APPLICATION OF NOISE FILTERING TECHNIQUES TO ENHANCE DIRECTIONAL STABILITY IN AUTONOMOUS VEHICLE CONTROL

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Abstract - This paper presents the application of the Kalman filter (KF) for navigation and motion stabilization of autonomous vehicles, aiming to improve the accuracy of positioning systems in complex environments. The KF, a linear estimation technique, is utilized to reduce noise in sensor signals, particularly those from long-range transmission devices that are vulnerable to electromagnetic interference, which can cause signal distortion or fluctuations. By integrating data from multiple sensors, including GPS, IMU, and LiDAR, the method enables autonomous vehicles to estimate their position and orientation accurately, even under conditions of signal interruption or noise. By estimating the system state and minimizing sensor errors, the KF enhances environmental perception and ensures stable navigation. The study involves both simulation and real-world experiments with autonomous vehicles in diverse traffic scenarios to evaluate the effectiveness and accuracy of the KF in navigation stabilization and autonomous driving performance improvement.

Key words - Kalman filter; sensors; self-propelled vehicles; navigation system; transfer function; GPS; IMU; LiDAR.

1. Introduction

In recent years, autonomous vehicles have become a focal point of research, driven by significant advancements in sensor technology, signal processing, and artificial intelligence. A major challenge in autonomous vehicle navigation is handling noise and errors in sensor data within complex real-world environments, where signals are often affected by electromagnetic interference, background fluctuations, or GPS outages. In this context, noise filtering techniques-particularly the Extended Kalman Filter (EKF)-play a crucial role in enhancing the accuracy and stability of navigation systems.

The KF, developed by Rudolf E. Kalman in 1960, is an efficient state estimation algorithm for dynamic systems, even when measurement data is noisy. The KF operates by employing a mathematical model of the system to predict the next state, then updating this prediction based on actual measurements. This process consists of two main steps [1], [2]:

- Prediction: Predicting the next state of the system and estimating the uncertainty of this prediction.

- Update: Using new measurements to update the prediction and reduce uncertainty.

This filter effectively eliminates interfering signals while retaining the essential information needed for state estimation. The KF has been widely applied in practice, especially in robot localization, and is integrated into systems to filter out noise from sensors and measurement devices, serving as a foundation for minimizing the positional error of autonomous systems during movement.

The EKF is an advanced version of the standard KF, designed for state estimation in nonlinear systems. This filter is highly effective in noise processing and provides more accurate estimates for systems with significant nonlinearity [3]. Linearization in the EKF transforms nonlinear systems into approximately linear ones using Taylor series expansion, enabling the application of standard KF tools, reducing computational complexity, and improving accuracy in localization applications for autonomous vehicles. Figure 1 illustrates the effect of noise in object displacement [4].

EKF is widely used in GPS-based positioning systems, robot control, and target tracking, especially in sensor fusion applications involving encoders (for relative position measurement) and IMU (for acceleration and angular velocity measurement) [5]. However, multi-sensor fusion often faces challenges due to cross-sensor noise and accumulated errors, which can reduce navigation stability. This study focuses on applying EKF to process and fuse data from encoders and IMU, aiming to stabilize navigation and reduce positional errors during autonomous vehicle movement.

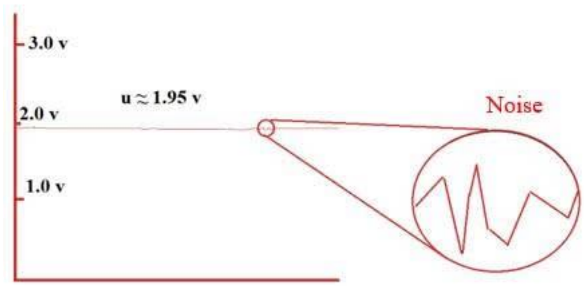

Figure 1. *Noise in object movement*

Previous studies have demonstrated the significant effectiveness of EKF in various fields. For example, study [6] proposed combining EKF with infrared sensors to address estimation errors caused by wheel slippage, surface roughness, and machine tolerance rates. The results indicated promising outcomes for EKF in mobile robot localization. Study [7] proposed integrating IMU with GPS and the KF to estimate vehicle state and position, concluding that the KF compensates for gyro drift during data fusion without requiring additional absolute orientation sensors such as magnetic compasses. Furthermore, since the pose estimation method does not rely on heading angles derived from Doppler effects, it remains effective even when the vehicle moves slowly or is stationary.

Nevertheless, in many practical applications, sensor fusion involving encoders (for relative position measurement) and IMU (for acceleration and angular velocity measurement) still encounters challenges related to accuracy and cross-sensor noise handling [8]. In this context, this paper proposes an EKF-based solution for processing and fusing data from encoders and IMU to improve the accuracy of localization and navigation in autonomous vehicles. This approach holds significant potential for developing low-cost localization systems that still ensure high performance and reliability.

The objective of this study is to design and simulate an EKF-based navigation system, as well as to experimentally compare the effectiveness between single-sensor configurations and EKF-integrated configurations. The results are expected to provide both theoretical and practical foundations for developing intelligent, low-cost autonomous vehicle systems that maintain high reliability and performance.

2. Sensor system design

The design of a sensor system is a complex process that involves multiple steps, from selecting appropriate sensors to integrating and testing the system. Typically, the process includes the following basic steps: defining system requirements, selecting sensors, designing electrical circuits and interfaces, integrating software, installation, and testing [9].

2.1. Speed sensor

The speed sensor (Encoder) is a mechanical sensor that converts the angular position or motion of a rotating shaft into digital signals. As the encoder operates, a disk rotates around the shaft; the disk contains slots through which optical signals pass. The presence or absence of signals passing through the slots is converted into electrical signals. In this paper, we propose using encoders to determine the vehicle's coordinates, direction of movement, and travel speed [10], as illustrated in Figure 2.

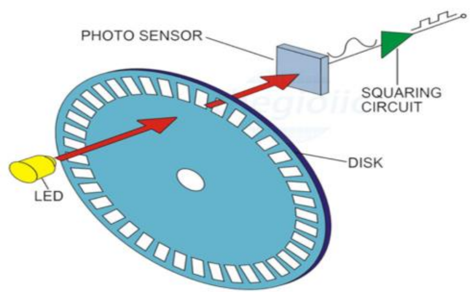

Figure 2. *Operating principle of the speed sensor*

2.2. Inertial Measurement Unit (IMU)

The Inertial Measurement Unit (IMU), shown in Figure 3, is a combination of an accelerometer and a gyroscope. In this study, we use the IMU to measure the motion of the vehicle and to minimize the positional errors of the encoder [11].

- Accelerometer: Measures linear acceleration along three axes (x, y, z), including gravitational acceleration, which helps determine the tilt angle of the object.

- Gyroscope: Measures angular velocity around three axes (x, y, z), which helps determine the rotational speed and direction of the object.

Accurate measurements of acceleration, velocity, position, and angular orientation provide the basis for improving accuracy when combined with encoder data for autonomous vehicle localization. In this study, the data collected during the movement of the autonomous device will be used to compare the error when combining both sensors versus using only the encoder.

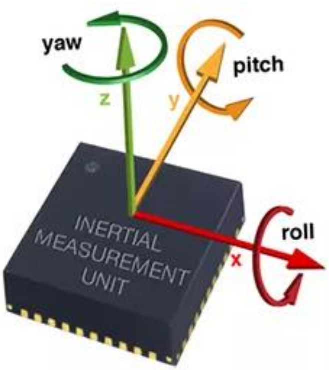

Figure 3. *Inertial Measurement Unit (IMU)*

2.3. Application of the EKF

In the localization system of autonomous vehicles, signals from sensors such as encoders and IMU are often affected by environmental noise and measurement errors. This results in deviations in determining the vehicle's position and direction, directly impacting stability and navigation. To address this issue, this paper proposes using the EKF to minimize errors and enhance the accuracy of the system [12].

The EKF is an advanced version of the standard KF, designed to handle nonlinear systems. EKF linearizes the system model at each time step through first-order Taylor expansion, allowing the application of linear estimation methods to nonlinear dynamics such as those found in autonomous vehicles.

By continuously performing the two main steps, EKF can eliminate random noise and errors caused by wheel slippage, thereby enabling real-time accurate position estimation.

In the prediction step, EKF uses the nonlinear kinematic model of the vehicle to predict the next state based on the current state and control signal. The model is represented by the equation:

$$x_{k+1} = f(x_k, u_k) + \boldsymbol{w}_k, \tag{1}$$

where, x_k is the system state, u_k the control signal, and $\boldsymbol{w}_k$ is the process noise. EKF linearizes the function $f(x_k, u_k)$ to construct the Jacobian matrix, which is then used to calculate the predicted state and covariance matrix.

In the update step, EKF compares the actual sensor measurements with the predicted values to generate a residual, and then uses the Kalman gain to update the state estimate:

$$y_k = z_k - h(x_k) \tag{2}$$

$$x_k = x_{k|k-1} + K_k y_k \tag{3}$$

$$K_k = P_{k|k-1} H_k^T \left(P_{k|k-1} H_k^T + R \right)^{-1} \tag{4}$$

where, z_k is the measurement value, $h(x_k)$ is the measurement function, K_k is the Kalman gain, and P is the covariance matrix.

3. Implementation of the EKF

3.1. Construction of the vehicle state model

An autonomous vehicle [13] is a type of vehicle that moves automatically without human intervention or control. During movement, it is subject to various unwanted influences affecting measurement and state determination, as shown in Figure 4.

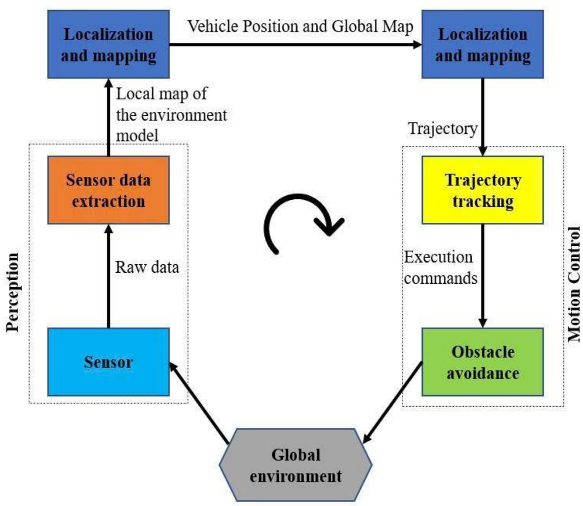

Figure 4. *Operating principle of the autonomous device*

The position of the autonomous vehicle is represented by the vector $[x, y, \theta]^T$ where x,y are the vehicle's coordinates, and θ is called the heading angle, which is the angle of the vehicle relative to the x-axis, as illustrated in Figure 5. By convention, when the vehicle rotates counterclockwise, the heading angle is $+\theta$ considered positive, and vice versa.

The state of the vehicle at time k and k-1 is expanded as follows:

$$X_k = \begin{bmatrix} x_k & y_k & \theta_k \end{bmatrix} \tag{5}$$

$$X_{k-1} = \begin{bmatrix} x_{k-1} & y_{k-1} & \theta_{k-1} \end{bmatrix} \tag{6}$$

Given the time interval Δt, the distance traveled by the wheels is calculated as $\Delta S_R = \Delta t.R.\omega_R$ for the right wheel and $\Delta S_L = \Delta t.R.\omega_L$ for the left wheel, where R is the wheel radius.

The distance and angle of the vehicle's center are calculated as follows:

$$\begin{cases} \Delta S = \dfrac{\Delta S_R + \Delta S_L}{2} \\ \Delta \theta = \dfrac{\Delta S_R + \Delta S_L}{L} \end{cases} \tag{7}$$

where L is the distance between the two wheel axes. The state model of the vehicle is then given by the formula:

$$x_k = \begin{bmatrix} x_k \\ y_k \\ \theta_k \end{bmatrix} = \begin{bmatrix} x_{k-1} \\ y_{k-1} \\ \theta_{k-1} \end{bmatrix} + \begin{bmatrix} \Delta_S.\cos(\theta_{k-1,k-1} + \dfrac{\Delta\theta_k}{2} \\ \Delta_S.\sin(\theta_{k-1,k-1} + \dfrac{\Delta\theta_k}{2} \\ \Delta\theta_k \end{bmatrix} \tag{8}$$

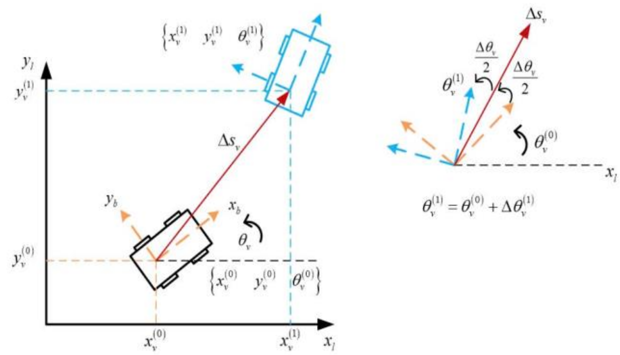

Figure 5. *Vehicle motion state*

3.2. Estimation

The estimation of the vehicle's movement state through coordinates is determined as follows:

$$x_{k,k-1} = f\left(\vec{x}_{k,k-1}, \vec{u}_k\right) \tag{9}$$

Expanding the function gives:

$$f\left(\vec{x}_{k,k-1}, \vec{u}_k\right) = \begin{bmatrix} f_1 \\ f_2 \\ f_3 \end{bmatrix} = \begin{bmatrix} x_{k-1,k-1} + \Delta_S.\cos(\theta_{k-1,k-1} + \dfrac{\Delta\theta_k}{2} \\ y_{k-1,k-1} + \Delta_S.\sin(\theta_{k-1,k-1} + \dfrac{\Delta\theta_k}{2} \\ \theta_{k-1,k-1} + \Delta\theta_k \end{bmatrix} \tag{10}$$

3.3. Measurement

$$P_{k,k-1} = F_k P_{k-1,k-1}.F_k{}^T + B_k.u.B_k{}^T + Q'_k \tag{11}$$

With matrices Fk and Bk calculated as:

$$F_k = \begin{bmatrix} f_1 \\ f_2 \\ f_3 \end{bmatrix} = \begin{bmatrix} \dfrac{\partial f_1}{\partial x} & \dfrac{\partial f_1}{\partial y} & \dfrac{\partial f_1}{\partial \theta} \\ \dfrac{\partial f_2}{\partial x} & \dfrac{\partial f_2}{\partial y} & \dfrac{\partial f_2}{\partial \theta} \\ \dfrac{\partial f_3}{\partial x} & \dfrac{\partial f_3}{\partial y} & \dfrac{\partial f_3}{\partial \theta} \end{bmatrix} = \begin{bmatrix} 1 & 0 & -\Delta s.\sin\left(\theta_{k-1,k-1} + \dfrac{\Delta\theta_k}{2}\right) \\ 0 & 1 & -\Delta s.\cos\left(\theta_{k-1,k-1} + \dfrac{\Delta\theta_k}{2}\right) \\ 0 & 0 & 1 \end{bmatrix} \tag{12}$$

$$B_k = \begin{bmatrix} f_1 \\ f_2 \\ f_3 \end{bmatrix} = \begin{bmatrix} \frac{\partial f_1}{\partial \Delta_S} & \frac{\partial f_1}{\partial \Delta_\theta} \\ \frac{\partial f_2}{\partial \Delta_S} & \frac{\partial f_2}{\partial \Delta_\theta} \\ \frac{\partial f_3}{\partial \Delta_S} & \frac{\partial f_3}{\partial \Delta_\theta} \end{bmatrix} = \begin{bmatrix} \cos\left(\theta_{k-1,k-1} + \frac{\Delta\theta_k}{2}\right) & -\frac{1}{2}\Delta_S.\sin\left(\theta_{k-1,k-1} + \frac{\Delta\theta_k}{2}\right) \\ \sin\left(\theta_{k-1,k-1} + \frac{\Delta\theta_k}{2}\right) & \frac{1}{2}\Delta s.\cos\left(\theta_{k-1,k-1} + \frac{\Delta\theta_k}{2}\right) \\ 0 & 1 \end{bmatrix} \tag{13}$$

3.4. State update

During the use of the EKF, the state update is a crucial step for adjusting estimates based on the difference between measured and predicted values. This process consists of two main stages: the prediction stage (based on the robot's kinematic model and control signals) and the update stage (using actual measurement data from sensors such as the IMU and encoder). The EKF uses a nonlinear measurement function to compare actual measurements with predicted states, then adjusts the state estimate via the Kalman gain to reduce error. This enables the autonomous vehicle's localization system to operate more accurately and stably in environments with significant noise and disturbances.

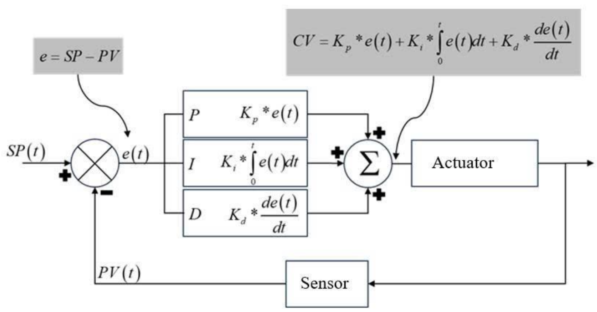

Figure 6. *PID speed controller*

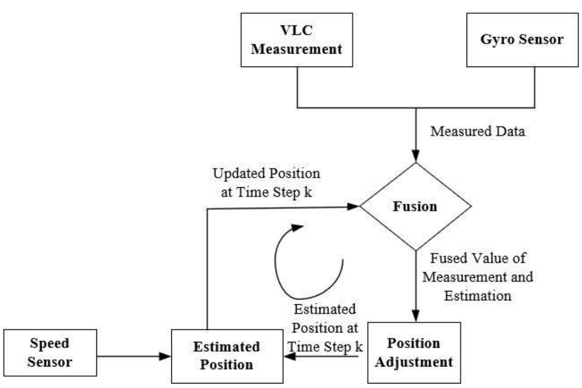

Figure 7. *Block diagram describing the operating principle of the robot localization system using EKF*

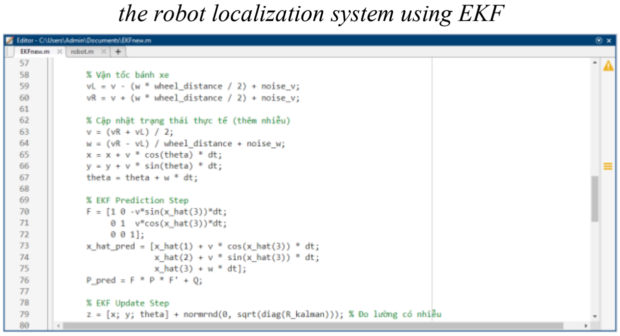

Figure 8. *Matlab simulation code for the vehicle*

The filter is applied to a four-wheeled robot configuration, driven by electric motors, equipped with a PID controller [13], [14], and speed control as shown in Figure 6. The experimental code is implemented in Matlab, integrating the KF for processing support. Figure 7 illustrates the control system's operational principle, and Figure 8 shows the Matlab simulation code setup.

4. Experimental results

Compared to traditional localization methods that use only the encoder or IMU individually, sensor data fusion using the EKF significantly improves both the accuracy and stability of the system.

- When combining EKF with IMU: the error further decreases to 5.1 cm, with repeated runs showing high reliability and fluctuations within ±2 cm.

- When applying the EKF: the error reduces to 9.3 cm, and the trajectory becomes smoother and more stable.

- When using only the encoder: the average error is about 18.5 cm, especially at curved sections where the error can reach up to 30 cm due to uncorrected position drift.

4.1. Result 1

Localization of the autonomous vehicle using the encoder and the EKF.

A simulation of a four-wheeled autonomous vehicle was conducted in Matlab, following a U-shaped trajectory. Two cases were simulated:

-Case 1: The vehicle's state was simulated using equation (8). The simulation results, shown in Figure 9, indicate that the system can effectively follow the pre-set trajectory even in the presence of disturbances. However, errors still occur at sharp turns due to system delay and nonlinearity. This suggests that the control algorithm needs further adjustment to minimize errors during sudden turns.

- Case 2: When the EKF is applied, the results are shown in Figure 10. It is evident that the vehicle's trajectory follows the reference path more accurately and stably than without the filter. The EKF helps reduce measurement noise and significantly improves state estimation accuracy. As a result, errors at turning points are also greatly reduced, enhancing the effectiveness and reliability of the navigation system.

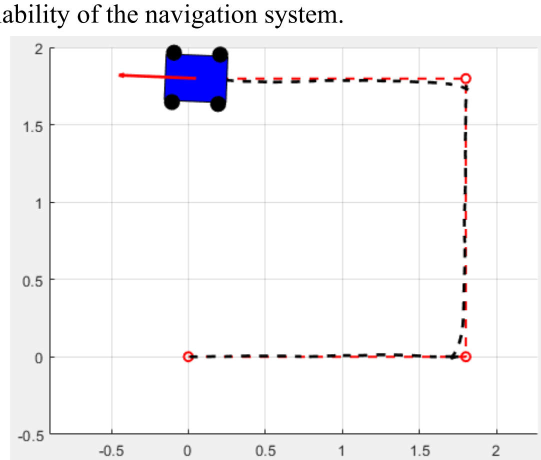

Figure 9. *Vehicle state simulation without EKF*

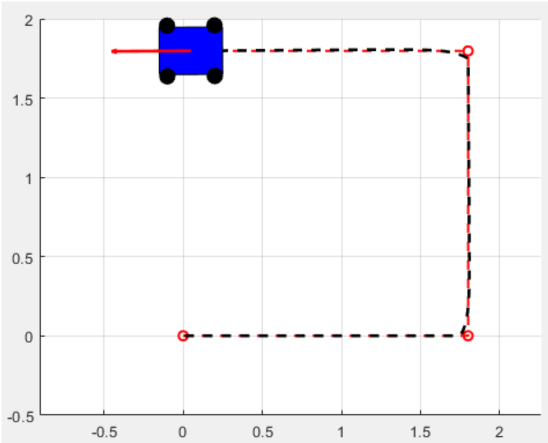

Figure 10. *Vehicle state simulation with EKF*

4.2. Result 2

Localization of the autonomous vehicle using encoder, EKF, and IMU

The control code was implemented on a mini autonomous vehicle, and the results showed that the traveled path closely matched the programmed trajectory. The team repeated the experiment multiple times with consistently reliable results. Figures 11 and 12 show the autonomous vehicle model, and Figure 13 presents the actual recorded trajectory.

Figure 11. *Experimental autonomous vehicle*

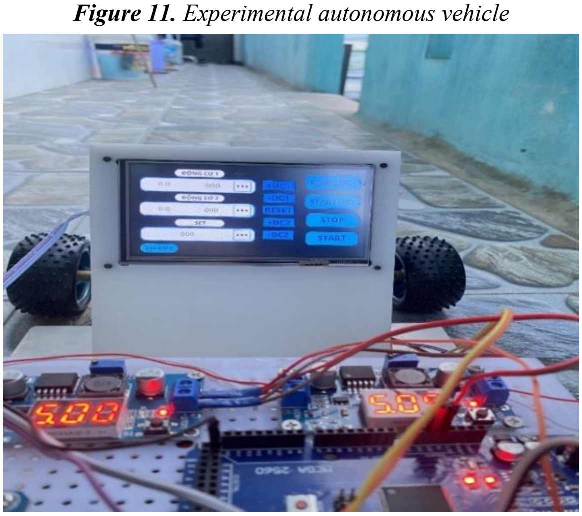

Figure 12. *Experimental autonomous vehicle*

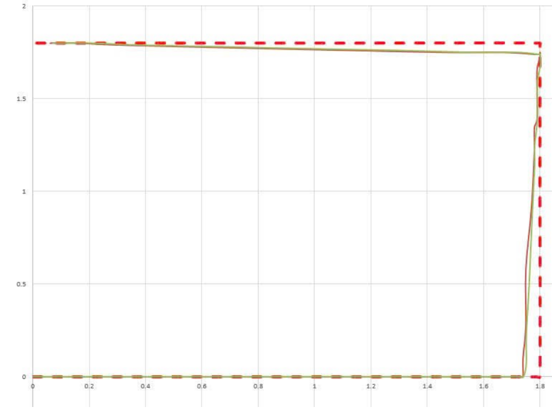

Figure 13. *Extracted and plotted coordinate values*

The experimental results in Figure 13 depict the actual trajectory of the autonomous vehicle when combining three sensor sources: encoder, IMU, and the EKF. It is clear that the vehicle's path using the combination of encoder and EKF (solid brown line) closely follows the reference trajectory (dashed red line). This demonstrates the precise localization capability of the sensor system and the filtering algorithm used in the model. When the IMU is further integrated, the vehicle's trajectory (solid green line) approaches the desired path even more closely, highlighting the improved accuracy of multi-sensor localization for autonomous vehicles.

Especially at sharp turns, the error remains within acceptable limits, showing that the EKF effectively reduces noise and corrects accumulated errors from both the encoder and IMU. The strong correlation between simulation and experimental data confirms the validity of the control model and the reliability of the integrated localization system.

5. Conclusion and future directions

The research team has successfully applied the KF for noise reduction in the control and stabilization of the autonomous vehicle's trajectory, ensuring it follows the pre-defined path. After repeated experimental trials, the robot achieved the required accuracy as set by the project objectives. By synthesizing knowledge from various references and with the support of colleagues, we have accomplished the goals of this study. The research holds practical significance for both learning and research at the university, serving as a theoretical foundation for real-world applications in larger autonomous vehicles that can assist with human mobility needs. Experimental results show that combining both encoder and IMU yields a more reliable localization system compared to using a single sensor. This confirms the practical value of applying KFing techniques in modern autonomous systems.

These future directions not only expand the application scope of the system but also contribute to the trend of developing intelligent and sustainable autonomous vehicles. Future research will focus on integrating intelligent control algorithms such as adaptive PID to enhance the flexibility and self-learning capabilities of autonomous systems. The system will be deployed on larger-scale autonomous vehicle models operating in complex environments such as urban areas or natural terrains. Additionally, nonlinear Kalman filters (UKF) or particle filters (PF) will be applied to compare their performance and accuracy with EKF. The research will also be extended by integrating additional sensors such as LiDAR and cameras to enhance environmental perception and obstacle avoidance capabilities.

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