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Performance analysis of position estimation in a quarter-car suspension system using kalman-bucy as a state observer

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Abstract
This study explores the implementation of the Kalman-Bucy observer for state estimation in a quarter-car suspension system operating under various real-world conditions. The research focuses on evaluating the observer’s performance in the presence of road surface disturbances, such as speed bumps, humps, and potholes, combined with stochastic noise and parameter variations. To test its robustness, the system is subjected to Gaussian white noise with an intensity of 10% in both the process and measurement signals. A sensitivity analysis is also carried out by varying the vehicle mass between 400 kilograms under unloaded conditions and 600 kilograms when fully loaded, thereby simulating different passenger and cargo scenarios. Simulation results demonstrate that the Kalman-Bucy observer consistently provides accurate and stable estimations of vehicle position, even in noisy and dynamically changing environments. The observer achieves a Root Mean Square Error (RMSE) of 3.3885 × 10^{-5} m, indicating near-perfect estimation accuracy. When integrated into a PID control framework, the proposed observer significantly improves system performance by reducing rise time from 9.76 s to 0.16 s, decreasing undershoot from −0.22 m to −0.15 m, and maintaining a similar settling time of approximately 25 s. Overall, the Kalman-Bucy observer proves to be a reliable and efficient method for state estimation and control enhancement in active suspension systems, showing strong potential for real-world automotive applications.

1. Introduction

Cars are a fundamental means of transportation and have become an essential part of daily life, enabling the movement of people from one location to another. Optimal ride comfort is achieved when the vehicle remains stable and experiences minimal shock, even when traversing uneven or damaged road surfaces [1][2]. The suspension system plays a crucial role in achieving this goal, as it functions to maintain vehicle stability, enhance ride comfort, and absorb vibrations caused by road irregularities [3]. In general, suspension systems are classified into two main categories: passive and active suspension. Passive suspension relies on mechanical components such as springs and dampers to control vibrations, while active suspension utilizes technologies such as actuators and sensors to dynamically adjust the suspension response in real-time [4]. Building upon this distinction, active suspension systems offer several advantages over their passive counterparts, particularly in terms of adaptability and ride performance. With the ability to respond dynamically to variations in road profile and vehicle load, active suspensions can maintain a higher level of comfort and stability. However, these benefits do not come automatically**.** Effective suspension performance depends heavily on appropriate control strategies that regulate actuator behavior based on sensor data and the vehicle's dynamic model. Without robust control, an active suspension system may operate inefficiently or become unstable under unpredictable road conditions. Hence, the development and implementation of suitable control methods are vital for the optimal operation of active suspension systems.

In response to this need, numerous studies on vehicle suspension control have been conducted, including the design of control strategies using Linear Quadratic Regulator (LQR) [5], Full State Feedback and Proportional Integral Derivative (PID) [6][7], Sliding Mode Controller (SMC) combined with PID [8][9], Magnetorheological dampers [10], Fuzzy Logic Controller (FLC) [11]-[13], Optimal Control techniques [14], and others. These studies have shown that various performance aspects of suspension systems can be improved; nonetheless, challenges such as slow transient responses, steady-state errors, and overshoots still persist [7][11]. To mitigate these issues, many researchers have adopted hybrid control strategies that integrate two control methods [5][6][8][9][15]. Although such approaches can improve performance, they also result in complex mathematical models. This complexity can lead to numerical issues during algorithm development. Therefore, simpler modeling approaches are needed—ones that maintain satisfactory control performance even when employing relatively basic controllers.

Beyond control strategy design, another major challenge lies in sensor reliability and state measurement. Sensors are often limited by resolution, accuracy, and susceptibility to noise [16]. Increasing the number of sensors may escalate system costs and introduce additional measurement noise, which can degrade estimation accuracy. Moreover, in many practical systems, it is not feasible to measure all internal state variables directly [17]. To address these challenges, state estimation techniques commonly referred to as observers are employed. Observers estimate the unmeasured internal states of a system based on available output measurements and known system dynamics, even in the presence of measurement noise [18][19]. By doing so, they enhance overall system performance by reducing estimation errors and improving control accuracy. Several recent studies have explored real-time observer implementation in automotive suspension systems, demonstrating the feasibility of applying estimation algorithms on embedded control hardware. For instance, Balestrieri et al. [16] discussed sensor and measurement integration for unmanned and automotive systems, while Listijorini et al. [20] and Sunarso et al. [21] investigated real-world modeling and evaluation of vehicle suspension performance. These studies reinforce the practical relevance of observer-based estimation and provide a foundation for the present study's simulation-based validation. Despite extensive research, several limitations remain. Most existing studies employ discrete-time Kalman filters or nonlinear observer designs that are computationally demanding and less practical for continuous-time systems such as vehicle suspensions. These methods often struggle to maintain accuracy under high measurement noise and varying load conditions. Therefore, there is a strong need for a continuous-time, noise-resilient observer capable of accurately estimating suspension states in real-world driving scenarios without increasing model or computational complexity.

To address the aforementioned challenges, this study proposes the use of the Kalman-Bucy observer, a continuous-time extension of the Kalman Filter, for state estimation in a quarter-car suspension system. The Kalman-Bucy Filter provides optimal state estimation in the presence of Gaussian process and measurement noise [22][23][24], making it well-suited for suspension systems exposed to dynamic road disturbances such as speed bumps, humps, and potholes. In this study, a mathematical model of the quarter-car suspension system is developed, and the Kalman-Bucy observer is implemented to estimate unmeasured states such as position and velocity. The performance of the observer is evaluated under different noise levels and vehicle-mass variations using MATLAB simulations. To further demonstrate its effectiveness, the Kalman-Bucy observer is integrated into a PID control framework and compared with a conventional PID controller that uses raw sensor data. The results show that incorporating the Kalman-Bucy observer improves estimation accuracy, reduces oscillation, and enhances disturbance rejection. These findings demonstrate that the Kalman-Bucy observer offers a simple yet robust continuous-time approach for accurate state estimation and control performance improvement in active suspension systems, as validated through simulation analysis. The remainder of this paper is organized as follows: Section 2 presents the research methodology and observer formulation, Section 3 discusses simulation results and performance analysis, and Section 4 concludes the study with key findings and recommendations for future work.

2. Research Method

2.1 Suspension system model

The suspension system is a component that connects the car body to its wheels [20]. The quarter-car model is used as a simplified representation to facilitate the analysis of suspension characteristics in cars [25]. In this model, only one-fourth of the car is considered, comprising a single wheel along with its suspension system and a portion of the car body mass supported by that wheel. It is assumed that the suspension systems on all four wheels are symmetric or identical, making this quarter section sufficient to represent the overall behavior of the suspension system. The quarter-car suspension system model is illustrated in Figure 1.

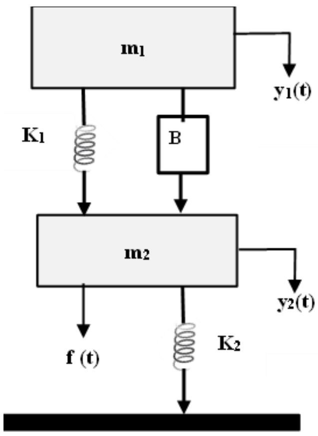

Figure 1. Quarter-Car Suspension System

Two equations arise from this system due to the presence of two independent displacements. The suspension system model is derived using Newton's Second Law, as presented in Equation 1:

$$\begin{aligned}\frac{d^2y_1(t)}{dt^2} &= -\frac{B}{m_1}\left(\frac{dy_1(t)}{dt}-\frac{dy_2(t)}{dt}\right)-\frac{k_1}{m_1}\left(y_1(t)-y_2(t)\right)\\ \frac{d^2y_2(t)}{dt^2} &= \frac{1}{m_2}f(t)-\frac{B}{m_2}\left(\frac{dy_2(t)}{dt}-\frac{dy_1(t)}{dt}\right)-\frac{k_1}{m_2}\left(y_2(t)-y_1(t)\right)-\frac{k_2}{m_2}y_1(t)\end{aligned} \quad (1)$$

From Equation 1, the model can be expresses in state-space representation, where w denotes Gaussian state, and v represents Gaussian measurement noise, as shown in Equations 2 and 3:

$$\begin{aligned}\dot{x}(t) &= Ax(t)+Bu(t)+w(t)\\ y(t) &= Cx(t)+Du(t)+v(t)\end{aligned} \quad (2)$$

with

$$A=\begin{pmatrix}0 & 1 & 0 & 0\\ -\frac{k_1}{m_1} & -\frac{B}{m_1} & \frac{k_1}{m_1} & \frac{B}{m_1}\\ 0 & 0 & 0 & 1\\ \frac{k_1}{m_2} & \frac{B}{m_2} & -\frac{(k_1+k_2)}{m_2} & -\frac{B}{m_2}\end{pmatrix};\ B=\begin{pmatrix}0\\0\\0\\1\end{pmatrix};\ C=\begin{pmatrix}1 & 0 & 0 & 0\end{pmatrix};\ D=0 \quad (3)$$

where $x(t)=\left[y_1(t)\ \dot{y}_1(t)\ y_2(t)\ \dot{y}_2(t)\right]^T$ is the state variable, $y(t)=\left[y_1(t)\ 0\ 0\ 0\right]$ is the system output, and $u(t)=\left[f(t)\ 0\ 0\ 0\right]^T$ is system input. The parameter data are shown in Table 1, which is based on a Toyota Kijang GRAND car. The car's curb weight is 1600 kg, while the fully loaded condition, including passengers and luggage, reaches up to 2400 kg. An intermediate load condition, representing half passenger capacity with luggage, results in a total mass of approximately 2000 kg. Since this study utilizes a quarter-car model, the parameters are proportionally adjusted to represent one-fourth of the total car mass, as presented in Table 1.

Table 1. Parameters of suspension car system

Symbol	Quantity	Unit
m_1	1/4 of the car's curb weight (empty mass)	400 kg
m_2	Wheel (unsprung) mass	15 kg
k_1	Spring constant	2500 N/m
k_2	Tire stiffness	3250 N/m
B	Damping coefficient	1250 N/m

2.2 The design of Kalman-Bucy as state observer

Considering a linear time-invariant continuous-time system affected by both process and measurement noise, the Kalman-Bucy filter is designed to estimate the unmeasured state vector under the assumption of observability. The system dynamics and measurement equations can be described as shown in Equation 4:

$$\begin{aligned}\dot{x}(t) &= Ax(t)+Bu(t)+w(t)\\ y(t) &= Cx(t)+v(t)\end{aligned} \quad (4)$$

where $x\in R^4$ is the state system, $u\in R^1$ is the input signal, and $y\in R^1$ is the output of the system. A,B,C and D are known matrices. $w(t)\sim(0,Q)$ is the process noise, and $v(t)\sim(0,R)$ is the measurements noise, with the matrices Q and *R* represent the covariances of the noise. The observer aims to estimate the true state $x(t)$ through an estimated state $\hat{x}(t)$, which is updated in real time according to the Kalman-Bucy observer equation given in Equation 5:

$$\dot{\hat{x}}(t) = A(t) + Bu(t) + L(t)\left(y(t) - \hat{y}(t)\right) \quad (5)$$

Here, $L(t) \in R^{n \times p}$ is the time-varying Kalman gain matrix that weights the innovation term $y(t) - C\hat{x}(t)$ which represents the difference between the measured output and the estimated output. To compute the optimal gain $L(t)$, the observer solves the continuous-time Riccati differential equation given in Equation 6:

$$\dot{P}(t) = A(t)P(t) + P(t)A^T(t) - P(t)C^T R^{-1}(t)CP(t) + Q(t) \quad (6)$$

The Kalman gain is then calculated as shown in Equation 7:

$$L(t) = P(t)C^T R^{-1}(t) \quad (7)$$

where $P(t) \in R^{n \times p}$ is the state estimation error covariance matrix, initialized with an appropriate positive-definite matrix $P(0) = P_0$. The filtering process runs continuously in real time. At each moment, the system simultaneously updates the state estimate $\hat{x}(t)$, the covariance matrix $P(t)$, and the Kalman gain $L(t)$. The result is an optimal observer that minimizes the mean squared estimation error, thereby providing accurate and robust state estimation even in the presence of noise and disturbances. The corresponding block diagram is shown in Figure 2.

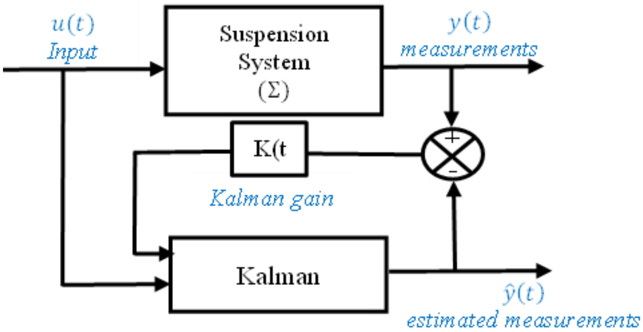

Figure 2. The Block Diagram of Kalman-Bucy

2.3 PID Controller

A PID controller combines three fundamental control actions: Proportional, Integral, and Derivative. The transfer function of the PID controller is given in Equation 8:

$$U(t) = K_p e(t) + K_D \frac{de(t)}{dt} + K_i \int_0^{t} e(t)\,dt \quad (8)$$

where K_p is the proportional gain, K_i is the integral gain, and K_d is the derivative gain. The Proportional controller (K_p) functions to reduce the rise time of the system response but cannot eliminate the steady-state error. The Integral controller (K_i) is effective in eliminating steady-state error; however, it may worsen the transient response if not properly tuned. Meanwhile, the Derivative controller (K_d) improves system stability, reduces steady-state error, and enhances the transient response by anticipating the error trend.

3. Results and Discussion

In the previous section, the design of a quarter-car suspension system using the Kalman-Bucy filter as a state observer was presented. Additionally, the implementation algorithm was formulated and prepared for testing. This section discusses the simulation results to evaluate the performance of the Kalman-Bucy filter in estimating the system output under various scenarios. The following evaluations were conducted:

3.1 Open-Loop Response with Noise

This simulation is conducted to analyze the dynamic response or behavior of the quarter-car suspension system without the application of any observer or control mechanism, under the influence of process and measurement noise. The primary objective of this test is to understand the system's natural behavior when subjected to external disturbances and to evaluate its stability and accuracy in estimating the output. The simulation result is shown in Figure 3.

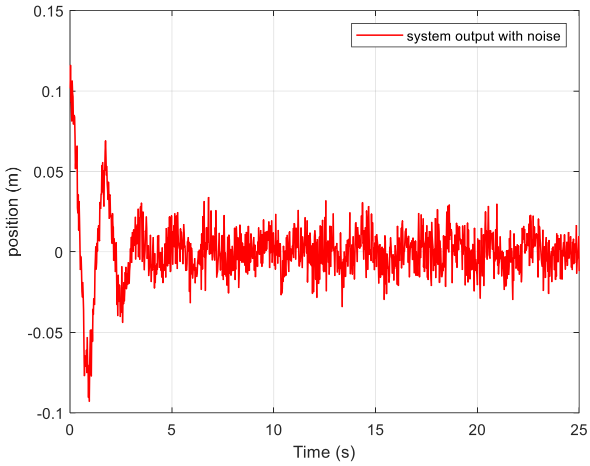

Figure 3. Output Result of the Car Suspension System in Open Loop with Noise

Figure 3 shows the open-loop response of the quarter-car suspension system under random road disturbances and measurement noise. The body displacement and velocity exhibit large oscillations, indicating that the system is underdamped and lacks vibration suppression capability. This response illustrates the inherent instability and sensitivity of the passive suspension model, highlighting the need for an observer-based approach to achieve smoother and faster transient behavior.

3.2 Performance analysis of Kalman-Bucy in estimating car position

This section investigates the performance of the Kalman-Bucy observer in estimating car position. Before assessing robustness and sensitivity, an initial test is conducted to examine the observer's ability to track system dynamics under varying road disturbances. The disturbance parameters are based on the Indonesian Ministry of Transportation Regulation No. PM 14/2021, which amends PM 48/2018 concerning road safety devices, as shown in Table 2 [21]. A disturbance is introduced at 10 seconds, and the resulting system response is presented in the Figure 4.

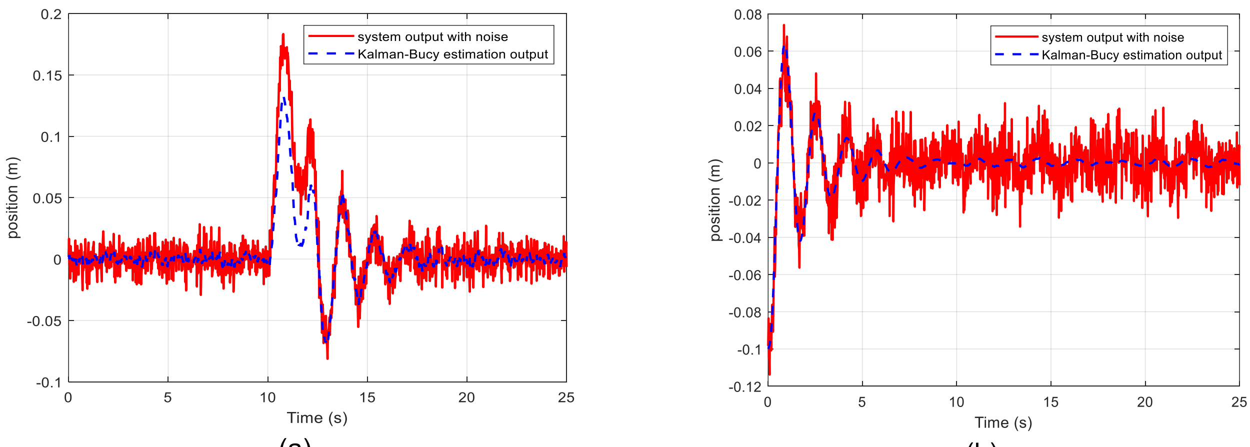

Figure 4. (a) Kalman-Bucy Performance as an Observer under 10 cm Road Disturbance (b) Kalman-Bucy Performance when Passing Through a 10 cm Pothole

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Table 2. Common Road Obstacles and Their Vertical Levels

Types of Speed Bumps	Level
Speed Hump	8-15 cm
Hole	-10 cm

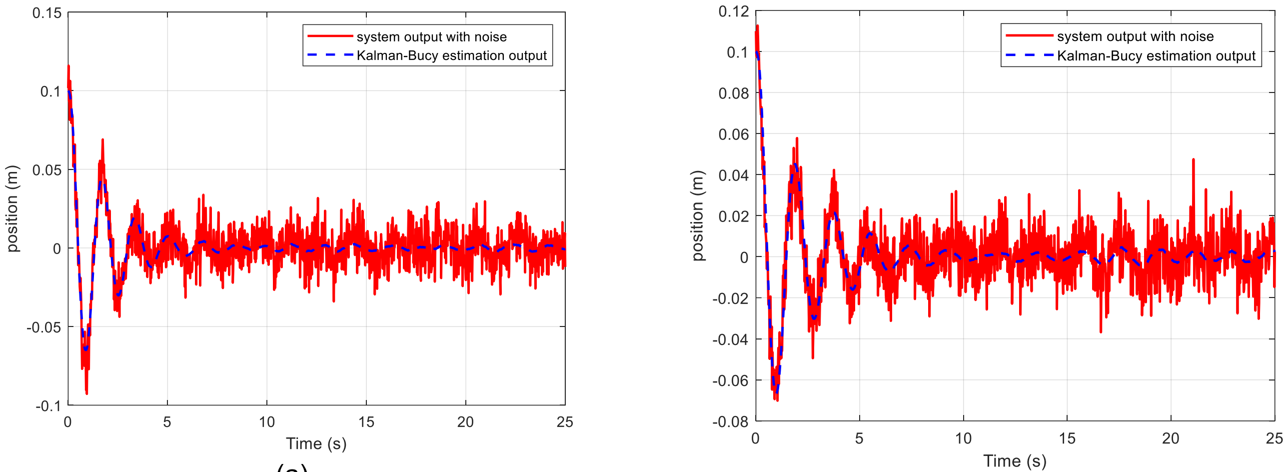
Figure 4(a) and (b) present the state estimation results obtained from the Kalman-Bucy observer for body position and velocity, respectively. The estimated states closely follow the actual values despite the presence of measurement noise, showing the observer's high accuracy and stability. The Kalman-Bucy observer effectively filters high-frequency noise components by minimizing the estimation error covariance in continuous time. The improved estimation enables a smoother control signal and enhances the dynamic performance of the suspension model compared to the open-loop case.

3.3 Sensitivity analysis of Kalman-Bucy to car mass variation

This sensitivity test aims to evaluate the performance of the Kalman-Bucy observer under varying car mass conditions representing different load scenarios. Two mass configurations are considered: an empty vehicle and a half-loaded car (with partial passenger and cargo load). The purpose of this analysis is to determine whether the Kalman-Bucy filter can maintain accurate state estimation despite variations in the car's mass parameter. The specific mass values for each scenario are presented in Table 3, and the corresponding simulation results are shown in Figure 5.

Table 3. Parameters and Conditions for Sensitivity Test on Vehicle Mass Variation

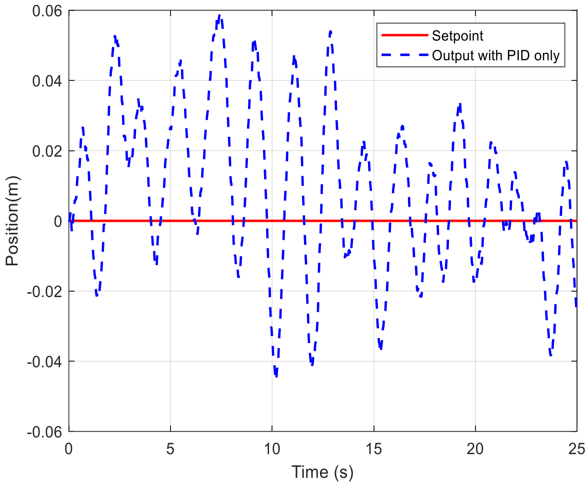
No	m_1	m_2	k_1	k_2	B	IC	*Noise*
1	400 kg	15 kg	2500 N/m	3250 N/m	1250 N/m	[0.1; 0; 0; 0]	10 %
2	500 kg	15 kg	2500 N/m	3250 N/m	1250 N/m	[0.1; 0; 0; 0]	10 %



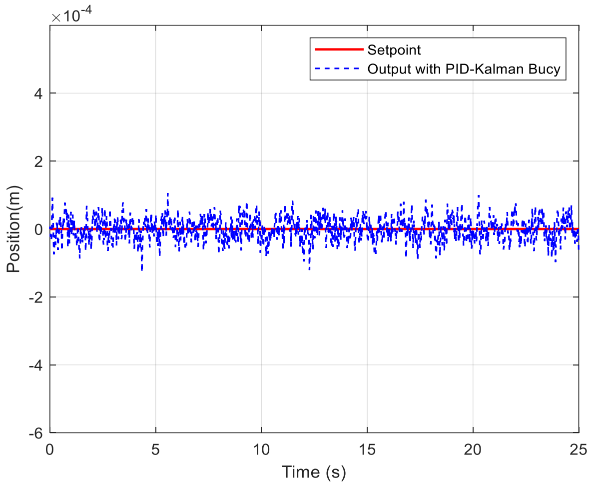
(a) (b)

Figure 5. (a) System response with 400 kg car mass (b) System response with 500 kg car mass

Figure 5(a) and (b) show the performance of the Kalman-Bucy observer under different vehicle body masses: 400 kg and 500 kg, respectively. The estimation accuracy remains stable across both mass variations, with only minor differences in transient response. This robustness demonstrates that the Kalman-Bucy observer maintains estimation consistency under parameter uncertainty. The observer's continuous covariance update compensates for changes in system inertia, ensuring reliable state estimation across different vehicle configurations. To evaluate the impact of the Kalman-Bucy observer on overall system control performance, Figure 6 compares the time-domain responses obtained using a PID controller alone and a PID controller assisted by the Kalman-Bucy observer. The observer-assisted configuration produces smoother responses, faster rise time, and reduced oscillations compared to the conventional PID control.



(a)



(b)

Figure 6. (a) System Response with PID Only (b) System Response with PID-Kalman Bucy

Figure 6(a) shows the suspension system response using only a PID controller. The output exhibits large oscillations and deviates from the reference, with a rise time of 9.76 s, a settling time of 24.98 s, an overshoot of 0.0676 m (67.60%), and an undershoot of −0.2178 m (217.75%). The computed RMSE between the actual and estimated position in the PID + Kalman-Bucy configuration is 3.3885×10^{-5} m, equivalent to a deviation of less than 0.04 millimeters. This extremely low error confirms that the Kalman-Bucy observer delivers near-perfect estimation accuracy under simulation conditions with 10% Gaussian noise, ensuring highly stable and precise control performance. These results indicate that the PID controller is slow and highly sensitive to noise and disturbances, resulting in poor vibration damping. In contrast, Figure 6 (b) illustrates the response when the PID controller is combined with a Kalman-Bucy observer. The PID parameters (P = 7737.55, I = 19167.66, D = 746.60) were tuned using the MATLAB/Simulink PID Tuner based on the standard automatic tuning method that minimizes the error and optimizes the rise time–overshoot trade-off. The system achieves a significantly faster rise time of 0.159 s and a similar settling time of 24.99 s, with a slightly higher overshoot (0.0737 m) but a reduced undershoot (−0.1469 m). The trajectory is smoother and more stable due to the observer's ability to filter noise and provide accurate state feedback, thereby improving overall control performance.

3.4 Comparative Analysis with Previous Studies

To provide broader context for evaluating the proposed Kalman-Bucy observer, a comparative discussion is presented with several recent studies on active and semi-active suspension systems. Nguyen et al. [8, 9] applied a Sliding Mode–PID hybrid controller and reported significant vibration reduction with high robustness, although the method involves relatively complex modeling and control laws. Erol and Delibaşı [6] developed an H∞–PID controller that demonstrated strong disturbance rejection, but its parameter tuning process was more demanding. Boulaaras et al. [5] implemented an LQR–FOPID strategy that improved steady-state performance but required careful parameter selection to achieve desirable transient behavior. Within this context, the present study examines the Kalman-Bucy observer as a simpler continuous-time approach for enhancing signal estimation in suspension control. The proposed method shows comparable trends in noise reduction and stability improvement based on simulation analysis, while maintaining lower model and computational complexity.

Table 4. Comparative Summary of Suspension System Performance from Various Studies (Approximate Trend-based Comparison)

Method	Approach Type	Rise Time (s)	Settling Time (s)	Overshoot (%)	Noise Sensitivity	Complexity
LQR [5]	Linear control	1.5	22.0	50	Medium	Medium
H∞–PID [6]	Robust control	0.8	26.5	65	Low	High
SMC–PID [8]	Hybrid nonlinear	0.2	25.0	70	Low	High
Fuzzy–PID [12]	Intelligent hybrid	0.5	24.0	62	Medium	High
PID only (this study)	Conventional	9.76	24.98	67.6	High	Low
PID + Kalman-Bucy (this study)	Proposed approach	0.16	24.99	73.7	Low	Low

The results presented in Table 4 indicate that hybrid controllers, such as SMC–PID and fuzzy-based systems, generally provide fast dynamic responses and strong robustness. However, their complex mathematical structures and tuning requirements may limit their applicability in simplified or real-time simulation environments. In contrast, the proposed PID controller assisted by the Kalman-Bucy observer demonstrates comparable transient and steady-state performance within a much simpler continuous-time simulation framework. Although the Kalman-Bucy–based approach is validated only through simulation, the findings suggest that it can serve as a practical and computationally efficient tool for studying active suspension behavior under noise and disturbance conditions, as well as a potential basis for future experimental validation.

4. Conclusion

Simulation results show that the Kalman-Bucy observer performs effectively and robustly under various test conditions. It maintains accurate state estimation when the system is subjected to road disturbances such as bumps, humps, and potholes, representing realistic driving scenarios. The observer preserves estimation accuracy even in the presence of 10% Gaussian noise and vehicle mass variations ranging from 400 kg (unloaded) to 600 kg (fully loaded), consistently providing stable position estimates. The computed RMSE between the actual and estimated positions in the PID + Kalman-Bucy configuration is 3.3885×10^{-5} m, corresponding to a deviation of less than 0.04 mm. This extremely low error confirms near-perfect estimation accuracy and highly stable control performance under noise conditions. When integrated into a PID control framework, the Kalman-Bucy observer significantly enhances system performance. Compared with the PID-only configuration, the combined system reduces rise time from 9.76 s to 0.16 s, decreases undershoot from −0.22 m to −0.15 m, and maintains a similar settling time of approximately 25 s. These improvements result in smoother suspension dynamics, improved noise attenuation, and enhanced stability under parameter variations.

However, the study is limited to a simulation-based linear quarter-car model without hardware validation. Future work will focus on implementing the Kalman-Bucy observer in a real-time embedded control system to validate its performance under practical operating conditions. Hardware-in-the-loop (HIL) simulations or experimental testing on an active quarter-car suspension prototype will be conducted to evaluate robustness against sensor noise and actuator nonlinearities. Additionally, future studies will explore nonlinear extensions, such as the Extended Kalman Filter (EKF) and $H\infty$ observer to improve adaptability to time-varying parameters and non-Gaussian noise environments.

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