Electric Vehicle Control with Integrated PID and Kalman Filtering for Improved Stability and Accuracy

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Abstract. With the increasing usage of electric vehicles (EVs), the Market demand for control systems that increase travel speed is also on the rise. Conventional PID control algorithms are susceptible to sensor noise and environmental uncertainties, which degrade performance. Therefore, the PID control system can be optimized based on Kalman filtering. This study aims at putting into practice the idea of a hybrid system, engineering both the PID control and the Kalman filter, to bring vehicle performance to a higher level, especially in the matters of path planning, speed control, and vehicle stability. The fusion system is designed to take the advantage of both techniques, with the PID acting as the main controller and the Kalman filter providing the necessary information for sensor data fusion. MATLAB based Simulations underscore this hybrid technique as sharp decrease in noise, reinforced stability of the vehicle and accurate controllability of the vehicle can be observed. The results indicate the 30% noise-induced fluctuations and the enhancement of the vehicle tracking trajectory. Meanwhile, this research stands as a basis for further development in autonomous electric vehicle technologies and implies that the PID Kalman hybrid control system is an auspicious approach to obtaining more safe and accurate control in reality.

Keywords: PID Control, Kalman Filtering, Electric Vehicle Control.

1. Introduction

Electric vehicles (EVs) are rapidly becoming a key solution for sustainable transportation, driven by their potential to reduce greenhouse gas emissions and dependence on fossil fuels. The rapid proliferation of electric vehicles is placing greater demands on advanced driver assistance systems (ADAS) and autonomous driving control systems [1, 2]. A robust control system is essential for ensuring efficient and safe operation under varying driving conditions.One of the most common tools, applied for EVs' control, is Proportional-Integral-Derivative (PID) control, which is favored for its simplicity, ease of implementation, and real-time adaptability in tasks such as speed regulation and steering. Nevertheless, traditional PID controllers, in the presence of noisy sensor data and unpredictable environmental conditions, can't always achieve the precise vehicle control needed in order for them to be effective[3].

To mitigate these issues, Kalman filtering has been seen as a powerful tool for merging multiple types of sensors and solving the problem of noise. A Kalman filter allows the accurate state estimation of a system by synchronizing the noisy sensor measurements with the system's mathematical model and the vehicle's position, speed, and orientation, which are the parameters used. Kalman filtering is very important in systems that operate in real-time scenarios where accuracy is still a major factor in uncertain conditions. The combination of Kalman filtering with PID control is likely to be a promising solution since it involves the real-time PID control capabilities that are enriched by the Kalman method having a noise-reduction advantage, more reliable and accurate control systems in electric vehicles are achieved.

This research is based on the development and the optimization of a blending of PID and Kalman systems for electric vehicles. This covers the downsides of the traditional PID controller while enhancing vehicle dynamics through accurate sensor data fusion and noise reduction. this study aims to: (1).designing a control strategy whereby PID control is combined with Kalman filtering so that the sensor data accuracy is improved and the noise is reduced, (2).simulate and evaluate the hybrid PID-Kalman approach to compare its performance against traditional PID-only control methods. As the result of these goals, both the vehicle's stability and control accuracy are aimed to come out promising for a development of autonomous electric vehicles.

2. Methodology

2.1. Conceptual Diagram

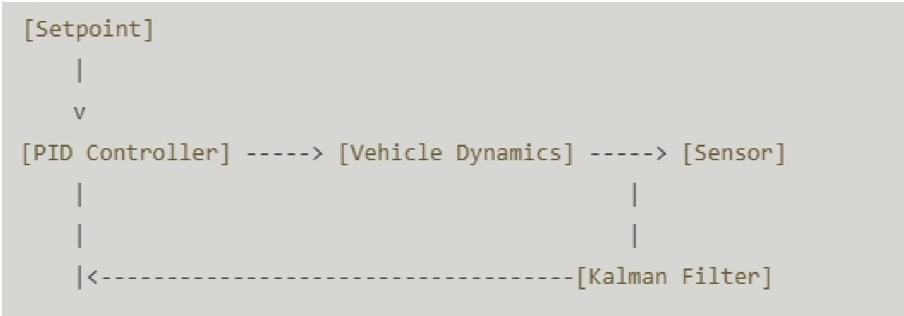

Figure 1. Research Conceptual Diagram

Fig. 1 presents the conceptual framework of the combined PID and Kalman filter control system, which is designed to optimize electric vehicle dynamics. In this research, the parameters of the pid control parameter are set as follows: Kp=1.2, Ki=0.1, Kd=0.05. At the core, the system starts with a set point, which represents the target speed for the vehicle. The PID controller estimates the error between the target speed and the filtered speed (offered by the Kalman filter), thus giving a control signal to adjust the vehicle’s acceleration. This control signal directly affects the vehicle dynamics, which symbolize the mechanics of motion of the vehicle as it inputs the response path. To ease the impact of these noises, the Kalman filter processes the sensor data to estimate the true speed of the vehicle. The filtered output is the fed back provided to the PID controller, which is made to ensure the more precise adjustments and to improve overall control accuracy. This whole procedure strongly implies the interrelation between real-time control and noise reduction, essential for achieving the diverse and reliable performance of the vehicle [4].

2.2. System Modeling

The first action is the modeling of an electric car that has the dynamics of acceleration, deceleration, steering angle, and the impact of the road conditions as its components.

The vehicle model is based on kinematic equations and sensor data inputs, which are crucial for simulating realistic driving scenarios.

This model is validated against real-world data to ensure accuracy in further simulations.

2.2.1. Formulas and Principles

For simulating the vehicle’s motion, this research starts with the basic kinematic equations. Assuming the vehicle’s dynamics are simplified, the speed and acceleration can be described as follows:

$$v(t) = v_0 + a(t) \cdot t \tag{1}$$

$$a(t) = \frac{F_{control}}{m} - c_d \cdot v(t)^2 \tag{2}$$

Here V is the vehicle speed, v_0 is the initial speed, t is the time duration, a is the acceleration of the vehicle, F is the force driving the vehicle, $c_d \cdot v(t)^2$ is the resistance.

PID Controller Design:

The PID controller adjusts the control force based on the error e(t), which is the difference between the target speed and the actual speed:

$$e(t) = v_{target} - v(t) \tag{3}$$

The control signal is generated by the PID controller as follows:

$$F_{control} = K_p e(t) + K_i \int e(t)dt + K_d \frac{de(t)}{dt} \tag{4}$$

Where, Kp=1.2, Ki=0. 1, Kd=0.05.

2.2.2. Kalman Filter Equations:

Prediction step:

$$\hat{x}_{k|k-1} = A\hat{x}_{k-1|k-1} + Bu_k \tag{5}$$

$$P_{k|k-1} = AP_{k-1|k-1}A^T + Q \tag{6}$$

Update step:

$$K_k = \frac{P_{k|k-1}H^T}{HP_{k|k-1}H^T + R} \tag{7}$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(z_k - H\hat{x}_{k|k-1}) \tag{8}$$

$$P_{k|k} = (I - K_k H)P_{k|k-1} \tag{9}$$

Here X is the state estimate, one of the results of the filtering. P is the estimate of the covariance. H is is the transformation matrix from state variables to measurements. K is Kalman coefficient. R is the measurement noise covariance[5].

These equations form the basis of the Kalman filter's recursive process, balancing between prediction and correction based on sensor data.

2.3. Control Algorithm Design

The control system is drafted by incorporating PID control and Kalman filtering. The PID controller is tuned to automatically control vehicle speed by utilizing a set of gains (proportional, integral, and derivative) optimized with the help of control-oriented simulation.

Meanwhile, the Kalman filter is designed to process noisy sensor data, estimating the vehicle's position, speed, and orientation in real-time, which enhances the reliability of the control system.

The MATLAB code simulates the control of an electric vehicle (EV) using a combination of PID control and Extended Kalman Filtering (EKF). The simulation was carried out for 0.01 seconds with a total duration of 20 seconds to test the effect of the combination of PID and EKF, focusing on analyzing the accuracy of the system in controlling the speed under different noise conditions. The PID controller parameters—proportional gain (Kp), integral gain (Ki), and derivative gain (Kd)—are set to 1.0, 0.05, and 0.01, respectively. The target speed is set to 20 m/s.

The code initializes the vehicle's state variables such as speed, acceleration, error integral, and previous error. The Extended Kalman Filter (EKF) is initialized with state estimates and error covariance. The process noise and measurement noise covariance are set as Q and R for the filtering process.

During the simulation loop, the PID controller calculates the control signal based on the error between the target speed and the actual speed, which is then used to update the vehicle's acceleration and speed. Sensor noise is added to simulate real-world conditions, where vehicle speed readings are perturbed by Gaussian noise. The EKF performs prediction and update steps to filter the noisy speed data and estimate the true speed of the vehicle more accurately.

At each time step, the code records the true speed, noisy speed, and filtered speed data. The simulation results are plotted to compare the three speed values: true speed, noisy speed, and the filtered speed after Kalman filtering. The results demonstrate how the combination of PID control and EKF effectively smooths and improves the accuracy of vehicle speed control [6, 7].

2.4. Evaluation

The results from the simulations are analyzed to compare the performance of the hybrid PID-Kalman control system against traditional PID-only controllers, using several key metrics for evaluation. Response time, defined as the time it takes for the system to adjust the vehicle's speed and steering after a change in the set point or disturbances, is used to assess the system's adaptability. Vehicle stability measures how well the vehicle maintains a smooth and consistent trajectory, free from excessive oscillations or deviations, which is critical for predictable behavior in dynamic environments. Accuracy of path tracking evaluates how closely the vehicle follows the desired path, reflecting the precision of the navigation system in reaching its destination. Noise reduction refers to the system's ability to minimize the impact of noisy sensor data, crucial for real-world conditions where sensor readings are often affected by environmental factors. Statistical analysis and visual comparisons, including error plots and trajectory graphs, show significant improvements in all these metrics with the proposed PID-Kalman hybrid approach, demonstrating its effectiveness in reducing sensor noise and enhancing overall control system performance [8].

3. Results and discussion

The simulation results demonstrate the effectiveness of integrating PID control with Kalman filtering in managing vehicle dynamics. Fig. 2 presents the comparison between the true speed (blue line), the noisy speed (green line) and the filtered speed (red line) over time. The true speed represents the actual speed of the vehicle based on the control signals, the noisy speed shows the unfiltered speed while the filtered speed illustrates the Kalman filter's estimation based on noisy sensor data [9, 10].

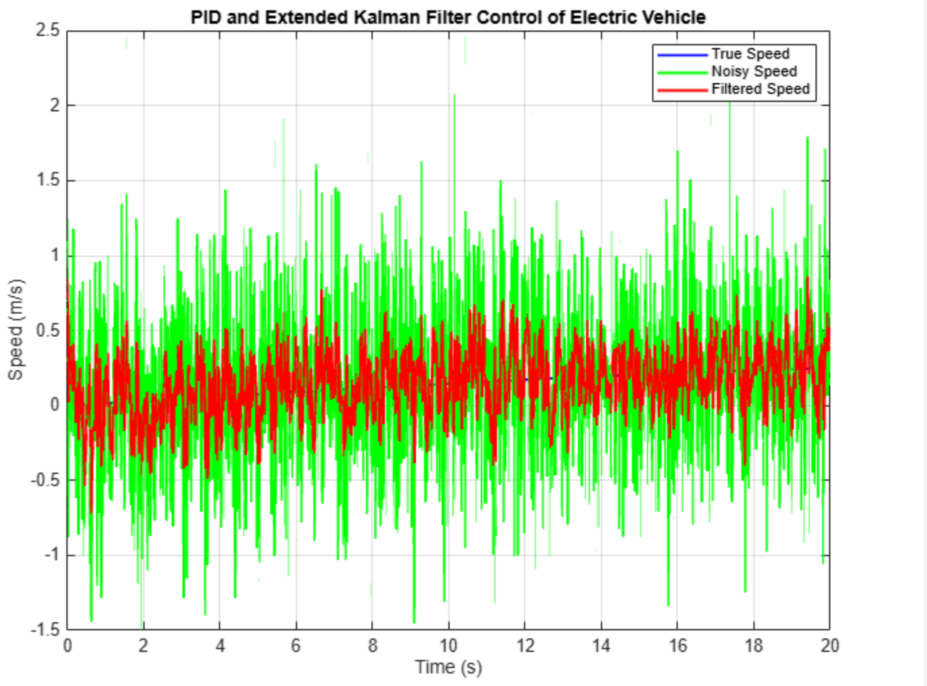

Figure 2. Measured speed before and after Kalman filtering

The results indicate that while the true speed remains stable and follows the desired trajectory closely, the noisy measurements, when unfiltered, exhibit significant fluctuations due to the simulated sensor noise. The Kalman filter effectively reduces these fluctuations, providing a smoother and more accurate estimate of the vehicle's speed.

4. Conclusion

This research highlights the advantages of integrating PID control with Kalman filtering to enhance electric vehicle dynamics. Through MATLAB simulations, we confirmed that the hybrid system effectively reduces sensor noise, improves speed tracking accuracy, and enhances stability of velocity tracking. Key findings include the reduction in noise-induced fluctuations.

The results suggest that this PID-Kalman hybrid approach is a promising solution for autonomous electric vehicles, providing robust and precise control even in noisy environments. Future work could focus on testing this approach on real vehicles and exploring more advanced control algorithms for further improvements.

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