Heading stabilization of a mecanum wheel mobile robot using Kalman filter and SMC under variation condition

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ABSTRACT

This paper presents a robust heading stabilization system for a mecanum wheel mobile robot by integrating a Kalman filter (KF) with sliding mode control (SMC). A two-state KF estimates the robot's heading angle and gyroscope bias from ICM20948 inertial measurement unit (IMU) measurements, reducing sensor noise by 65% and compensating for bias drift of 0.3° per second. The estimated heading is regulated using SMC with a boundary layer to minimize chattering. Implemented on a Raspberry Pi 3B, the system was validated under varying surface friction conditions and external disturbances. The controller achieved heading stabilization with root mean square error (RMSE) between 0.380° and 0.589° across all surfaces, steady-state error within ±0.5°, and convergence within 2.0–2.6 seconds. Under severe disturbances causing heading deviations up to 238°, rapid recovery within 0.5 seconds was achieved with only 3.04° final steady-state error. The results demonstrate the feasibility of implementing robust heading stabilization on low-cost embedded platforms for autonomous navigation applications.

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1. INTRODUCTION

With the growth of automation technology, omnidirectional mobile robot systems have become widely used in the industrial sector, particularly for transporting and sorting materials in warehouses [1]. A robot capable of moving in any direction without the need to rotate or make a turn, for instance, a mecanum-wheel mobile robot [2], [3], provides the essential flexibility in industrial and warehouse environments which are narrow, dynamic, and filled with obstacles. The mobility advantages of omnidirectional robots enable them to execute maneuvers more efficiently, minimize the travel time, and enhance productivity in complex warehouse operations. Consequently, the use of mecanum wheel mobile robots within the industrial sector has become an important focus in the development of autonomous robotic systems.

Although mecanum wheel mobile robots provide superior mobility, they still encounter a major challenge, the heading stabilization issues influenced by several external factors, including surface-friction variations, external interference, and sensor inaccuracies [4], [5]. Therefore, the effectiveness and efficiency of the system are essential to ensure heading stability through its operation. The reliable heading stabilization is crucial, especially when the robot has to operate autonomously in environments filled with obstacles and varying surface conditions, hence the accuracy and response speed of the control system significantly determine the overall performance of the robot.

In an effort to address these challenges, several control methods have been proposed, among these is the combination of the Kalman filter (KF) [4], [6] and sliding mode control (SMC) [5], [7] KF is used to estimate the robot's heading angle in a more efficient way by handling sensor noise and bias drift, while SMC provides the robust stability against interference and inaccuracy, including the variations of friction on the surface which often occurs to mecanum robot. Although these techniques have been widely used in the literatures [5], [8] the implementation of the combined KF-SMC approach on mecanum robot under real world conditions, for instance, the variations in surface friction and external interferences, is still immensely limited. This research aims to develop and validate the control system for heading stabilization on the mecanum robot with the utilization of KF for heading estimation and gyroscope bias as well as SMC for heading controller, which is implemented on a low-cost embedded platform.

Mecanum wheel mobile robots have gained significant attention in industrial automation due to their omnidirectional mobility capabilities [9]-[11]. Unlike conventional differential-drive robots, these platforms can move in any direction without reorientation, making them particularly suitable for confined and dynamic environments [12]-[14]. However, their mechanical complexity introduces challenges in achieving precise heading control, especially with wheel slippage, uneven surface friction, and external disturbances [15]-[17].

Heading stabilization is fundamental for autonomous navigation systems, directly affecting trajectory tracking accuracy [18]-[22]. While proportional–integral–derivative (PID) controllers are widely used, they exhibit sensitivity to parameter variations and disturbances [23]-[25]. Advanced control strategies, for instance, SMC offers robustness against uncertainties but suffer from chattering phenomena [26]-[30]. The boundary layer technique mitigates chattering by replacing discontinuous switching with continuous approximation.

Accurate state estimation is crucial for model-based control [31]-[33]. Inertial measurement units (IMUs) provide angular velocity data but are susceptible to noise and bias drift. The KF offers optimal recursive estimation for linear systems with Gaussian noise [34], [35]. A two-state KF can simultaneously estimate heading angle and gyroscope bias, compensating for sensor drift [36], [37].

Recent research has explored various control approaches for mecanum-wheel robots [38]-[42], with several studies combining KF and SMC for mobile robot applications [43]-[50]. However, comprehensive experimental validation under varying surface conditions and external disturbances remains limited. This study investigates the integration of KF and SMC for heading stabilization of a mecanum-wheel mobile robot.

The main contributions of this paper are development of a mathematical model for heading dynamics incorporating wheel kinematics and disturbance effects, design and implementation of a two-state KF for real-time heading and bias estimation, experimental validation of the proposed KF-SMC under various operating conditions, demonstrating significant improvements over conventional approaches.

2. RESEARCH METHOD

2.1. System overview

The system utilizes ICM20948 IMU as a sensor, a Raspberry Pi 3B as the main processor and 4 pieces of direct current (DC) motor for actuator as shown in the Figure 1, with the complete hardware specifications summarized in Table 1. The KF for state estimation and a SMC for heading regulation are embedded at main procesor. The IMU measures the robot's angular velocity at 100 Hz, processed by a Raspberry Pi 3B. A two-state KF estimates heading angle (θ_{kf}) and gyroscope bias. The estimated heading is compared with the target (θ_{target}) to generate error for the SMC. The SMC computes control signals sent to four DC motors via PWM. An Android interface enables real-time monitoring and parameter adjustment. The control loop runs at 50 Hz (20 ms period) on the Raspberry Pi 3B. A closed-loop control system used for setting the mecanum robot's heading, is shown in Figure 2.

Table 1. Hardware specifications of the mecanum-wheel mobile robot

Component	Specification
Processor	Raspberry Pi 3B
IMU sensor	ICM20948, 100 Hz, ±2000 deg/s
Motors	4×Mecanum wheels and DC motors with PWM drivers
Power supply	10000 mAh power bank + 7.4V Li-ion battery

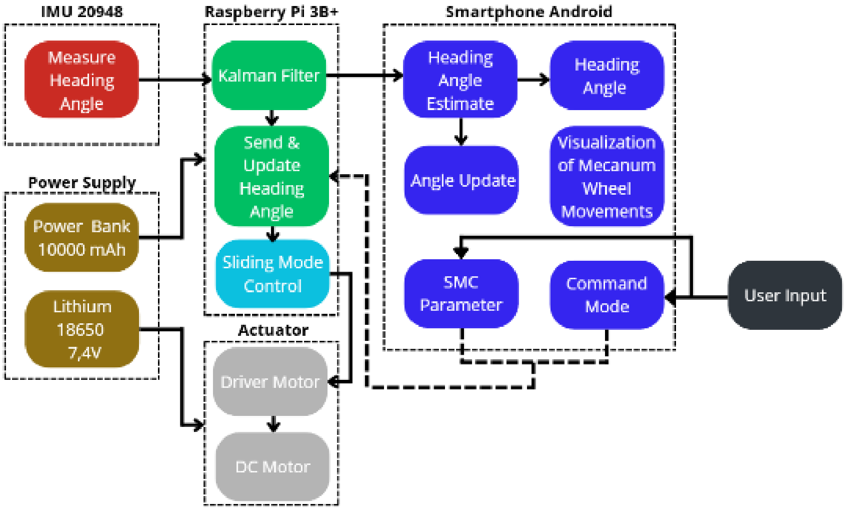

Figure 1. Architectural system of mecanum robot

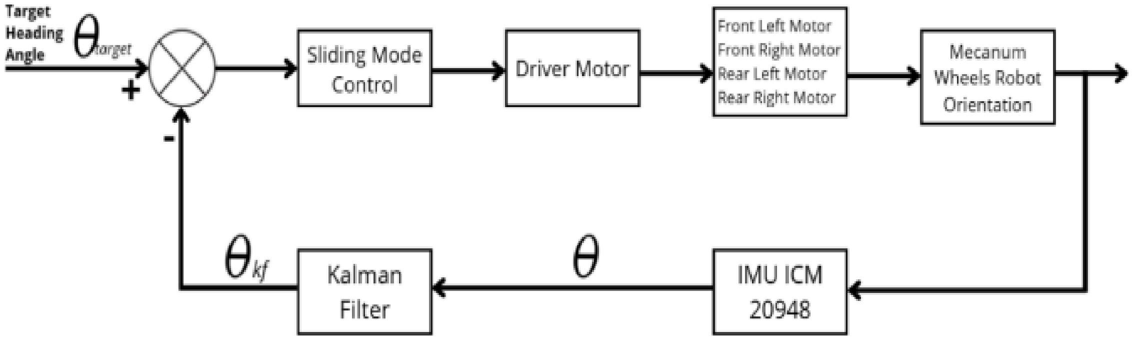

Figure 2. Closed-loop system of mecanum robot

2.2. System modeling

The heading dynamics of a mecanum-wheel mobile robot can be modeled as a second-order system with external disturbances. Let θ denote the heading angle of the robot with respect to a global reference frame. The angular velocity ω is measured by the IMU. The simplified heading dynamics can be expressed as:

$$\dot{\theta} = \omega + b_g + w_\theta \tag{1}$$

$$\dot{b}_g = w_b \tag{2}$$

where b_g represents the gyroscope bias, w_θ is the process noise in heading measurement, and w_b is the bias drift noise. The measurement equation from the IMU is given by:

$$z = \omega + b_g + v \tag{3}$$

where z is the measured angular velocity and v is the measurement noise. Both process and measurement noises are assumed to be zero-mean Gaussian white noise processes with covariances Q and R respectively.

For control design purposes, the heading error dynamics can be written as:

$$\dot{e} = \dot{\theta}_d - \dot{\theta} = -\omega - b_g + \omega_d \tag{4}$$

with $\omega_d = \dot{\theta}_d$. The control objective is to drive e to zero.

2.3. KF design

A discrete-time two-state KF is designed to estimate the heading angle and gyroscope bias. The state vector is defined as:

$$x_k = \begin{bmatrix} \theta_k \\ b_{g,k} \end{bmatrix} \tag{5}$$

The discrete-time state-space model with sampling time Δt is:

$$\mathrm{x}_k = \mathrm{F}\mathrm{x}_{k-1} + \mathrm{G}u_{k-1} + \mathrm{w}_{k-1} \tag{6}$$

$$z_k = \mathrm{H}\mathrm{x}_k + v_k \tag{7}$$

where $u_k = \omega_k$ is the measured angular velocity (input), and:

$$\mathrm{F} = \begin{bmatrix} 1 & -\Delta t \\ 0 & 1 \end{bmatrix}, \mathrm{G} = \begin{bmatrix} \Delta t \\ 0 \end{bmatrix}, \mathrm{H} = \begin{bmatrix} 1 & 0 \end{bmatrix} \tag{8}$$

The process noise covariance Q and measurement noise covariance R are tuned as:

$$\mathrm{Q} = \begin{bmatrix} 0.001 & 0 \\ 0 & 0.0001 \end{bmatrix}, R = 0.5 \tag{9}$$

The KF operates recursively through prediction and update steps to produce optimal estimates $\hat{\theta}_k$ and $\hat{b}_{g,k}$.

2.4. SMC design

The sliding mode controller is designed to regulate the heading error. A sliding surface s is defined as:

$$s = \dot{e} + \lambda e \tag{10}$$

where $\lambda > 0$ is a design parameter that determines the convergence rate. When the system is on the sliding surface ($s = 0$), the error dynamics become $\dot{e} = -\lambda e$, ensuring exponential convergence. The control law consists of two components:

$$u = u_{eq} + u_{sw} \tag{11}$$

The equivalent control u_{eq} is derived from $\dot{s} = 0$:

$$u_{eq} = \dot{\omega}_d + \lambda \dot{e} \tag{12}$$

To suppress chattering, a boundary layer approach is used for the switching control:

$$u_{sw} = -k \cdot \mathrm{sat}\left(\frac{s}{\varphi}\right) \tag{13}$$

where k is the switching gain, φ is the boundary layer thickness, and the saturation function is defined as:

$$\mathrm{sat}\left(\frac{s}{\varphi}\right) = \begin{cases} \frac{s}{\varphi}, & \text{if } |s| < \varphi \\ \mathrm{sgn}(s), & \text{otherwise} \end{cases} \tag{14}$$

The complete control law is:

$$u = \dot{\omega}_d + \lambda \dot{e} - k \cdot \mathrm{sat}\left(\frac{s}{\varphi}\right) \tag{15}$$

The controller parameters are selected as: $\lambda = 3.5$, $k = 10.0$, and $\varphi = 50$.

2.5. Experimental setup

The performance of the proposed KF-SMC system is evaluated through three experimental scenarios:

a. Scenario 1: setting parameter SMC and nominal heading stabilization. The robot maintains a fixed heading on a smooth tile surface without external disturbances.
b. Scenario 2: heading control on varying surfaces. The robot performs heading stabilization on different surfaces: tile (high friction), paving blocks (medium friction), and rubber mat (low friction).
c. Scenario 3: disturbance rejection. The robot stabilizes its heading while subjected to lateral push disturbances (approximately 10 N) applied manually.

The control loop runs at 50 Hz on the Raspberry Pi 3B. Data logging includes heading angle, heading error, control signals, and sensor readings for post-processing and analysis.

3. RESULTS AND DISCUSSION

The mecanum robot used in the experiment is shown in Figure 3. The sensor is placed at the center of the robot's body which is also its center of rotation. The sensor ICM 20948 is installed 12 cm away from the robot's body and mounted using a polylactic acid (PLA) bracket to avoid noise coming from either the actuator or electric wiring on the robot. With the configuration that has been made, robot is able to perform the holonomic movements during operation.

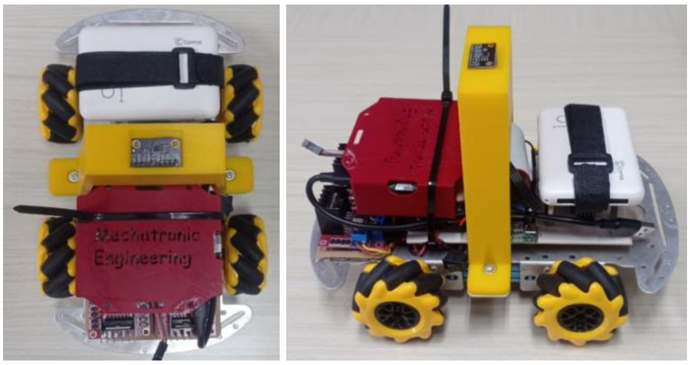

Figure 3. Hardware realitation of mecanum robot

3.1. Heading response comparison for five SMC parameter tunings

In the first experiment, SMC parameter tuning is carried out by evaluating the robot's heading response across five different parameter configurations. These configurations cover variations in switching gain (k), sliding surface slope (λ), and boundary layer thickness (φ) as shown in Table 2. The purpose of this tuning is to observe the influence of each parameter on convergence speed, overshoot, and steady-state oscillation, and to determine the most suitable settings for the implementation of heading stabilization on the mecanum robot.

Table 2. Performance comparison 5 SMC parameter tunings

Parameter	RMS error	Chattering
$K = 5.0, \lambda = 2.0, \varphi = 20.0$	90.48°	2.67°
$K = 5.0, \lambda = 5.0, \varphi = 70.0$	27.84°	16.77°
$K = 10.0, \lambda = 3.5, \varphi = 50.0$	24.52°	2.29°
$K = 10.0, \lambda = 2.0, \varphi = 70.0$	31.16°	1.20°
$K = 15.0, \lambda = 3.5, \varphi = 50.0$	43.56°	12.09°

Figure 4 displays the heading response curves over time (in samples) for the five configurations, with the reference line set at 120°. From the curves, it can be observed that the configuration $k = 10$, $\lambda = 3.5$, and $\varphi = 50$ provides a significant response with minimal overshoot of about 2° and fast convergence with a settling time of 2.1 seconds. The combination of a relatively large gain k and a moderate λ value produce a strong control force while maintaining smoothness due to the boundary layer thickness of 50.

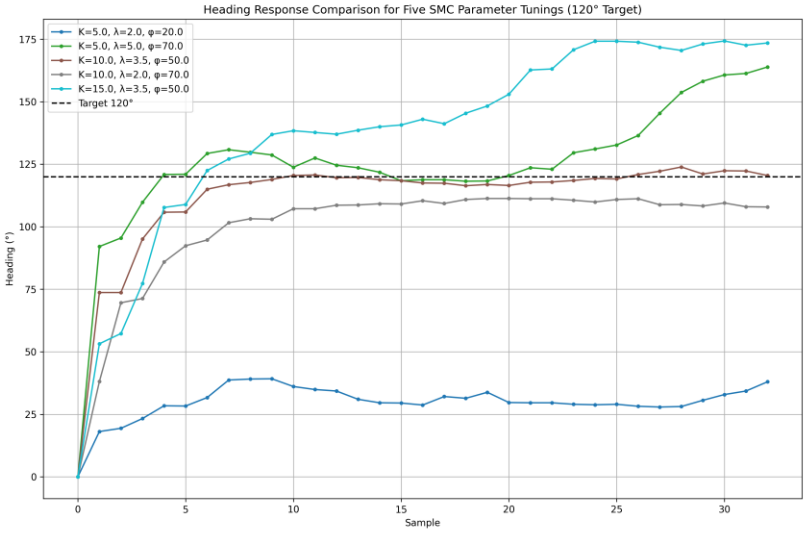

Figure 4. Heading response comparison for SMC parameter tunings

Table 2 shows that the configuration of $k = 10$, $\lambda = 3.5$, and $\varphi = 50$ achieves the lowest root mean square error (RMSE) (24.52°) and relatively low chattering (2.29°), indicating good tracking accuracy and smooth control. For comparison, the configuration $k = 5$, $\lambda = 2.0$, and $\varphi = 20$ yields the highest RMSE (90.48°) with moderate chattering (2.67°), while $k = 5$, $\lambda = 5.0$, and $\varphi = 70$ exhibits high chattering (16.77°) despite a moderate RMSE (27.84°). The configuration $k = 15$, $\lambda = 3.5$, and $\varphi = 50$ has high chattering (12.09°) and a larger RMSE (43.56°), indicating excessive gain. Meanwhile, the configuration $k = 10$, $\lambda = 2.0$, and $\varphi = 70$ produces the lowest chattering (1.20°) but a slightly higher RMSE (31.16°). Based on these results, the configuration $k = 10$, $\lambda = 3.5$, and $\varphi = 50$ is chosen as optimal because it achieves a balance between accuracy (lowest RMSE) and chattering suppression.

3.2. Heading stabilization performance on different surfaces

The performance of the proposed KF-SMC is evaluated under three surface conditions representing varying friction characteristics. The first test scenario is running on tile surface. The experimental results are analyzed in terms of heading tracking accuracy, steady-state error, and robustness to tile surface. Figure 5 shows heading tracking on smooth tile surface with target 300.63°. The system achieves steady state within 2.0 seconds from 15° initial error, with minimal overshoot (<2°) and steady-state error within 0.5°. This represents the best-case performance, as high friction minimizes wheel slippage, allowing precise control.

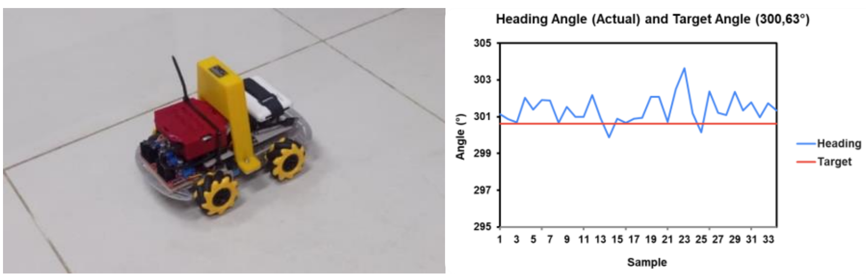

Figure 5. Heading angle tracking performance on the tile surface with target angle 300.63°

The second test is running on paving block surface. The experimental results are analyzed in terms of stability and robustness to paving block surface. Figure 6 illustrates performance on textured paving blocks. Despite surface irregularities introducing periodic disturbances, the controller maintains stability with RMSE 0.451°. The slightly higher RMSE compared to tile (19% increase) reflects active compensation for surface variations, demonstrating SMC robustness.

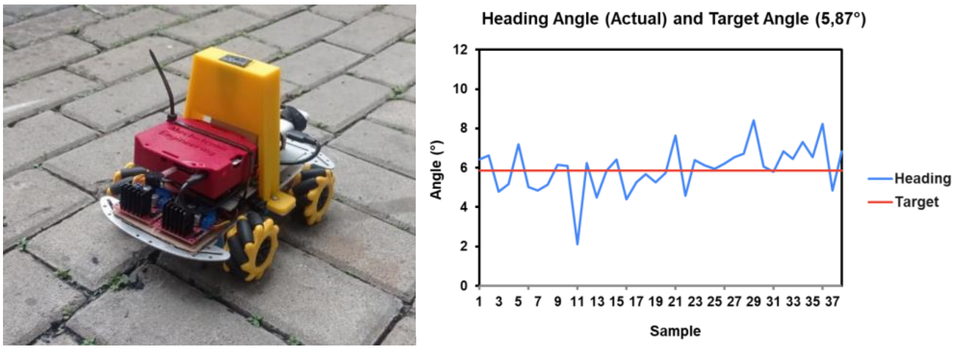

Figure 6. Heading tracking performance on paving block surface with target angle 5.87° showing maintained stability despite medium friction conditions

The third test is running on low-friction rubber mat surface. As shown in Figure 7, it demonstrates the controller's adaptive behavior on slippery rubber mat with target angle 204.95°. The system exhibits gradual convergence (settling time 2.6 s) to prevent wheel spin, achieving RMSE 0.589°. Notably, the maximum error is lowest (1.85°) among all surfaces, indicating appropriate response moderation for low-friction conditions.

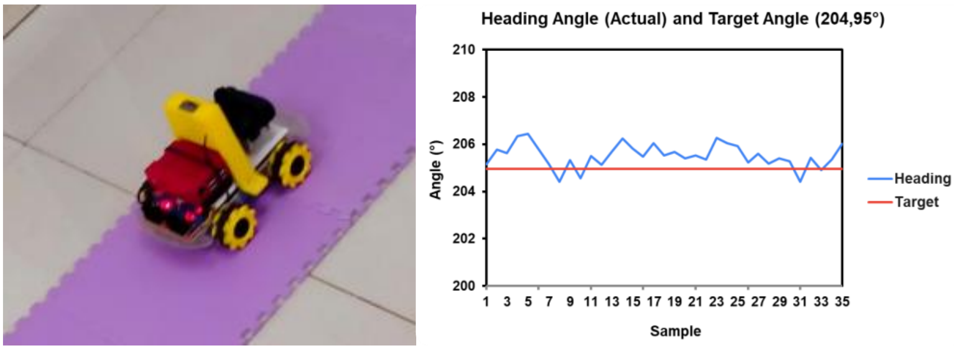

Figure 7. Heading tracking on rubber mat surface (low friction) with target angle 204.95° showing gradual convergence appropriate for slip-prone conditions

Table 3 summarizes the quantitative performance metrics, demonstrating the controller's robustness against friction variations. Based on the experiment data, the value of RMSE at tile is the lowest with 0.380. It shows that the shift of heading's angle on the surface tile tend to lower than others surface. It is also shown by the settling time which is in the lowest value of 2.0 seconds although with the big maximum error value around 6.09°. The overall experiment implicates that the method which has been proposed is succeeded to keep the heading angle through different surfaces.

Table 3. Performance comparison across surface conditions

Surface type	RMSE (°)	Maximum error (°)	Settling time (s)
Tile	0.380	6.09	2.0
Paving block	0.451	3.77	2.3
Rubber mat	0.589	1.85	2.6

3.3. Disturbance rejection performance

The fourth test scenario evaluates the disturbance rejection capability of the proposed KF-SMC system over tile surface. Figure 8 presents system response under external disturbances (10 N lateral pushes). The controller recovers from 238° heading deviation within 0.5 seconds, achieving final steady-state error of 3.04°. This rapid recovery demonstrates the SMC's reaching law effectiveness.

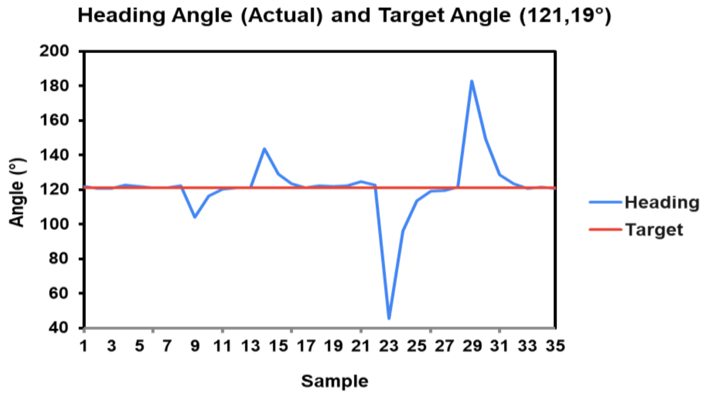

Figure 8. System response under external disturbance conditions and multiple disturbance events are rapidly rejected by the KF-SMC controller

As shown in Figure 9, the evolution of heading error during disturbance rejection can be observed. The system exhibits controlled oscillations with decreasing amplitude, demonstrating critically damped behavior and excellent disturbance rejection capability. In detail, significant error fluctuations are observed at samples 23 and 29, where the system encounters substantial disturbances before stabilizing back toward zero. Despite momentary error spikes with the highest peak reaching approximately 80 degree, the system demonstrates a rapid response, eliminating the error within only a few subsequent samples. This confirms that the implemented SMC control algorithm is highly responsive in maintaining heading stability even when subjected to impulsive external disturbances.

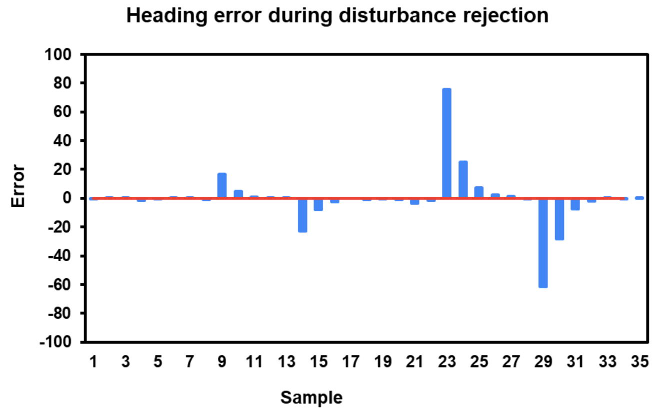

Figure 9. Heading error evolution during disturbance rejection

4. CONCLUSION

This study has successfully developed and validated a KF-SMC system for heading stabilization of mecanum-wheel mobile robots. The proposed integration addresses key challenges in omnidirectional navigation: sensor noise and bias drift through optimal filtering, surface friction variations through SMC robustness, and external disturbances through rapid sliding mode dynamics. The experimental results demonstrate that the KF-SMC achieves consistent performance across varying surface conditions, with RMSE between 0.380° and 0.589°, steady-state error within ±0.5°, and convergence within 2.0–2.6 seconds. Under severe disturbances causing 238° heading deviations, the system recovers within 0.5 seconds with only 3.04° final error. The configuration of $k = 10$, $\lambda = 3.5$, and $\varphi = 50.0$ effectively suppresses chattering while maintaining robust control, producing smooth motor commands suitable for practical implementation. Future work will focus on adaptive parameter tuning for λ, k, and φ based on online performance metrics, and integration with obstacle avoidance systems for complete autonomous navigation in dynamic environments.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

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