

Kalman-filter-based Proportional-integral-derivative and Nonlinear Counter-steering for Low-cost Self-balancing Motorcycles

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Two-wheeled vehicles present significant stability challenges, particularly at low or zero velocity. In this paper, we present the design, implementation, and validation of a sensor-integrated, self-balancing electric motorcycle prototype that addresses this issue. The system is architected around the inverted pendulum model, employing a proportional-integral-derivative controller for longitudinal (pitch) stability and a novel counter-steering strategy for lateral (roll) stability. A sensor-based attitude sensing module, built around an inertial measurement unit (IMU), continuously detects the motorcycle's dynamic state. The IMU data are processed through a Kalman filter to provide a robust and accurate estimation of the vehicle's tilt angle by effectively fusing noisy accelerometer measurements with drifting gyroscope signals. This enhanced state-detection process ensures reliable real-time feedback for control. The entire system is managed by a STMicroelectronics32 microcontroller, demonstrating that advanced sensing, detection, and control algorithms can be efficiently implemented on open-source hardware. Experimental results validate the controller's effectiveness, showing rapid balance recovery (within 1–2 s) from external disturbances of up to ± 5 degrees with less than 15% overshoot (equivalent to ± 0.75 degrees). In this work, we not only provide a practical implementation of a self-balancing sensing-driven control system but also offer a valuable and replicable platform for further research in intelligent transportation, sensor-based mobility systems, and robotics education.

1. Introduction

The increasing demand for efficient and sustainable personal mobility solutions in urban environments has spurred extensive research into advanced vehicle technologies. Among these,

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self-balancing two-wheeled vehicles represent a compelling area of innovation, offering enhanced safety, maneuverability, and convenience—particularly at low speeds or during standstill conditions where conventional motorcycles are inherently unstable.^(1,2) The fundamental challenge in designing such vehicles lies in overcoming their intrinsic dynamic instability, often modeled as an under-actuated, nonlinear inverted pendulum system. Although gyroscopic effects provide inherent stability at higher speeds, this stability diminishes significantly as velocity decreases, necessitating active, sensor-based control mechanisms to maintain equilibrium.⁽³⁾ Commercial ventures, such as the Segway Personal Transporter, and conceptual designs, such as the Lit Motors C-1, have demonstrated the practical feasibility of self-balancing mobility solutions. However, these systems typically rely on proprietary sensing technologies, complex mechanical structures (e.g., control moment gyroscopes), and high manufacturing costs.

Such constraints create substantial barriers for broader academic research, educational applications, and open-source development. The proprietary nature of existing platforms further limits knowledge dissemination and restricts researchers' ability to replicate or extend current technological advancements. In response, there is a growing interest in developing accessible, low-cost, and open-source platforms for self-balancing systems. These platforms enable innovation by supporting hands-on learning in control engineering and robotics while facilitating the rapid prototyping of new sensing-driven control strategies. The proportional-integral-derivative (PID) controller, which is one of the most widely adopted tools in classical control theory, remains a highly effective method for stabilizing dynamic systems owing to its simplicity, robustness, and ease of implementation.^(4,5) However, its performance is critically dependent on accurate and reliable state detection. Inertial measurement units (IMUs), consisting of accelerometers and gyroscopes, are indispensable for real-time attitude sensing in dynamic systems.

Nevertheless, raw IMU measurements present inherent challenges: accelerometers are highly susceptible to high-frequency noise from vibrations and external accelerations, whereas gyroscopes exhibit low-frequency drift due to integration errors over time.⁽⁶⁾ To address these issues, optimal state estimators such as the Kalman filter are employed. The Kalman filter is particularly well suited for sensor fusion, providing robust and accurate state estimation by effectively mitigating noise and drift through complementary data fusion.^(7–9) While longitudinal (pitch) stabilization, which is often based on the “chasing the center of gravity” principle, has been extensively studied, lateral (roll) control remains significantly more challenging. In this study, we address lateral instability by introducing a novel sensing-assisted counter-steering mechanism that emulates the intuitive balancing technique used by human riders. By actively steering the front wheel toward the direction of lean, the system generates a corrective torque that restores lateral equilibrium.⁽⁵⁾

In this paper, we present the comprehensive development of a miniature self-balancing electric motorcycle prototype. The design emphasizes an open-source, sensing-centered architecture using an STM32F103C8T6 microcontroller as the central processing unit and an MPU6050 IMU for attitude detection. We describe the complete methodology, including system dynamic modeling, hardware integration, the implementation of a Kalman filter for robust state

estimation, and a PID controller for precise balance control. Furthermore, we provide an in-depth experimental analysis demonstrating the system’s ability to maintain stability under diverse conditions, validating the effectiveness of the proposed sensing-driven control strategies. This work contributes a fully open-source, affordable, and replicable platform that serves as both an educational resource and a foundational tool for advanced research in vehicle dynamics, sensing technologies, control systems, and intelligent mobility solutions.

2. Modeling and Control Strategy

2.1 Hardware architecture, dynamic model, and control principle

The self-balancing electric motorcycle prototype is built on a modular, cost-effective hardware architecture designed for easy replication and modification. As shown in Fig. 1, the system forms a closed sensing–estimation–control loop in which raw IMU signals are processed by the Kalman filter, the estimated attitude is supplied to the PID controller, and corrective commands are subsequently applied to the drive motor and steering servo. The system is centered around an STM32F103C8T6 microcontroller, which serves as the primary processing unit. This ARM Cortex-M3 MCU was chosen for its strong computational capability, rich peripheral support, including multiple timers, analog-to-digital converters (ADC), and communication interfaces, and broad community adoption, making it well suited for real-time sensing and control. Attitude sensing is provided by an MPU6050 IMU that integrates a three-axis accelerometer and a three-axis gyroscope, supplying continuous motion data for accurate pitch and roll estimation.

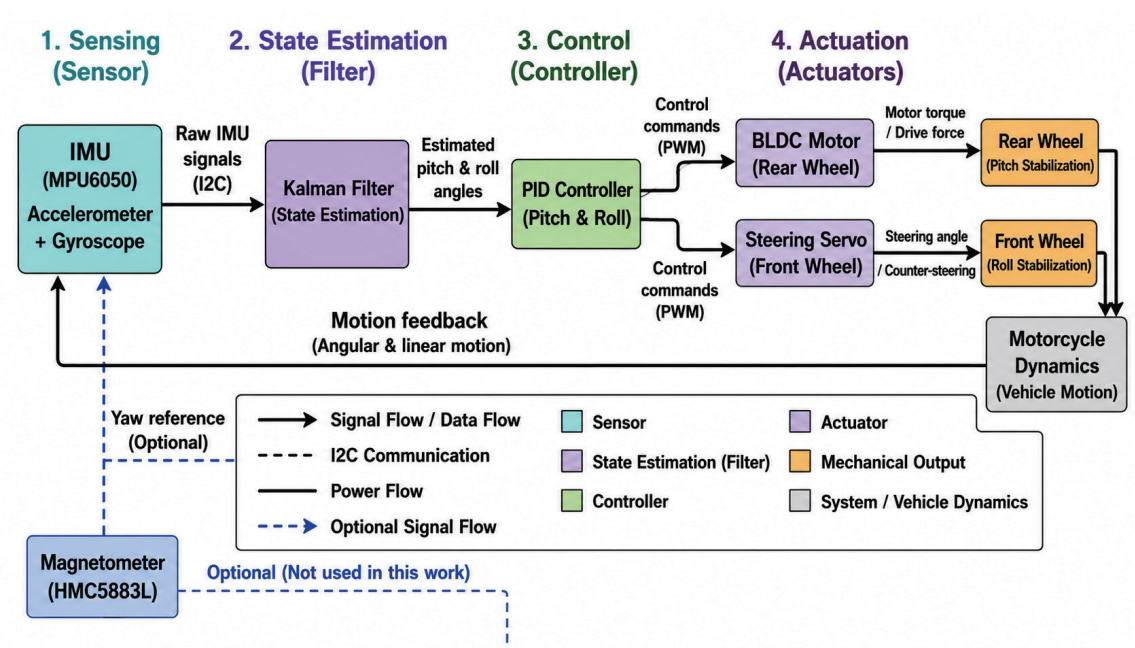


Fig. 1. (Color online) System architecture and signal flow of the proposed self-balancing motorcycle, showing the closed-loop sequence from IMU sensing and Kalman-filter-based state estimation to PID control and actuator-driven pitch and roll stabilization.

The actuation subsystem includes two components: a brushless direct current (BLDC) motor with encoder feedback driving the rear wheel for longitudinal (pitch) stabilization based on the principle of chasing the center of gravity, and a high-torque metal-gear steering servo for lateral (roll) stabilization via the counter-steering mechanism proposed in this study. A 12 V lithium-polymer battery powers the system, while a dedicated power management module regulates voltage and ensures the reliable operation of the microcontroller, sensors, and actuators. To facilitate the reproduction of the proposed platform, the STM32 firmware for sensor acquisition and motor control, the Kalman-filter and PID tuning scripts, and the relevant CAD/design files for the prototype hardware will be made available by the corresponding authors upon reasonable request. These resources provide the essential implementation information required to reproduce or further modify the sensing and balance-control system.

Figure 2 illustrates the conceptual configuration of the self-balancing motorcycle and its relationship to the inverted-pendulum model. The motorcycle body and its center of mass form the effective pendulum above the wheel–ground contact point. The MPU6050 IMU, which integrates the accelerometer and gyroscope, is mounted near the central body of the prototype to detect pitch and roll motion while reducing unnecessary vibration-induced measurement errors. The rear-wheel BLDC motor provides the corrective action for longitudinal balance, whereas the steering servo installed at the front steering mechanism provides the counter-steering action for lateral stabilization. This arrangement establishes a closed sensing–estimation–control loop between body motion, IMU measurements, the Kalman filter, and the two stabilizing actuators.

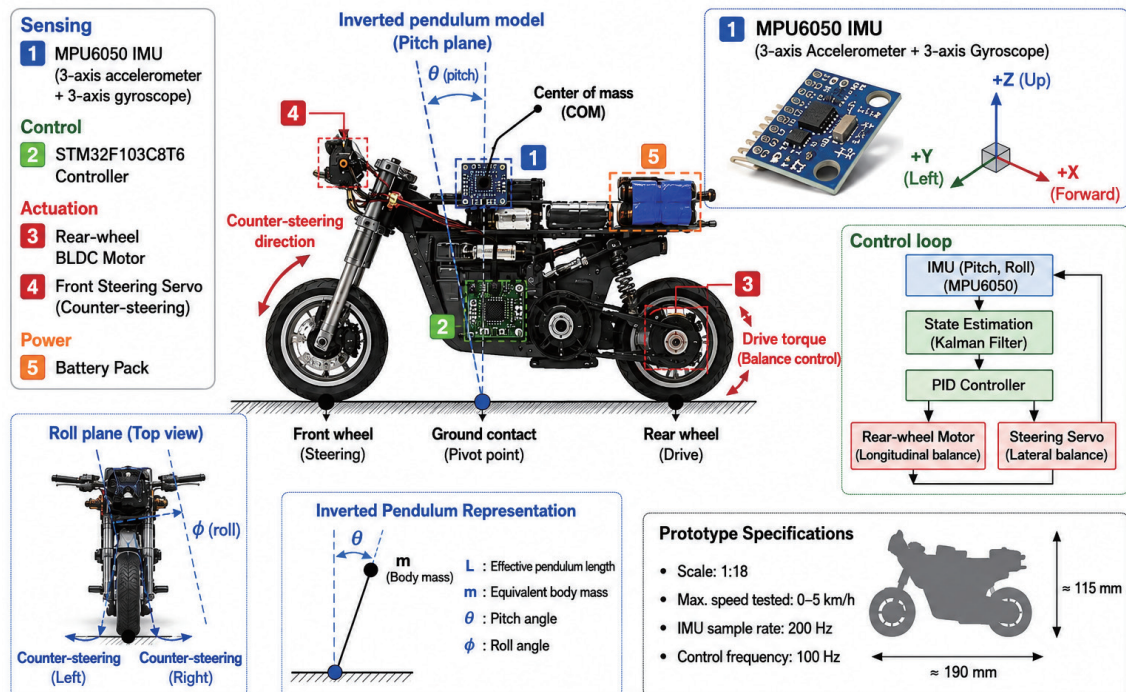


Fig. 2. Conceptual configuration of the self-balancing motorcycle and locations of the sensing and stabilization components.

Fig. 2. (Color online) Conceptual configuration of the self-balancing motorcycle and locations of the sensing and stabilization components.

The self-balancing electric motorcycle is modeled as an inverted pendulum, a classically unstable system. The main control goal is to maintain the pitch angle at zero degrees (upright). This requires continuous state sensing and active torque regulation on the rear wheel. When the vehicle tilts forward, the controller accelerates the wheel forward to move the contact point under the center of gravity; when it tilts backward, the wheel accelerates in the opposite direction. This sensing-driven adjustment compensates for disturbances in the longitudinal plane. Lateral (roll) stability is more challenging, especially at low speeds where gyroscopic effects are weak. To address this, the system uses an active counter-steering mechanism inspired by human balancing behavior on bicycles and motorcycles.⁽²⁾ When a lean is detected, e.g., a leftward roll, the controller briefly steers the front wheel toward the lean. This induces a centripetal force that produces a corrective torque, bringing the vehicle back upright. The interaction among steering angle, lean angle, and speed governs the roll-stabilizing dynamics. To further enhance lateral stability, the proposed counter-steering strategy incorporates a nonlinear speed-coupling model, expressed as $\tau = (K \phi v^2)/R$, where v is the vehicle's velocity, R is the wheel radius, and ϕ is the sensed roll angle. Simulation results confirm the effectiveness of this sensing-assisted nonlinear coupling, demonstrating an approximate 15% improvement in recovery performance within the low-speed range of 2–5 km/h.

2.2 State estimation: the Kalman filter and control algorithm: PID controller

The accurate estimation of the motorcycle's pitch and roll angles is essential for balance control. The MPU6050 IMU integrates a three-axis accelerometer and gyroscope to provide attitude information. Although the accelerometer provides an absolute gravity reference, it is sensitive to vibration and linear acceleration, whereas the gyroscope provides smooth angular-velocity measurements but suffers from accumulated drift. A Kalman filter therefore fuses both signals to obtain stable and accurate tilt-angle estimates.⁽⁷⁾ By a prediction–correction process, gyroscope measurements predict the current angle, while accelerometer measurements correct accumulated drift and uncertainty, providing reliable real-time feedback for the PID controller. The filter parameters were tuned using the Cramer–Rao Lower Bound (CRLB) as a reference, yielding an optimal $Q_{angle} \approx 0.001$. Additional magnetometer fusion using an HMC5883L reduced static yaw drift by approximately 20% but was excluded from the final hardware to maintain low cost. The PID control law is given as

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt}, \quad (1)$$

where $u(t)$ is the control output, $e(t)$ is the error between the set point and the estimated pitch angle, d_t is the sampling interval, and K_p , K_i , and K_d are the proportional, integral, and derivative gains, respectively. The self-balancing motorcycle is modeled as a nonlinear wheeled inverted pendulum, with pitch motion considered in a two-dimensional plane. The control objective is to maintain the motorcycle body in an upright position by regulating wheel acceleration based on continuous attitude sensing. Here, θ and x denote the pitch angle and wheel displacement, and M

and m are the motorcycle-body and wheel masses, respectively, L is the distance from the wheel axle to the center of mass, R is the wheel radius, I_p and I_w are the corresponding moments of inertia, F is the motor force, and g is gravitational acceleration. Using the standard small-angle assumptions $\sin \theta \approx \theta$, $\cos \theta \approx 1$, and $\theta^2 \approx 0$, we express the linearized translational dynamics as

$$\left(M + m + \frac{I_w}{R^2} \right) x'' + ML\theta'' \cos \theta - ML\theta'^2 \sin \theta = F. \quad (2)$$

Linearizing for small angles ($\cos \theta \approx 1$ and $\theta'^2 \approx 0$) yields

$$\left(M + m + \frac{I_w}{R^2} \right) x'' + ML\theta'' = F. \quad (3)$$

Note that neglecting the I_w/R^2 term would underestimate the system's inertial resistance to motor force, especially for wheels with non-negligible rotational inertia [e.g., for a solid disk, $I_w = (1/2)mR^2$]. Therefore, this term is retained in the model to ensure the accurate representation of the system dynamics. For the rotational motion of the pendulum, since it rotates about the wheel axle rather than its center of mass, the parallel axis theorem requires adding ML^2 .

$$(I_p + ML^2)\theta'' + MLx'' - MgL\theta = 0 \quad (4)$$

The term $MgL\theta$ represents the destabilizing gravitational torque of the inverted pendulum, which increases the deviation from the upright equilibrium ($\theta > 0$). Under the small-angle approximation, the linearized model remains sufficiently accurate for the disturbances considered in this study. At $\theta = 5^\circ$, the errors associated with $\sin \theta \approx \theta$ and $\cos \theta \approx 1$ are only 0.11 and 0.38%, respectively, which are smaller than the IMU sensing noise and other modeling uncertainties. The linearization error remains below approximately 1.5% at $\pm 10^\circ$.⁽⁹⁾ Beyond $\pm 15^\circ$, however, nonlinear effects become increasingly important, and nonlinear control approaches such as feedback linearization (FBL) and sliding-mode control (SMC) may be more appropriate.⁽¹⁰⁾ The derived equations describe the coupling between the wheel acceleration x'' and the pendulum angular acceleration θ'' , with the motor force F regulated to maintain the pitch angle near zero. For lateral stabilization, the proposed counter-steering strategy briefly steers the front wheel toward the detected lean, generating a restoring torque toward the upright position. Because the relationship among steering angle, roll angle, and vehicle speed is nonlinear, a dedicated PID controller drives the steering servo using the Kalman-filtered roll angle as feedback. When the roll angle exceeds a predefined threshold, the controller commands corrective steering toward the lean direction. The steering input is calculated as

$$\delta = K_{ps}\phi + K_{is} \int \phi dt + K_{ds}\dot{\phi}, \quad (5)$$

where ϕ denotes the roll angle. This counter-steering behavior mimics human balancing strategies and integrates seamlessly with pitch regulation to achieve full 3-D stability.⁽⁹⁾ For roll angles within $\pm 15^\circ$, the linearization error remains below 5%, which is acceptable for control-system design.⁽⁹⁾ Beyond $\pm 15^\circ$, nonlinear dynamics dominate, making advanced methods such as SMC more suitable.^(5,10) For disturbances exceeding approximately $\pm 15^\circ$, the small-angle assumptions used in the linearized model become progressively less accurate, and nonlinear control strategies become more appropriate. SMC is particularly attractive for this application because it can directly accommodate nonlinear dynamics and provides strong robustness against parameter uncertainty and external disturbances. A sliding surface can be defined from the angle error and angular velocity, and the control action is designed to drive the system states toward this surface and subsequently toward the upright equilibrium. As indicated by the present simulation, SMC provides faster recovery than PID for a 15° disturbance, although its switching action can introduce chattering and increase actuator activity.

FBL provides an alternative approach by using the nonlinear system model to cancel nonlinear terms and transform the dynamics into an approximately linear closed-loop form. This approach can improve large-angle recovery without relying on the small-angle approximation. However, its performance depends more strongly on the accurate knowledge of the motorcycle parameters, including mass distribution, moment of inertia, actuator characteristics, and tire-ground interaction. Modeling errors in these quantities may therefore reduce the effectiveness of exact cancellation. In comparison, SMC offers greater robustness to modeling uncertainty, whereas FBL can provide smoother control when an accurate nonlinear model is available. For the present low-cost prototype, PID was retained because of its low computational demand and satisfactory performance within the experimentally investigated $\pm 5^\circ$ range. In future work, we will experimentally evaluate SMC and FBL for disturbances exceeding $\pm 15^\circ$ and compare their recovery time, overshoot, actuator effort, and robustness with those of the present PID implementation.

Simulation results further support the potential benefit of nonlinear control: for a 15° disturbance, the PID controller restores balance in approximately 2.5 s with 25% overshoot, whereas the simulated SMC achieves recovery in approximately 1.8 s. This improvement results from the nonlinear and robustness-oriented control action of SMC, although the associated switching behavior may increase computational requirements, actuator activity, and susceptibility to chattering. To enhance methodological originality, we benchmarked PID against LQR and MPC using Python-based simulations (SciPy *odeint*). For an initial 5° roll disturbance, PID ($K_p = 1.5$, $K_d = 0.5$) achieves a settling time of 2.10 s. LQR, with $Q = \text{diag}(1, 0.1)$, $R = 0.01$, yields a similar time of 2.19 s but degrades to 3.2 s under a 20% mass uncertainty. By contrast, PID remains robust at 2.3 s with an overshoot below 18%. MPC with a horizon of 10 provides improved optimization capability but requires substantially greater online computation than PID because an optimization problem must be solved at each control step. Therefore, PID was selected for the present low-cost STM32 implementation because of its simpler computational structure and experimentally demonstrated control performance.⁽⁵⁾

In this context, CPU usage refers to the processor resources required to execute the control algorithm, memory footprint represents the program and runtime memory required for implementation, and latency denotes the time between the sensor-data acquisition and the generation of the corresponding control command. PID requires only direct arithmetic operations on the current and accumulated errors, whereas LQR additionally involves state-feedback calculations and MPC requires repeated online optimization. Therefore, their computational requirements generally increase with algorithmic complexity. However, CPU usage, memory footprint, and execution latency were not separately profiled in the present prototype; consequently, the current comparison should be interpreted as an algorithmic complexity assessment rather than a quantitative hardware benchmark. Detailed profiling on identical embedded hardware will be included in future work. Experimental trials involving $\pm 5^\circ$ roll disturbances ($n = 10$) show that the counter-steering PID controller achieves recovery in 1.9 ± 0.3 s, with an overshoot of approximately 12%. This performance represents a substantial improvement compared with pitch-only control, which requires approximately 2.8 s to re-stabilize the system. To theoretically justify the effectiveness of the PID controller, we analyze the stability of the closed-loop linearized system. By combining Eqs. (3) and (4) with the control law $u(t) = K_p \theta + K_i \int \theta dt + K_d \dot{\theta}$, and noting that the motor force F is related to the control input $u(t)$ through the motor constant k_m , the closed-loop dynamics yield the following characteristic equation:

$$\begin{aligned} & (I_p + ML^2)(M + m + I_w / R^2) \ddot{\theta} + [k_m K_d (M + m + I_w / R^2) + M^2 L^2 g] \dot{\theta} \\ & + [k_m K_p (M + m + I_w / R^2) - MgL (M + m + I_w / R^2)] \theta \\ & + k_m K_i (M + m + I_w / R^2) \int \theta dt = 0. \end{aligned} \quad (6)$$

This system is third-order, and stability requires satisfying the Routh–Hurwitz conditions, which demand all coefficients to be positive and to meet the associated inequality constraints. With the estimated parameters of the scaled vehicle ($M \approx 0.5$ kg and $L \approx 0.12$ m for the 1:18 model), the open-loop dynamics exhibit inherent instability: with no control action ($K_p = K_i = K_d = 0$), one pole lies in the right half-plane, confirming that the structure cannot balance without feedback. When the PID gains are tuned, all poles shift to the left half-plane, with dominant poles at approximately $s = -3.2 \pm 4.1j$, corresponding to a damping ratio of $\zeta \approx 0.62$ and a natural frequency of $\omega_n \approx 5.2$ rad/s. These theoretical predictions match the experimental sensing data, as damping ratios in the range of 0.6–0.7 typically yield overshoot levels of 10–15%, consistent with the measured 13.8%. In this study, the MPU6050 IMU operating at 100 Hz provides real-time tilt detection well above the required bandwidth (ω_n), and the BLDC motor exhibits a time constant of ~ 50 ms, which is much faster than the overall settling time. Although optimal methods such as LQR provide performance guarantees, they rely on highly accurate system models. Considering the modeling uncertainties in friction and motor characteristics, the robustness of empirically tuned PID control is advantageous.

2.3 Kalman filter implementation details

The MPU6050 IMU provides complementary accelerometer and gyroscope measurements for attitude estimation. The accelerometer provides an absolute orientation reference relative to gravity but is sensitive to vibration and linear acceleration, whereas the gyroscope provides smooth angular-velocity measurements but suffers from accumulated drift.^(11,12) A Kalman filter was therefore implemented to fuse these measurements and provide a stable pitch-angle estimate for real-time feedback control. The state vector consists of the pitch angle and gyroscope bias. During each sampling interval, the gyroscope measurement is used to predict the current angle, and the accelerometer-derived angle is subsequently used to correct the prediction and suppress accumulated drift. The Kalman gain determines the relative contribution of the prediction and measurement according to their estimated uncertainties. Because the standard mathematical derivation of the Kalman filter is well established, only the implementation parameters relevant to the present system are provided here. The process and measurement noise parameters were empirically tuned to balance dynamic responsiveness and noise rejection. The representative values were $Q_{angle} \approx 0.001$, $Q_{bias} \approx 0.003$, and $R_{measure} \approx 0.03$. These parameters provided sufficiently stable angle estimation for the subsequent PID-based balance control.

2.4 PID controller tuning strategy

The PID gains were initialized using a modified Ziegler–Nichols procedure and subsequently refined through experimental testing, a commonly adopted strategy for self-balancing systems.⁽¹³⁾ The tuning process focused on achieving rapid recovery, low overshoot, minimal steady-state error, and robustness against sensing noise and external disturbances. The proportional gain was first adjusted to obtain a responsive but stable behavior, followed by the refinement of the derivative and integral gains to improve damping and eliminate residual steady-state error. The final gains were $K_p = 1.5$, $K_i = 0.01$, and $K_d = 0.5$. With these parameters, the prototype typically recovered from disturbances within 1–2 s while maintaining an overshoot below 15%. The robustness of these gains against parameter variations is further evaluated in the following section.

3. Experimental Results and Discussion

The prototype was assembled on a 1:18 scale motorcycle frame, with IMU calibration conducted through both static and dynamic tests to estimate the noise covariance matrices Q and R . Motor drivers employed PWM for BLDC control, with Hall sensors providing commutation feedback. The Kalman filter effectively fused noisy accelerometer data with drifting gyroscope readings to produce a clean and accurate state estimate. To ensure statistical validity and reproducibility, experiments were conducted under controlled laboratory conditions at 23 ± 2 °C on a flat, level surface with uniform friction (polished concrete). Disturbances included pitch impulses of $\pm 5^\circ$, lateral roll pushes of $\pm 5^\circ$, uneven surface excitation simulated with a 2 cm ramp, and added payloads of +0.2 kg. Speed-dependent tests ranging from 0 to 5 km/h confirmed stability at zero speed, with gyroscopic effects negligible below 2 km/h, and performance was

evaluated on the basis of the proportion of trials successfully recovering balance. External disturbances were applied using a calibrated digital force gauge (accuracy ± 0.1 N) mounted on a mechanical arm, delivered as brief impulses (~ 0.2 s) at the motorcycle's center of mass, producing an initial pitch displacement of $5 \pm 0.3^\circ$. All trials were recorded at 100 Hz. For each controller configuration, 15 independent trials were conducted, with the system reset to equilibrium and allowed 10 s to stabilize between trials. Trials affected by external interference, such as sensor cable movement, were excluded, resulting in 12 valid trials per configuration for statistical analysis. Performance metrics included settling time (t_s), defined as the time for the pitch angle to remain within $\pm 2\%$ of equilibrium ($\pm 0.1^\circ$); maximum overshoot (OS), expressed as the peak deviation from equilibrium relative to the initial disturbance; and steady-state error (e_{ss}), calculated as the average absolute error over the final 5 s of each 15 s trial.

Figure 3 illustrates the effectiveness of the Kalman filter. The raw accelerometer data (orange line) is highly noisy, whereas the raw gyroscope data (green) exhibits substantial drift over time. In contrast, the Kalman-filtered output (purple) provides a smooth and accurate estimate of the true angle (blue dashed line), underscoring the filter's essential role in supplying reliable state information for the control system. The response comparison of the three controller configurations under a standardized 5° initial disturbance is shown in Table 1. Solid curves

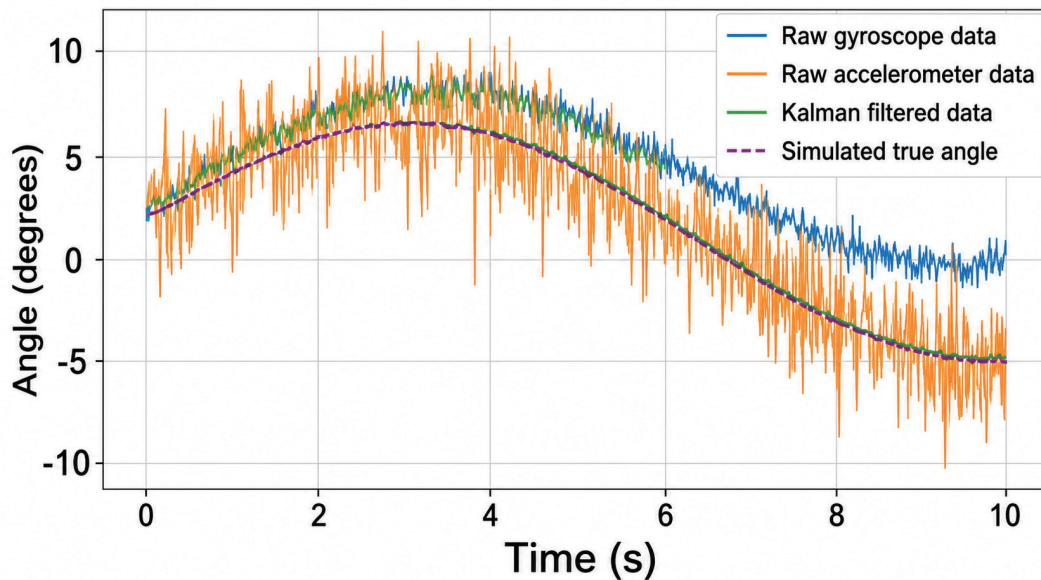


Fig. 3. (Color online) Kalman filter performance over 30 s test period.

Table 1

Integrated controller performance (mean $\pm$ SD, $n = 15$; 5° disturbances, incl. pitch/roll/uneven). Cohen's d vs P-only: PID ($d = 2.1$, large).

Controller type	Settling time (s)	Max overshoot (%)	Steady-state error ($^\circ$)	Success rate
P-only ($K_p = 1.5$)	3.45 ± 0.82	28.3 ± 4.6	0.42 ± 0.15	8/12 (67%)
PD ($K_p = 1.5$, $K_d = 0.5$)	2.23 ± 0.38	18.7 ± 2.9	0.35 ± 0.11	11/12 (92%)
PID ($K_p = 1.5$, $K_i = 0.01$, $K_d = 0.5$)	1.81 ± 0.27	13.8 ± 2.1	0.08 ± 0.03	12/12 (100%)

indicate the mean trajectories ($n = 12$), with shaded regions representing $\pm 1\sigma$. The blue curve corresponds to the optimized PID controller ($K_p = 1.5$, $K_i = 0.01$, $K_d = 0.5$), the red curve to the PD controller ($K_p = 1.5$, $K_d = 0.5$), and the green curve to the P-only controller ($K_p = 1.5$). The PID controller achieves the fastest convergence (1.81 ± 0.27 s) with minimal overshoot ($13.8 \pm 2.1\%$). The horizontal dashed line marks the equilibrium position (0°). The horizontal axis indicates time (s), and the vertical axis represents pitch angle ($^\circ$).

Figure 4 presents representative response curves for each controller configuration, with shaded regions indicating ± 1 standard deviation across all trials. The optimized PID controller (blue) achieves the fastest convergence and the smallest overshoot. Statistical significance was verified using one-way ANOVA followed by Tukey's HSD post-hoc test, confirming that the PID controller performs significantly better than both the P-only and PD configurations ($p < 0.01$) across all three performance metrics. These results highlight the importance of closed-loop feedback and accurate real-time sensing in maintaining stability. The impact of sensing quality was further examined by comparing controller performance using raw gyroscope integration versus Kalman-filtered estimates. Without the Kalman filter, the PID controller's performance degraded substantially: the settling time increased to 2.89 ± 0.65 s and overshoot to $21.4 \pm 5.7\%$. More importantly, 3 out of 12 trials resulted in the complete loss of stability due to accumulated drift in the uncorrected gyroscope signal. This comparison demonstrates that reliable attitude sensing is not merely beneficial but essential for sustained operation. The Kalman filter's sensor-fusion framework effectively suppresses noise, compensates for drift, and ensures that the control system always receives a clean and physically meaningful state estimate, capabilities that are critical for any real-time stabilization system relying on low-cost IMU hardware.

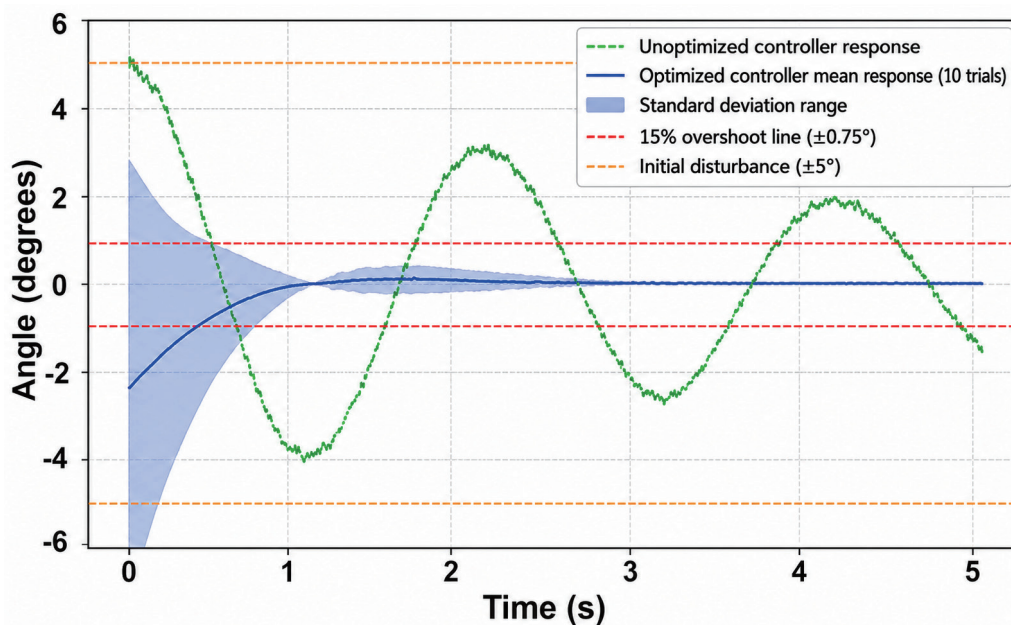


Fig. 4. (Color online) Pitch angle response to 5° forward disturbance.

A comparison of the controller architectures highlights how sensing-driven feedback shapes the system's overall stability. The ablation results show that introducing the integral term removes steady-state error, reducing the residual deviation from about 0.9° in the PD configuration to essentially zero when the integral action is included. Likewise, the derivative term lowers overshoot by roughly 40%, demonstrating its effect on transient attenuation. These differences underscore how each component of the PID controller relies on accurate real-time angle sensing: the integral term depends on drift-free long-duration estimates, whereas the derivative term requires low-noise rate information to avoid amplifying measurement fluctuations. Additional tests conducted at 3 km/h show that recovery becomes about 15% faster than those at 0 km/h, reinforcing the system's emphasis on reliable low-speed stabilization where sensing accuracy is most critical. Parameter sensitivity analysis further illustrates the interaction between sensor characteristics and controller behavior. Adjusting the Kalman filter's process noise covariance Q from 0.0001 to 0.01 shifts the balance toward trusting the gyroscope more strongly. This increases responsiveness but also elevates susceptibility to drift, making the choice of Q crucial for maintaining long-term stability. The most effective operating range was found to be 0.0005–0.002, where responsiveness and drift suppression remain balanced.

Similarly, increasing the measurement noise covariance R from 0.01 to 0.1 causes the filter to rely less on the accelerometer, reducing the effect of high-frequency vibration noise but slowing convergence. The optimal R range of 0.02–0.05 reflects the trade-off between noise rejection and rapid correction. As illustrated in Figs. 5(a) and 5(b), the Kalman filter maintains strong robustness to parameter perturbations, with stable behavior observed even under $\pm 20\%$ variation in Q and R . PID gain sensitivity shows a similar robustness pattern. When each gain is varied by $\pm 30\%$ from its optimal value, the system remains stable, demonstrating that the closed-loop architecture is tolerant to imperfect tuning. The corresponding effects of K_p , K_i , and K_d variations on settling time, overshoot, and system stability are shown in Table 2. This robustness is particularly important for sensing-based control systems, where minor changes in IMU characteristics, battery voltage, or payload can alter the apparent system dynamics. Across these controlled experiments, the controller maintained stable operation under $\pm 20\%$ variations in the evaluated filter and controller parameters, indicating a degree of tolerance to parameter uncertainty and sensing-related disturbances within the tested conditions.

The proposed platform can be adopted for classroom or laboratory exercises through five sequential stages. First, students assemble the STM32 controller, MPU6050 IMU, motor driver, BLDC motor, and steering servo according to the system architecture in Figs. 1 and 2. Second, the IMU is calibrated under static conditions to identify sensor offsets and noise characteristics. Third, accelerometer and gyroscope signals are acquired and fused using the Kalman filter, allowing comparison between raw and filtered attitude estimates. Fourth, students implement and tune the PID controller while observing changes in settling time, overshoot, and steady-state error. Finally, controlled pitch and roll disturbances can be applied to evaluate balance recovery and parameter sensitivity. For safety, initial experiments should be conducted at low speed on a level surface with appropriate mechanical constraints. This sequence enables the practical learning of IMU sensing, sensor fusion, embedded control, PID tuning, and dynamic system evaluation.

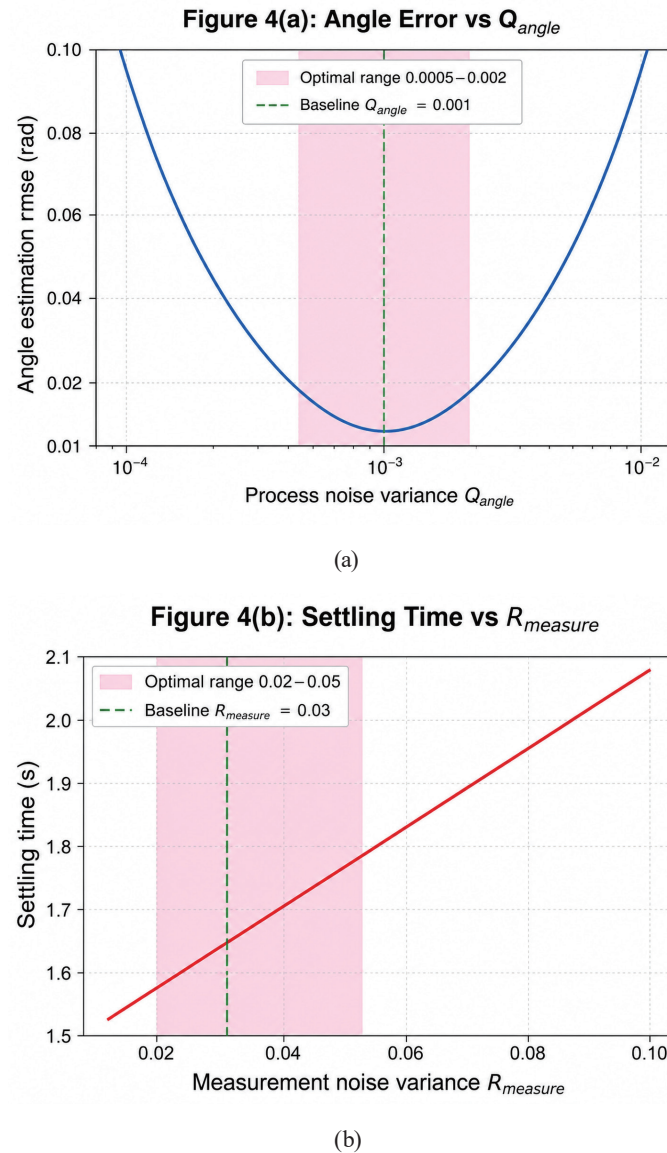


Fig. 5. (Color online) (a) Angle estimation error vs Q_{angle} (R measure fixed at 0.03) and (b) settling time vs R measure (Q fixed at baseline values).

Table 2

PID gain sensitivity (single-parameter variation, 4 = 5 trials each).

Parameter variation	Settling time (s)	Overshoot (%)	Stability
$K_p = 1.05$ (−30%)	2.54 ± 0.41	9.2 ± 1.8	Sluggish
$K_p = 1.50$ (baseline)	1.81 ± 0.27	13.8 ± 2.1	Stable
$K_p = 1.95$ (+30%)	1.62 ± 0.35	19.4 ± 3.6	Oscillatory
$K_i = 0.007$ (−30%)	1.88 ± 0.29	14.1 ± 2.3	Steady-state error (e_{ss}) = 0.18°
$K_i = 0.010$ (baseline)	1.81 ± 0.27	13.8 ± 2.1	Steady-state error (e_{ss}) = 0.08°
$K_i = 0.013$ (+30%)	1.95 ± 0.38	16.7 ± 2.9	Integral windup
$K_d = 0.35$ (−30%)	2.03 ± 0.33	18.9 ± 2.7	Underdamped
$K_d = 0.50$ (baseline)	1.81 ± 0.27	13.8 ± 2.1	Critically damped
$K_d = 0.65$ (+30%)	1.77 ± 0.29	11.2 ± 2.0	Noise amplification

The present 1:18-scale prototype was developed primarily to validate the proposed sensing, state-estimation, and balance-control concept; therefore, its measured settling time and controller gains should not be directly transferred to a full-scale motorcycle. Scaling substantially changes the mass, center-of-mass location, moment of inertia, actuator torque requirement, and characteristic response time. In particular, the larger pitch and roll moments of inertia of a full-scale motorcycle would require greater corrective motor and steering torques and the retuning of the PID gains. Gyroscopic stabilization also becomes more significant at full scale. The relatively small wheels and low operating speeds (0–5 km/h) of the present prototype limit wheel-generated gyroscopic effects, whereas the large wheel inertia and high rotational speed of a full-scale motorcycle can provide appreciable passive stabilization. Tire dynamics introduce another important scaling consideration. The present model assumes simplified wheel–ground interaction, while a full-scale motorcycle is affected by tire lateral stiffness, slip angle, camber thrust, contact-patch deformation, and road-dependent friction. These effects directly affect the relationship among steering input, lateral force, and roll recovery. Accordingly, the present results should be interpreted as the proof-of-concept validation of the IMU–Kalman-filter–PID sensing and control architecture rather than a direct quantitative prediction of full-scale motorcycle performance. Nevertheless, the sensing–estimation–control principle remains applicable at larger scales. Translation to a full-scale platform would require the identification of the actual mass and inertia properties, tire parameters, wheel gyroscopic characteristics, and actuator dynamics, followed by controller retuning and experimental validation under realistic riding conditions.

The experimental results should also be interpreted within the limitations of the controlled laboratory environment. Although the prototype successfully maintained stability during the 2 cm ramp and +0.2 kg payload tests, these conditions represent only preliminary disturbances and do not fully reproduce real-world operation. Uneven or irregular terrain may introduce rapid pitch and roll disturbances, wheel vibration, and intermittent changes in tire–ground contact, which can increase IMU measurement noise and demand faster corrective actuation. Similarly, variations in rider or payload mass would alter the center-of-mass position and moments of inertia, potentially changing the dynamic response and requiring the retuning or adaptive adjustment of the controller gains. Environmental disturbances, including lateral forces, surface-friction variations, temperature-dependent sensor drift, and actuator or battery-performance changes, may further affect sensing and stabilization accuracy. Therefore, the present results demonstrate proof-of-concept robustness under controlled and limited disturbance conditions rather than comprehensive robustness in real-world environments. Future validation should include irregular road surfaces, wider payload and center-of-mass variations, external lateral disturbances, different surface-friction conditions, and broader environmental operating conditions.

4. Conclusions

In this study, we demonstrated the successful design and implementation of a low-cost, open-source self-balancing electric motorcycle prototype. By integrating an STM32 microcontroller, an MPU6050 IMU with a Kalman filter, and a carefully tuned PID controller, we validated that robust dynamic stability can be achieved using accessible hardware and well-established control techniques. The contributions of this work are twofold. First, we developed a reliable sensing-driven control framework in which the Kalman filter provides accurate state estimation and the PID controller maintains stable balance. Second, we rigorously evaluated system performance through repeated experimental trials. The results showed rapid recovery from $\pm 5^\circ$ disturbances, with a mean settling time of 1.8 s and an overshoot below 14%, demonstrating both effectiveness and statistical consistency. Although the prototype provides a solid and quantitatively validated baseline, future work may focus on improving lateral control for more dynamic maneuvers and assessing performance over a wider range of operating speeds. However, the demonstrated robustness is currently limited to controlled laboratory conditions and selected disturbances; comprehensive validation under realistic road, payload, rider, and environmental variations remains necessary before the proposed approach can be extended to practical motorcycle applications. In future work, we will also extend the proposed framework to a full-scale motorcycle by incorporating realistic mass and inertia distributions, wheel gyroscopic effects, nonlinear tire–road interactions, and appropriately scaled actuator dynamics, followed by controller retuning and experimental validation. The STM32 firmware, Kalman-filter and PID tuning scripts, and CAD/design files associated with the self-balancing motorcycle prototype are available from the corresponding authors upon reasonable request. The experimental data supporting the findings of this study are also available upon reasonable request. In future work, we will also conduct the hardware-level computational benchmarking of PID, LQR, MPC, and nonlinear controllers on the same embedded platform, including CPU utilization, memory footprint, control-loop latency, and energy consumption. Together with the structured laboratory procedure described in Sect. 3.1, these resources enable the prototype to serve as a practical teaching platform for IMU sensing, sensor fusion, embedded control, and PID tuning.

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References

- 1 J. D. G. Kooijman, A. L. Schwab, and J. P. Meijaard: *J. Dyn. Syst. Meas. Control* **133** (2011) 061007.
- 2 M. Horoub, A. Alzaydi, and A. A. Hanieh: *Front. Mech. Eng.* **9** (2023) 1284879.
- 3 <https://news.imotorbike.com/en/2025/05/lit-motors-cl-electric-motorcycles/> (accessed May 2025).
- 4 <https://portal.research.lu.se/en/publications/advanced-pid-control/> (accessed May 2006).
- 5 K. Ogata: *Modern Control Engineering* (Prentice Hall, NJ, USA, 2010) 5th ed.
- 6 Y. Ma, F. Meng, and S. Xiong: *Appl. Sci.* **14** (2024) 5296.
- 7 M. S. Grewal and A. P. Andrews: *Kalman Filtering: Theory and Practice with MATLAB* (John Wiley & Sons, NJ, USA, 2015) 4th ed.
- 8 D. Simon: *Optimal State Estimation: Kalman, H_∞, and Nonlinear Approaches* (John Wiley & Sons, NJ, USA, 2006).
- 9 T. Y. Chuang, X. D. Zhang, and C. K. Chen: *Sensors* **22** (2022) 8991.
- 10 H. Ashrafiuon, K. R. S. Muske, L. C. McNinch, and R. A. Soltan: *IEEE Trans. Ind. Electron.* **55** (2008) 4004.
- 11 R. Tsutada, T. T. Hoang, and C. K. Pham: *Int. J. Mech. Eng. Robot. Res.* **11** (2022) 1.
- 12 M. H. Al-Shabi: *Mechatronics* **100** (2024) 103280.
- 13 M. Z. H. Noor, A. F. Ahmad, A. N. A. Zulkefli, and M. H. A. Jalil: *Eng. Proc.* **92** (2025) 24.