International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper

A Novel Color-Guided Navigation Framework for Autonomous Robots Using Sensor Fusion

V. Sowjanya[1*], Pottabathini Vithesh[2], Vasagoni Sai Charan Goud[2], Kanchukatla Sneha[2,], Maheshwarapu Siddu[2]

[1]Assistant Professor, [2]UG Student, [1,2]Department of Computer Science and Engineering

[1,2]Kommuri Pratap Reddy Institute of Technology, Ghanpur, Ghatkesar, 501301, Telangana, India.

*Correspondence: V. Sowjanya (sowjanya.vuriti89@gmail.com)

ABSTRACT

Reliable indoor navigation for mobile robots in industrial environments remains a challenging task due to the limitations of conventional control methods. Many existing systems depend on open-loop motor control or basic proximity sensors, which often lead to cumulative positioning errors, wheel slippage on smooth surfaces, and the inability to verify actual position against planned coordinates. To overcome these issues, this work presents a color-guided autonomous rover that integrates sensor fusion with an intelligent navigation approach to achieve accurate localization within a structured grid environment. The system is built around an ESP32 controller and incorporates an MPU6050 inertial measurement unit along with wheel encoders to enable closed-loop PID control, allowing continuous correction of motion deviations for precise linear and rotational movements. A dual I2C communication architecture is implemented to separate high-frequency motion sensing from color detection operations carried out by the TCS34725 sensor, thereby improving processing efficiency. The navigation mechanism is driven by a custom algorithm that converts grid-based target positions into directional commands and distance measures. At each designated node, the rover validates its position using predefined color markers embedded in the grid layout. Additionally, a WebSocket-enabled interface supports both manual adjustment and autonomous operation, enhancing system flexibility. Experimental results indicate that the integration of inertial feedback significantly reduces drift compared to traditional approaches, demonstrating a reliable and intelligent solution for precision-oriented indoor robotic navigation.

Keywords: Indoor Navigation, Mobile Robotics, RGB Color Sensing, WebSocket Interface, Grid-Based Localization, Quadrature Encoders.

1. INTRODUCTION

The rapid advancement of Industry 4.0 has fundamentally redefined industrial ecosystems by enabling deep integration between cyber-physical systems, intelligent automation, and real-time data-driven decision frameworks. A major outcome of this transformation is the widespread adoption of autonomous robotic platforms for internal logistics, material transport, and workflow optimization. In modern smart factories and automated warehouses, these robotic systems are expected to navigate efficiently across structured operational zones such as storage areas, assembly units, and dispatch sections. These environments are typically organized using grid-based layouts to maximize spatial efficiency and maintain systematic process flow. However, achieving accurate indoor navigation remains a technically demanding problem, primarily due to the ineffectiveness of the Global Positioning System in enclosed spaces, where signal degradation, obstruction from infrastructure, and multipath propagation prevent reliable positioning. As a result, robotic systems must depend heavily

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper

on onboard sensing modalities, motion estimation techniques, and external validation references, commonly referred to as ground truth, to ensure accurate localization.

Initial indoor navigation solutions were dominated by Automated Guided Vehicles, which relied on predefined physical guides such as embedded wires, magnetic strips, or optical tracks. While these systems provided high reliability and operational safety, they lacked adaptability and required costly infrastructure modifications whenever route changes were necessary. The transition to Autonomous Mobile Robots introduced a higher level of flexibility, enabling robots to perceive and respond dynamically to their surroundings using onboard sensors. Technologies such as LiDAR, ultrasonic sensing, and wheel encoders allowed these systems to perform environmental mapping and estimate displacement through odometry. However, these methods were inherently susceptible to cumulative errors, often referred to as dead reckoning drift, where even minimal inaccuracies in motion estimation progressively led to significant positional deviations over time.

The integration of MEMS-based sensing technologies marked a critical improvement in addressing these limitations. Inertial sensing units capable of measuring acceleration and angular velocity in real time allow continuous estimation of orientation and motion dynamics. When combined with encoder-based measurements through sensor fusion algorithms, these systems significantly reduce heading and positional errors. Furthermore, the adoption of closed-loop control strategies, particularly PID-based control, enables continuous feedback-driven correction of motor outputs, ensuring stable and precise movement even under varying load conditions, surface irregularities, and mechanical inconsistencies.

The necessity for high-precision indoor navigation is further emphasized by the rapid expansion of the global mobile robotics sector, driven by increasing demand for automation and operational efficiency. Industrial deployments have demonstrated substantial performance improvements, including reduced operational time and increased throughput. Nevertheless, conventional open-loop motor control systems still exhibit positional inaccuracies due to factors such as wheel slippage, uneven terrain, and dynamic load variations, creating a persistent accuracy gap in real-world scenarios. To overcome these challenges, contemporary robotic systems employ hybrid navigation strategies that integrate dead reckoning with periodic environmental validation techniques. Methods such as optical markers or color-based reference points provide intermittent ground truth corrections, allowing the system to compensate for accumulated drift. By combining sensor fusion, adaptive control mechanisms, and environmental feedback, modern indoor robotic platforms achieve enhanced localization accuracy, robustness, and reliability, making them highly suitable for precision-critical applications including automated warehousing, laboratory automation, and advanced manufacturing processes.

2. LITERATURE SURVEY

Chen, et al. [1] surveyed the application of deep learning techniques in visual localization and mapping, presenting a detailed comparison between classical geometric pipelines and data-driven neural approaches. Their study explained how convolutional neural networks and deep feature descriptors improved robustness against illumination variation, viewpoint changes, and dynamic environmental conditions. They also examined end-to-end pose regression models that directly estimated camera position from raw images, reducing dependency on handcrafted feature extraction and matching. Furthermore, they discussed hybrid frameworks that combined deep learning with traditional SLAM pipelines for improved accuracy. However, the authors highlighted critical limitations, including the requirement for large annotated datasets, high training time, overfitting risks, and significant computational and memory demands during inference, which restrict deployment on embedded and real-time robotic systems. Grisetti, et al. [2] provided an in-depth tutorial on graph-based SLAM, where localization and mapping were formulated as a global optimization problem over a graph structure. They described how nodes represented robot poses while edges encoded spatial constraints derived from sensor observations such as odometry and scan matching. Their work explained optimization methods including nonlinear least squares and sparse matrix factorization to efficiently solve large-scale problems. They also detailed the importance of loop closure detection in correcting accumulated drift and maintaining global consistency. Additionally, they discussed computational challenges, scalability issues, and real-time implementation considerations, making their work a foundational reference for modern SLAM systems. Al-Okby, et al. [3] reviewed UWB-based RTLS technologies for indoor positioning, providing a comprehensive analysis of system architectures, signal propagation models, and localization algorithms. They explained how UWB systems utilized ultra-short pulses to achieve high temporal resolution, enabling precise distance estimation through techniques such as Time of Arrival and Time Difference of Arrival. Their study also evaluated system performance under multipath conditions and interference scenarios. Despite achieving centimeter-level accuracy, they identified significant challenges such as high deployment cost, infrastructure dependency on multiple anchor nodes, synchronization complexity, and increased power consumption, which limit scalability and adoption in low-cost robotic platforms. Doucet, et al. [4] presented a comprehensive study of Sequential Monte Carlo methods, focusing on their application in nonlinear and non-Gaussian state estimation problems. They explained the theoretical foundations of particle filters, including importance sampling, proposal distributions, resampling strategies, and weight normalization. Their work demonstrated how these methods could approximate complex posterior distributions and handle multimodal uncertainties that traditional filters like Kalman filters could not address. They also discussed practical challenges such as particle degeneracy, sample impoverishment, and computational complexity, along with strategies to mitigate these issues. This made their work highly relevant for robotic localization in uncertain and dynamic environments.

Cadena, et al. [5] provided a broad survey of SLAM development, covering its evolution from early probabilistic approaches such as Extended Kalman Filter-based SLAM to modern optimization-based and graph-based techniques. They categorized SLAM methods based on representation and inference strategies, and analyzed their strengths and limitations in terms of accuracy, scalability, and computational efficiency. Their study emphasized the need for long-term autonomy, robustness to sensor failures, and adaptability to dynamic environments. They also highlighted emerging trends such as semantic SLAM, multi-sensor fusion, and lifelong mapping, where robots continuously update and refine their understanding of the environment. Fuentes-Pacheco, et al. [6] surveyed visual SLAM techniques, offering a detailed classification of algorithms into feature-based and direct methods. They analyzed key components such as feature detection, descriptor matching, motion estimation, and map representation. Their work compared different approaches based on accuracy, robustness, and computational requirements, particularly in real-time applications. They also discussed practical challenges such as sensitivity to lighting changes, scale ambiguity in monocular systems, and computational constraints in embedded platforms. Their study concluded that while visual SLAM provides rich environmental understanding, its performance is highly dependent on scene conditions and hardware capabilities, making simpler structured approaches suitable for controlled environments. Alarifi, et al. [7] reviewed Ultra-Wideband (UWB) indoor positioning systems, presenting a comprehensive analysis of signal characteristics, system architecture, and localization algorithms. They explained how UWB utilized extremely short-duration pulses to achieve high temporal resolution, enabling precise distance estimation through techniques such as Time of

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper

Arrival and Time Difference of Arrival. Their study examined system performance under challenging indoor conditions, including multipath propagation and non-line-of-sight scenarios, where UWB demonstrated strong robustness compared to conventional radio-frequency methods. They also discussed positioning algorithms such as trilateration and multilateration, along with synchronization requirements between anchor nodes. Despite achieving centimeter-level accuracy, they identified major limitations including high infrastructure cost, complex deployment, calibration overhead, and increased power consumption, which restrict its adoption in lightweight and cost-sensitive robotic platforms.

Endres, et al. [8] evaluated RGB-D SLAM systems that combined visual and depth sensing for indoor localization and mapping. Their work provided a detailed comparison of different SLAM implementations using depth cameras, analyzing factors such as accuracy, robustness, and computational efficiency. They explained how depth information resolved scale ambiguity present in monocular systems and improved feature matching reliability. Their experiments demonstrated that integrating color and depth data significantly enhanced mapping precision and trajectory estimation. However, they also highlighted limitations such as sensor noise, sensitivity to reflective or transparent surfaces, limited sensing range, and increased computational requirements, which can impact real-time performance on embedded systems. Dellaert, et al. [9] introduced factor graph-based methods for solving localization and mapping problems, presenting a probabilistic framework that modeled navigation as a global optimization problem. They explained how variables such as robot poses and landmarks were represented as nodes, while sensor measurements formed constraints between them. Their work detailed inference techniques such as nonlinear optimization and smoothing, which improved estimation accuracy compared to filtering-based approaches. They also discussed the advantages of factor graphs in handling large-scale environments, incremental updates, and loop closure corrections. Additionally, their framework enabled efficient use of sparse matrix structures, making it computationally scalable for complex robotic applications.

Aggarwal, et al. [10] focused on calibration and error modeling for MEMS inertial sensors, providing a structured methodology to identify and compensate for systematic and random errors. They explained sources of error such as bias instability, scale factor variation, misalignment, and noise, and introduced stochastic models to characterize these effects. Their work demonstrated how proper calibration procedures, including static and dynamic testing, significantly improved the accuracy and reliability of IMU measurements. They also emphasized the importance of temperature compensation and long-term stability analysis, making their study critical for applications requiring precise motion tracking and reduced drift. Groves, et al. [11] presented a comprehensive analysis of integrated navigation systems that combined GNSS, IMU, and additional sensors through sensor fusion techniques. Their work explained different integration architectures such as loosely coupled and tightly coupled systems, along with error propagation models. They analyzed how combining inertial and external measurements reduced cumulative drift and improved positioning accuracy, especially in environments where GNSS signals were degraded or unavailable. The study also discussed advanced filtering methods and the role of redundancy in improving system robustness, providing a strong theoretical foundation for multi-sensor navigation systems. Ahmed, et al. [12] provided a detailed survey on the evolution of GNSS and GPS technologies, covering their historical development, system architecture, and modern applications. They explained how satellite constellations, signal structures, and positioning algorithms evolved to improve accuracy and global coverage. Their study highlighted critical challenges in indoor environments, including signal attenuation caused by walls and structures, multipath interference, and reduced satellite visibility. They emphasized that these

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper

limitations make GPS unreliable for indoor localization, thereby reinforcing the need for alternative approaches such as sensor fusion, vision-based systems, and infrastructure-independent navigation methods. Erfani, et al. [13] compared different data fusion methods for wheeled mobile robot localization under challenging environmental conditions. Their study analyzed how sensor noise, wheel slippage, and uneven terrain affected localization accuracy, particularly in outdoor and semi-structured environments. They evaluated multiple fusion techniques, including Extended Kalman Filters and other estimation models, by integrating data from IMU and wheel encoders. Their results showed that Kalman filter-based approaches provided more stable and accurate state estimation by continuously correcting prediction errors using sensor feedback. They also discussed limitations such as sensitivity to model assumptions and computational overhead in real-time applications.

3. PROPOSED SYSTEM

The proposed system architecture is structured as a multi-layered and tightly integrated framework that combines user interaction, sensing, decision-making, control, and validation mechanisms to achieve high-precision indoor navigation. At the top layer, a web-based user interface enables operators to select target grid coordinates, which are transmitted via WiFi to the ESP32 controller, acting as the central computational and communication hub. The ESP32 is responsible for initializing all hardware components, managing task scheduling, and coordinating real-time data exchange across modules. A dual I2C communication architecture is adopted to optimize performance, where the MPU6050 continuously streams inertial data including angular velocity and acceleration for orientation estimation, while the TCS34725 sensor independently performs color detection tasks to avoid bus contention and latency issues. As illustrated in Fig. 4.1, the smart navigation engine forms the core intelligence of the system, translating grid-based destination inputs into a sequence of directional commands and displacement values by evaluating current pose, heading angle, and relative target position.

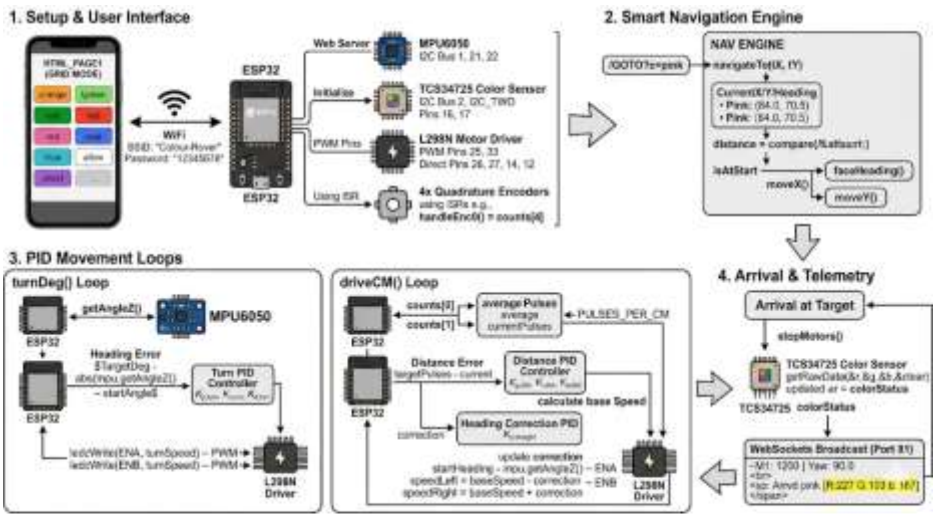

Fig. 4.1: Proposed color-guided autonomous rover system architecture.

The navigation logic incorporates decision conditions such as start alignment, directional correction, and movement segmentation to ensure structured traversal within the grid. For motion execution, the system employs dual closed-loop PID control mechanisms, one dedicated to heading correction during turning operations and another for distance regulation during forward motion. The heading control loop utilizes inertial feedback from the MPU6050 to compute angular error and generate corrective signals, while the distance control loop leverages quadrature encoder pulse counts to estimate traveled distance and adjust speed accordingly. Encoder readings are processed to compute pulses per centimeter, enabling accurate conversion between physical displacement and control signals. The L298N motor driver module receives PWM outputs from the ESP32, translating them into precise motor actuation with differential speed adjustments for left and right wheels. During continuous operation, real-time feedback ensures dynamic correction of deviations caused by wheel slippage, surface irregularities, or mechanical inconsistencies. Upon reaching each designated grid location, the rover performs position validation using color detection, comparing sensed RGB values against predefined thresholds mapped to specific nodes, thereby providing an external ground truth reference to correct accumulated drift. Additionally, the system incorporates a WebSocket-based telemetry layer that broadcasts real-time parameters such as position coordinates, heading angle, sensor readings, and system states to a monitoring interface, enabling live visualization, debugging, and parameter tuning. This modular yet cohesive architecture ensures efficient synchronization between sensing, computation, control, and validation processes, ultimately delivering a robust, scalable, and highly accurate indoor navigation solution suitable for industrial automation environments.

4. RESULTS AND DISCUSSION

Fig. 2 illustrates the front view of a four-wheeled mobile robot platform integrated with essential hardware components such as the ESP32 microcontroller, L298N motor driver module, MPU6050 IMU sensor, and quadrature encoder interfaces. The configuration presents a symmetric wheel alignment that ensures stable motion and controlled navigation. The front section reflects the integration of control circuitry and feedback indicators connected to the processing unit. The internal wiring structure represents the connectivity between sensing, computation, and actuation modules.

Fig. 2: Front View of a Four-Wheeled Mobile Robot Platform

Received: 08-03-2026 | Accepted: 16-04-2026 | Published: 23-04-2026

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper

Fig. 3: Top View of Four-Wheeled Robot Chassis Showing Mounting Plate and Wheel Configuration

Fig. 3 depicts the top view of the four-wheeled robot chassis, highlighting the mounting platform used for assembling hardware components including the ESP32 board, motor driver module, battery pack, and sensor units. The arrangement supports efficient spatial distribution of components to maintain system balance and operational stability. The wheel configuration enables differential drive functionality for precise maneuverability. The central region facilitates organized routing of electrical connections and signal pathways.

Fig. 4 represents the side view of the mobile robot platform, showcasing the placement of hardware elements such as the battery unit, power switch, motor driver module, and DC geared motors. The structural alignment contributes to balanced weight distribution and efficient power management. The elevation illustrates the integration of mechanical and electronic subsystems within a compact framework. The wheel and motor arrangement supports effective torque delivery and smooth locomotion.

Fig. 5 illustrates the experimental setup of the mobile robot operating on a grid-based colored navigation mat, incorporating hardware components such as the ESP32 microcontroller, color sensing unit, motor driver module, and encoder feedback system. The structured grid enables the robot to interpret color inputs and execute navigation decisions accordingly. The integration of sensing and control units supports real-time path planning and motion correction. The setup demonstrates the interaction between perception, processing, and actuation modules in a controlled environment.

Received: 08-03-2026 | Accepted: 16-04-2026 | Published: 23-04-2026

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper

Fig. 4: Side View of Four-Wheeled Mobile Robot Platform with Power Switch and Integrated Electronics

Fig. 5: Experimental Setup of Mobile Robot on Grid-Based Colored Navigation Mat

5. CONCLUSION

The developed color-assisted autonomous rover presents a robust solution for accurate indoor navigation through an efficient sensor fusion framework. By integrating an ESP32 controller with an MPU6050 unit and wheel encoders, the system effectively minimizes cumulative localization errors typically observed in open-loop approaches. The use of closed-loop PID-based control ensures continuous correction of motion, resulting in stable straight-line travel and precise rotational movements. Incorporating the TCS34725 sensor enables position verification using environmental color markers, adding an external reference for improved reliability. A dual I2C communication mechanism enhances data management by separating motion sensing and color detection processes. Performance analysis indicates a clear improvement in positional precision compared to traditional navigation methods. The architecture is both cost-effective and scalable, making it well-suited for indoor robotic applications where satellite-based positioning is unavailable.

Received: 08-03-2026 | Accepted: 16-04-2026 | Published: 23-04-2026

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515 www.zesterapublications.com Original Research Paper

REFERENCES

[1] C. Chen, B. Wang, C. X. Lu, N. Trigoni, and A. Markham, "Deep learning for visual localization and mapping: A survey," IEEE Trans. Neural Netw. Learn. Syst., 2023.

[2] G. Grisetti, R. Kümmerle, S. Stachniss, and W. Burgard, "A tutorial on graph-based slam," IEEE Intell. Transp. Syst. Magaz., vol. 2, pp. 31–43, 2010.

[3] M. Al-Okby, S. Junginger, T. Roddelkopf, and K. Thurow, "UWB-based real-time Indoor Positioning Systems: A Comprehensive Review," Applied Sciences, vol. 14, no. 23, p. 11005, 2024.

[4] A. Doucet, N. Freitas, and N. Gordon, *Sequential Monte Carlo Methods in Practice*. Springer, New York, 2001.

[5] C. Cadena et al., "Past, present, and future of simultaneous localization and mapping: Toward the robust-perception age," IEEE Transactions on Robotics, vol. 32, no. 6, pp. 1309–1332, 2016.

[6] J. Fuentes-Pacheco, J. Ruiz-Ascencio, and J. M. Rendón-Mancha, "Visual simultaneous localization and mapping: A survey," Artif. Intell. Rev., vol. 43, no. 1, pp. 55–81, 2015.

[7] A. Alarifi et al., "Ultra-Wideband (UWB) Indoor Positioning System: Current status and future perspective," J. Commun., vol. 11, no. 12, pp. 1092–1105, 2016.

[8] F. Endres et al., "An evaluation of the rgb-d slam system," 2012, pp. 1691–1696.

[9] F. Dellaert, "Factor graphs and gtsam: A hands-on introduction," Technical Report GT-RIM-CP_R-2012-002, Georgia Institute of Technology, 2012.

[10] P. Aggarwal, Z. Syed, X. Niu, and N. El-Sheimy, "A standard testing and calibration procedure for low cost MEMS inertial sensors and units," J. Navig., vol. 61, no. 2, pp. 323–336, 2008.

[11] P. Groves, Principles of GNSS, Inertial, and Multisensor Integrated Navigation Systems, Second Edition, 2013.

[12] W. A. Ahmed, L. A. Isiaka, B. Mala, and S. F. Olatoyinbo, "Evolution of GNSS/GPS technology and its applications from ancient times to the present," Next Res., vol. 2, no. 3, p. 100387, 2025.

[13] S. Erfani, A. Jafari, and A. Hajiahmad, "Comparison of two data fusion methods for localization of wheeled mobile robot in farm conditions," Artif. Intell. Agric., vol. 1, pp. 48–55, 2019.