An Adaptive Autonomous Rover Architecture for Chromatic Environment Interpretation and Sensor-Fusion-Based Motion Optimization

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ABSTRACT

Achieving reliable indoor positioning for mobile robots continues to be a complex problem in modern industrial automation, particularly in environments where Global Positioning System (GPS) signals are unavailable and surface conditions introduce motion inconsistencies. Many conventional robotic systems depend on simple motion control strategies or proximity-based sensing, which often lead to inaccurate positioning due to wheel slip, accumulated motion errors, and absence of real-time positional validation. This work introduces a Color-Assisted Autonomous Rover (CAAR) that combines sensor-driven feedback with an intelligent navigation framework to improve localization accuracy within a predefined grid layout. The platform is powered by an ESP32 microcontroller unit (MCU) and incorporates a Micro-Electro-Mechanical Systems (MEMS)-based Inertial Measurement Unit (IMU) along with quadrature encoders to enable closed-loop Proportional-Integral-Derivative (PID) control, ensuring stable linear and angular movement despite environmental disturbances. A dual-channel Inter-Integrated Circuit (I2C) communication configuration is employed to efficiently manage simultaneous data streams from motion sensors and a TCS34725 Red-Green-Blue (RGB) color sensor, minimizing communication delays. The navigation logic converts Cartesian coordinate inputs into directional commands, enabling the robot to traverse systematically across grid points. At each target location, the system validates its position through color detection within a structured matrix, adding a layer of environmental confirmation. A WebSocket-based communication interface supports both manual adjustments and automated navigation modes. Experimental observations indicate a noticeable reduction in positional drift compared to traditional methods, demonstrating improved consistency and reliability.

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

1. INTRODUCTION

The emergence of Industry 4.0 (I4.0) has driven a profound transformation in industrial automation by enabling seamless integration of intelligent machines, data-driven decision systems, and interconnected physical infrastructure. One of the most impactful developments within this paradigm is the adoption of autonomous mobile robots for indoor logistics and material handling tasks. In environments such as smart factories and automated warehouses, robotic systems are expected to move efficiently across predefined zones including storage, processing, and dispatch areas. These environments are typically designed using grid-based layouts to ensure maximum space utilization and structured workflow management. However, indoor navigation presents unique challenges, primarily due to the unavailability of the Global Positioning System (GPS), which fails indoors because of signal attenuation, obstruction by physical structures, and multipath interference. As a result, robotic systems must depend on onboard sensing technologies, motion estimation techniques, and external environmental references, often referred to as ground truth, to maintain accurate localization.

Historically, indoor navigation systems began with Automated Guided Vehicles (AGVs), which relied on fixed physical guides such as embedded wires, magnetic strips, or optical tracks. While these systems offered reliability and safety, they lacked flexibility and required costly infrastructure changes whenever route modifications were needed. The transition to Autonomous Mobile Robots (AMRs) introduced a higher degree of autonomy, allowing robots to navigate dynamically using onboard sensors. Technologies such as Light Detection and Ranging (LiDAR), ultrasonic sensors, and wheel encoders enabled these systems to perceive surroundings and estimate motion through odometry. However, these approaches were still prone to cumulative positioning errors, commonly known as dead reckoning drift, where even minor inaccuracies in wheel rotation measurements accumulated over time, leading to significant deviations from the actual position.

The introduction of Micro-Electro-Mechanical Systems (MEMS) sensors marked a major advancement in improving navigation accuracy. Devices such as the MPU6050 Inertial Measurement Unit (IMU) provide real-time measurements of acceleration and angular velocity, allowing robots to continuously estimate orientation and motion. When integrated with encoder data through sensor fusion techniques, these systems can significantly reduce heading errors. Furthermore, the use of closed-loop control mechanisms, particularly Proportional-Integral-Derivative (PID) control, enables continuous correction of motor output based on feedback, ensuring stable and accurate movement even under varying surface conditions and mechanical inconsistencies.

The importance of precise indoor navigation is further emphasized by industrial trends and performance requirements. The global mobile robotics market, valued at over $20 billion in 2023, is expected to exceed $40 billion by 2030, reflecting rapid adoption across industries. Leading logistics companies such as DHL and FedEx have reported efficiency improvements of 20% to 40% through the deployment of autonomous robotic systems in warehouse operations. Despite these advancements, traditional open-loop direct current (DC) motor systems still exhibit positional errors ranging from 5% to 10% due to factors such as wheel slippage, uneven surfaces, and load variations. This creates a significant precision gap in practical implementations.

To overcome these limitations, modern robotic systems adopt a hybrid navigation approach that combines dead reckoning with environmental validation. Closed-loop PID control reduces instantaneous motion errors, while additional sensing methods such as optical or color-based verification provide periodic ground truth confirmation. This layered approach allows the system to correct accumulated drift and maintain accurate positioning over time. By integrating motion control, sensor fusion, and environmental feedback, indoor robotic platforms can achieve high levels of spatial accuracy and reliability, making them suitable for demanding applications such as automated warehousing, laboratory automation, and precision manufacturing systems.

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 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 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 system architecture is designed as a comprehensive closed-loop autonomous navigation framework that integrates multi-modal sensing, embedded computation, intelligent control, and differential drive actuation to achieve high-precision rover movement in structured environments. It incorporates an MPU6050 IMU for continuous measurement of angular velocity and orientation, enabling accurate yaw estimation for heading correction, while a TCS34725 color sensor provides RGB-based environmental perception to identify grid-based navigation cues. Additionally, quadrature wheel encoders generate pulse signals that are processed for precise distance estimation and velocity tracking, forming a reliable basis for odometry. These heterogeneous sensor inputs are synchronized and processed through sensor fusion techniques within the ESP32 microcontroller, which serves as the central processing unit responsible for real-time data acquisition, filtering, and decision-making.

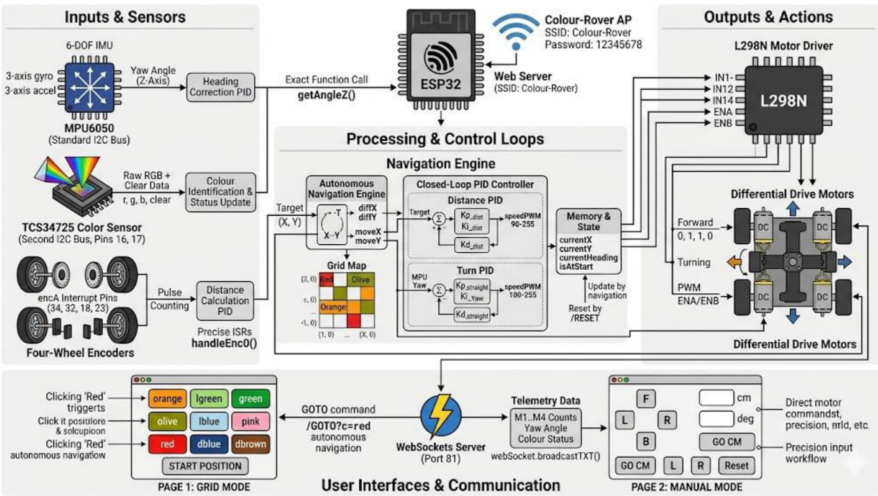

Fig. 4.1: Proposed color-guided autonomous rover system architecture.

The navigation engine is built upon dual PID control loops, where one loop minimizes heading error using IMU feedback and the other regulates displacement using encoder-derived distance measurements, ensuring accurate trajectory tracking and compensation for drift, slippage, and mechanical inconsistencies. A grid-based mapping mechanism is integrated into the system, allowing the rover to interpret discrete color-coded regions as navigational states and execute corresponding movement actions based on predefined logic. The control architecture maintains internal memory states such as current position, target coordinates, previous heading, and movement history to support adaptive corrections and improve navigation reliability over time as illustrated in Fig. 1. The system also incorporates a communication layer through a Wi-Fi-enabled web server hosted on the ESP32, facilitating real-time telemetry transmission and remote command execution via WebSocket protocols. This enables monitoring of parameters such as yaw angle, motor speed, navigation status, and sensor outputs, as well as switching between autonomous and manual operation modes. In manual mode, user inputs are directly translated into motion commands, while in autonomous mode, decisions are driven entirely by sensor feedback and control logic. The L298N motor driver module functions as the actuation interface, converting low-power control signals into high-current outputs required to drive DC geared motors. The differential drive configuration allows independent speed and direction control of each wheel pair, enabling forward motion, rotation, and smooth turning maneuvers. Furthermore, the architecture ensures efficient power distribution through a regulated battery supply and incorporates interrupt-driven processing for encoder signals to maintain high temporal accuracy. Overall, the system demonstrates a robust integration of perception, computation, control, and actuation layers, resulting in a scalable, responsive, and reliable autonomous robotic navigation platform.

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.

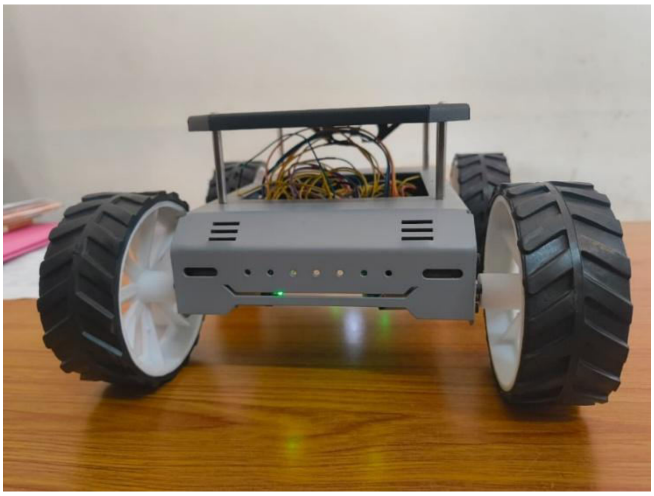

Fig. 2: Front View of a Four-Wheeled Mobile Robot Platform

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. 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

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.

5. CONCLUSION

The Color-Guided Autonomous Rover demonstrated an effective and precise approach for indoor navigation using a low-cost sensor fusion architecture. By combining an ESP32 microcontroller with an MPU6050 IMU and quadrature encoders, the system reduced cumulative odometry errors commonly found in open-loop control methods. The implementation of closed-loop PID control enabled real-time correction of motion deviations, ensuring accurate linear movement and precise turning. The integration of the TCS34725 color sensor added an external validation layer, allowing the rover to confirm its position within a structured grid. A dual I2C communication setup ensured efficient handling of both high-speed motion data and lower-frequency sensor inputs. Experimental evaluation showed a significant improvement in positional accuracy compared to conventional systems. The system provides a reliable and scalable solution for indoor automation in GPS-denied environments.

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