta_k)\Delta t & 0 \\
0 & 0 & 1 & 0 & 0 & \Delta t \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 1
\end{pmatrix} \tag{5}
$$

$$
H_k = \begin{pmatrix}
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 1
\end{pmatrix} \tag{6}
$$

3. Simulation Results and Analysis

This paper compares it to ground truth data from Gazebo to evaluate the performance of estimated states from the fused measured data. Furthermore, this paper also compares the localization by dead reckoning from encoder data to see the improvement made by the proposed method.

The performance of the proposed method shows a better result as can be seen in Fig. 1 and Fig. 2. Dead reckoning localization produces RMSE of 0.024 and MAE of 0.029. On the other hand, the fused sensor data with EKF returns a lower error with RMSE of 0.011 and MAE of 0.012.

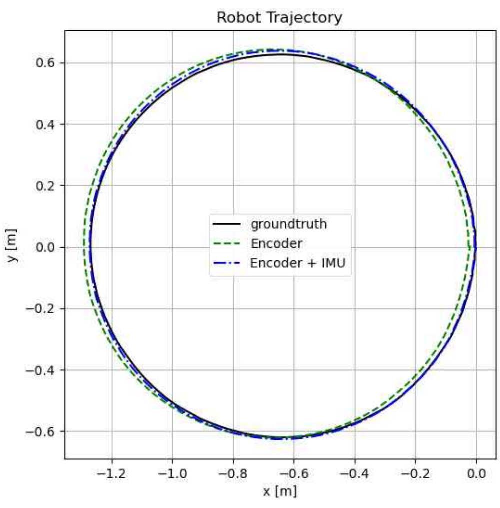

Fig. 1 Tracking Trajectory

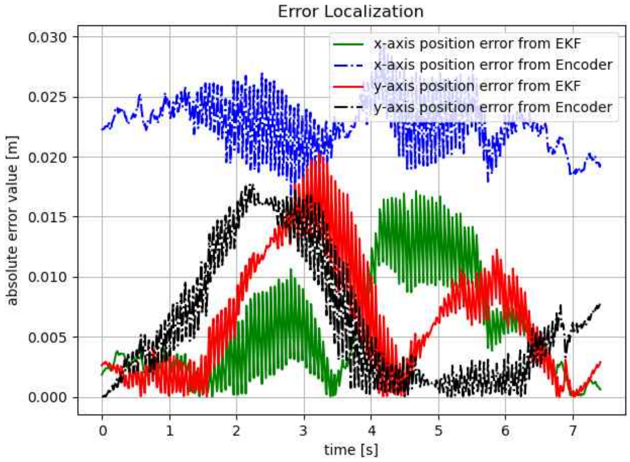

Fig. 2 Error localization compared to ground truth

4. Conclusion

This paper presents a proper localization technique to improve the localization from dead reckoning by wheel odometry. To this end, a sensor fusion and state estimation using an extended Kalman filter is designed. Experiment results show that fusing encoder with IMU data for mecanum-wheeled mobile robot improves the localization from the wheel dead reckoning method. The possibility of fusing more sensors might be considered as the next direction of this research.

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