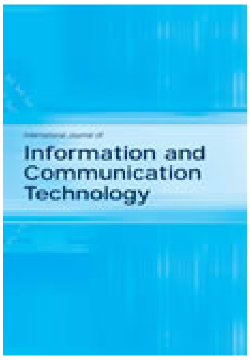

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Qi Chen, Xilong Qu, Xiao Tan, Siyang Yu, Guangjun Luo, Liqiang Tan

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Enhanced cartographer and TEB-based autonomous navigation for mobile robots in dynamic environments

Qi Chen and Xilong Qu

College of Information Science and Engineering,
Changsha Normal University,
Changsha, 410100, China
Email: chenqi_lina2005@163.com
Email: quxilong@126.com

Xiao Tan* and Siyang Yu

School of Information Technology and Management,
Hunan University of Finance and Economics,
Changsha, 410205, China
Email: tanxiao@hufe.edu.cn
Email: yusiyang@hufe.edu.cn
*Corresponding author

Guangjun Luo and Liqiang Tan

College of Information Science and Engineering,
Changsha Normal University,
Changsha, 410100, China
Email: 2100056410@qq.com
Email: 3280922867@qq.com

Abstract: This study addresses the challenge of autonomous navigation for intelligent mobile robots (IMRs) operating in dynamic environments by proposing a navigation framework that integrates an improved Google cartographer algorithm with a hybrid path planning strategy. The enhanced cartographer algorithm incorporates a KD-tree-based keypoint extraction technique for point cloud data, effectively reducing the amount of data required for point cloud matching to 10%–20% of the original volume. Furthermore, an adaptive loop closure detection mechanism is introduced, leading to a reduction of approximately 20% in mapping error. For path planning, a hybrid algorithm combining A* global planning with timed elastic band (TEB) local optimisation is developed. This approach dynamically adjusts the robot's pose sequence and time intervals, achieving a 98% success rate in obstacle avoidance while increasing path length by only 5%–10%. The planning cycle remains consistently within 100 ms. The proposed system demonstrates robust performance across practical scenarios, including warehouse logistics (with a 40% increase in handling efficiency) and medical delivery (achieving an 80% task completion rate). This research presents an efficient and scalable solution for autonomous navigation in complex dynamic environments, contributing both algorithmic innovation and significant engineering applicability.

Keywords: robot operating system; ROS; simultaneous localisation and mapping; SLAM; cartographer algorithm; adaptive loop closure detection; hybrid path planning; dynamic obstacle avoidance.

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Biographical notes: Qi Chen holds a PhD from Beihang University and serves as a Research Professor. His academic focus centres on network and information security, with demonstrated leadership in multiple national-level research projects. He has delivered core computer science courses including C Programming, Python Programming, Computer Networks, and Network Information Security. He has mentored student teams to achieve distinctions at provincial-level competitions such as the Hunan Collegiate IoT Application Innovation Design Competition and Hunan Collegiate Computer Programming Competition. His scholarly contributions include over ten peer-reviewed publications and intellectual property achievements encompassing four state-authorised invention patents and three registered software copyrights.

Xilong Qu is a distinguished figure in the field of artificial intelligence and machine learning, with a keen interest in ethical AI development. His expertise encompasses the creation of algorithms that can learn from and adapt to their environment, improving decision-making processes in various sectors such as healthcare, finance, and autonomous vehicles. His work focuses on ensuring that AI systems are developed with fairness, accountability, and transparency, to benefit society as a whole.

Xiao Tan holds a PhD in Computer Science from Hunan University and is currently a Lecturer at the School of Information Technology and Management, Hunan University of Finance and Economics. His doctoral research and current expertise centre on internet of things (IoT) technology, big data, and artificial intelligence. His work focuses on leveraging these pivotal technologies to develop intelligent systems, enable data-driven decision-making, and contribute to technological advancements in various application domains.

Siyang Yu received his PhD in Computer Science and Technology from Hunan University, China in 2017. He is currently a teacher at Hunan University of Finance and Economics. His research interests include industrial internet of things, abnormal analysis, and intrusion detection.

Guangjun Luo is majoring in internet of things engineering and currently pursuing his undergraduate studies at Changsha Normal University. He has a broad interest in the fields of embedded systems and artificial intelligence, and has participated in related projects.

Liqiang Tan is currently pursuing a Bachelor's in Internet of Things Engineering at Changsha Normal University, engaging in related academic studies and research.

1 Introduction

With the rapid advancement of autonomous driving technologies, intelligent mobile systems have attracted significant attention for their potential across a wide range of application scenarios. In particular, achieving efficient and accurate path planning and environmental perception in dynamic environments has emerged as a prominent research challenge. Traditional localisation and path planning methods face considerable difficulties under such conditions – especially in complex and uncertain environments – where ensuring system robustness and real-time performance remains a critical and unresolved issue.

In recent years, cartographer and timed elastic band (TEB) have become two widely adopted approaches for simultaneous localisation and mapping (SLAM) and path planning. Cartographer, which leverages LiDAR and camera sensors, has demonstrated high mapping accuracy in static environments. However, when applied to dynamic settings, the traditional cartographer algorithm often struggles with increased computational demands and reduced stability, particularly in handling moving obstacles and real-time updates. On the other hand, the TEB algorithm offers a flexible path optimisation framework that allows for dynamic obstacle avoidance and smooth trajectory generation. Nevertheless, it suffers from relatively high computational complexity and is sensitive to parameter tuning, which may limit its performance in highly complex environments.

This study aims to integrate the respective strengths of cartographer and TEB while addressing their limitations. We propose an intelligent navigation system that fuses an enhanced version of the cartographer algorithm with the TEB planner. The system enhances cartographer's ability to identify and adapt to dynamic obstacles, while leveraging TEB's trajectory optimisation to improve planning precision and responsiveness. A key innovation of our approach lies in the introduction of a novel dynamic obstacle processing mechanism, coupled with an adaptive parameter adjustment method tailored to varying environmental characteristics. These enhancements significantly improve both the real-time performance and robustness of the navigation system without compromising path planning accuracy.

What fundamentally differentiates our approach from previous work that merely cascades SLAM and path planning modules is the deep, synergistic optimisation between the perception and planning layers. Instead of treating cartographer as a black-box map generator, we enhance its internal mechanisms – specifically by integrating a KD-tree-based keypoint extraction and an adaptive loop closure mechanism. This ensures that the map fed to the planner is not just a static output, but a more accurate, error-resilient, and computationally efficient representation of the dynamic environment. This principle of enhancing the upstream mapping quality to directly empower downstream planning performance forms a positive feedback loop, which is the core distinction from loosely-coupled integration strategies.

The main contributions of this paper are as follows:

1 we propose a hybrid path planning framework that combines an improved cartographer algorithm with the TEB planner, enhancing adaptability in dynamic environments

2 we develop an adaptive dynamic obstacle detection and update method, which effectively reduces computational overhead and improves real-time planning performance

3 we validate the proposed system across multiple experimental scenarios, demonstrating its superior performance in complex and dynamic environments.

2 Related work

In recent years, with the continuous advancement of robotics technology, the autonomous navigation capabilities of intelligent mobile robots (IMRs) in complex and dynamic environments have emerged as a prominent research focus. To achieve high-precision localisation and efficient path planning, researchers have extensively explored SLAM technologies, path planning algorithms, and multi-sensor data fusion strategies.

2.1 Advances in SLAM technology

SLAM serves as the cornerstone of autonomous navigation for mobile robots, encompassing environmental perception, map construction, and self-localisation. Current mainstream SLAM systems primarily include filter-based approaches (e.g., EKF-SLAM) and graph optimisation-based approaches (e.g., GTSAM and cartographer). Among these, cartographer has gained widespread adoption in both 2D and 3D scenarios due to its real-time performance and high accuracy. However, studies have revealed that conventional cartographer suffers from sensitivity to dynamic objects, which compromises localisation precision. To address this limitation, various enhancement strategies have been proposed, such as dynamic object filtering and sub-map optimisation.

2.2 Path planning algorithms

In the domain of path planning, classical algorithms such as Dijkstra and A* are well-regarded for their stability but often fall short in meeting the real-time demands of dynamic environments. More recently, optimisation-based methods, particularly the TEB algorithm, have attracted significant attention. TEB excels at local obstacle avoidance and models robot kinematic constraints effectively, making it well-suited for complex scenarios. Nonetheless, TEB exhibits limitations in responding swiftly to abrupt changes in obstacle configurations. To mitigate these issues, researchers have proposed hybrid strategies that combine TEB with global path planners and incorporate dynamic obstacle prediction models.

2.3 Multi-sensor fusion

To enhance the robustness of SLAM systems in dynamic environments, integrating data from multiple sensors has become a prevalent approach. The fusion of LiDAR with inertial measurement units (IMUs) and RGB-D cameras, for instance, has proven effective in maintaining stable localisation and mapping under occlusions and varying lighting conditions. Literature reports indicate that improvements in point cloud registration and filtering algorithms can significantly suppress the impact of environmental noise and dynamic interferences, thereby improving overall system performance.

2.4 Dynamic object handling strategies

Dynamic objects pose a major challenge to the stability and accuracy of SLAM systems. To mitigate their impact, a range of techniques have been proposed, including foreground-background separation, clustering-based motion detection, and motion consistency analysis, all aimed at isolating or removing dynamic elements to retain a static map representation. In addition, emerging approaches based on deep learning offer enhanced scene understanding by learning to detect and segment dynamic targets, further boosting the adaptability and intelligence of SLAM frameworks in real-world scenarios.

In summary, while the literature presents numerous improvements to either SLAM or path planning individually, a common limitation in integrated systems is the treatment of these components as separate, sequential processes. This ‘black-box’ approach often overlooks the fact that errors and uncertainties from the SLAM process inevitably propagate to and degrade the performance of the path planner.

Our work diverges from this conventional paradigm. The core of our contribution lies not in simply combining two algorithms, but in creating a co-optimised framework where the SLAM system is purposefully enhanced to serve the specific needs of the dynamic path planner. By actively reducing data volume and mapping errors at the source (within cartographer), we provide a higher-fidelity and more stable world model. This allows the downstream A* and TEB planners to operate more effectively, reducing their vulnerability to map noise and localisation inaccuracies, which is a key distinction from prior integration efforts.

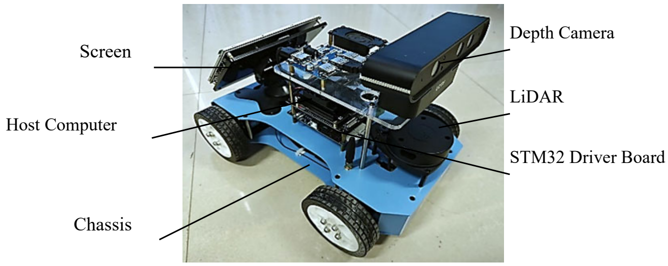
3 System design and methodology

The application of robotics has moved from theory to reality, profoundly transforming key industries. In warehouse automation, giants like Amazon and Maersk operate highly automated fulfilment centres where autonomous mobile robots (AMRs) and intelligent sorting systems handle, retrieve, and sort goods 24/7, dramatically increasing logistical efficiency and order processing speed.

Similarly, in the healthcare sector, service robots are playing an increasingly vital role. For example, robots like Moxi assist nurses by delivering medications and medical supplies, freeing them to focus on patient care, while the da Vinci surgical system enables surgeons to perform complex, minimally invasive procedures with high-precision robotic arms, significantly improving patient outcomes. These instances clearly illustrate that robotics is a core driver for boosting productivity, safety, and service quality.

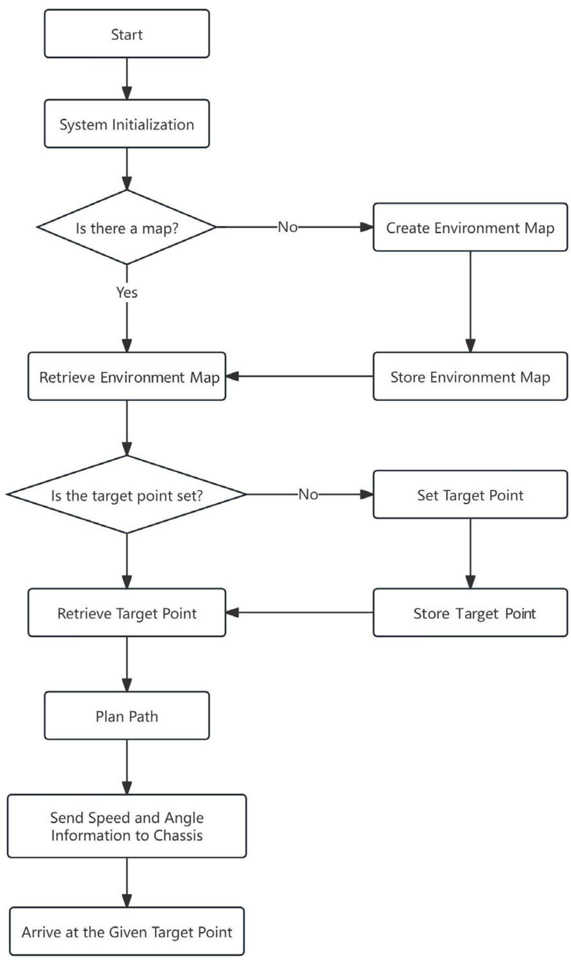
The autonomous mobility of IMRs fundamentally relies on the synergistic operation of multiple sensors and efficient system integration. As illustrated in Figure 1, the experimental platform in this study employs an Ackermann steering chassis, integrated with several core components: a host computer running the robot operating system (ROS), a LiDAR sensor (LeiShen LS01B), an IMU, and an NXP development board serving as the underlying driver module.

Figure 1 Intelligent mobile robot (see online version for colours)



The modular architecture of the system facilitates data exchange through ROS's distributed communication framework. Figure 2 presents the comprehensive workflow of the mobile robot system, which encompasses four primary functional layers: environmental perception, map construction, path planning, and motion control.

Figure 2 Mobile robot workflows



This multi-layered architecture ensures robust and efficient operation through the following mechanisms:

1 the environmental perception layer utilises LiDAR and IMU data fusion to achieve precise environmental awareness

2 the map construction layer implements SLAM algorithms to generate accurate environmental representations

3 the path planning layer employs advanced algorithms to determine optimal navigation routes

4 the motion control layer executes precise movement commands through the integrated control system.

3.1 Primary sensors

3.1.1 LiDAR

Light detection and ranging (LiDAR) serves as the core sensor for environmental perception in robotic systems. It operates by emitting laser beams and capturing their reflections to generate high-precision three-dimensional point cloud data. For this experiment, the LeiShen LS01B LiDAR (technical specifications detailed in Table 1) was selected. This sensor employs the principle of triangulation-based ranging, offering a detection range of 0.1–12 meters, an angular resolution of 1°, and a scanning frequency of 10 Hz. The point cloud data is transmitted in real-time to the main control unit via the ROS /scan topic, facilitating SLAM as well as real-time navigation (Baratta et al., 2025).

Table 1 Technical specifications of LeiShen LS01B LiDAR

Parameter	*Specification*
Detection range	0.1–12 metres
Angular resolution	1°
Scanning frequency	10 Hz
Operating principle	Triangulation-based ranging
Data transmission	ROS/scan topic

3.1.2 Low-level driver module

The low-level driver module employs the NXP RT1064 development board, which is responsible for motor control, sensor data acquisition, and chassis motion control. The development board interfaces with motor drivers via the CAN bus and utilises a PID algorithm to achieve closed-loop motor speed control (with a control cycle of 1 ms), ensuring smooth and precise chassis movement. Additionally, the development board integrates an IMU (MPU6050) to collect real-time data on the robot's pitch, roll, yaw angles, and acceleration. These data, along with encoder pulse counts, are transmitted to the host computer via a USB interface. To minimise communication latency, the low-level driver module employs a custom serial protocol.

3.2 Software architecture and algorithm implementation

3.2.1 ROS distributed communication and modular design

ROS adopts a peer-to-peer (P2P) loosely coupled network architecture, enabling distributed task scheduling and data exchange through communication mechanisms such as topics, services, and actions (Bolodurina et al., 2024). A key advantage of this architecture lies in its high code reusability: by leveraging open-source packages for SLAM, navigation, and control, redundant development efforts are significantly reduced, accelerating the research and development cycle. Furthermore, ROS supports distributed deployment of modules, allowing different functional components to run on independent hosts. This effectively distributes computational load, enhancing system real-time performance and stability.

The modular design of ROS, coupled with standardised interfaces, enables functional decoupling, allowing individual modules to be flexibly extended, replaced, or ported across platforms. This design not only reduces system complexity but also provides a robust software foundation for autonomous navigation tasks in complex and dynamic environments.

3.2.2 SLAM technology

SLAM is a core technology for autonomous robot mobility. Its primary objective is to simultaneously estimate the robot's pose and construct a high-precision map in an unknown environment using sensor data such as LiDAR point clouds or visual images. Current mainstream SLAM technologies can be categorised into two types:

1 Laser SLAM: this approach relies on the high-precision ranging data from LiDAR and is well-suited for static, structured environments such as warehouses and laboratories. However, it is susceptible to interference in dynamic scenarios.

2 Visual SLAM (VSLAM): based on image features captured by cameras, VSLAM offers lower hardware costs and supports semantic understanding. However, its performance degrades in low-light or texture-deficient environments (Bolodurina et al., 2024).

In this study, a laser SLAM solution was adopted, leveraging the cartographer algorithm for real-time mapping. Cartographer's strength lies in its multi-level optimisation strategy, which balances accuracy and computational efficiency, making it particularly suitable for indoor mobile robot applications.

3.2.3 Introduction to the cartographer algorithm

Cartographer, developed by Google, is a graph optimisation-based SLAM algorithm specifically designed for real-time indoor mapping. It generates high-resolution grid maps with a precision of 5 cm, making it suitable for autonomous navigation tasks in complex environments. In the front-end processing, cartographer achieves scan matching using LiDAR scan data on adjacent submaps. The submap construction process is an iterative optimisation procedure, where scan results are continuously aligned with the submap coordinate system to gradually generate an accurate map representation. This hierarchical optimisation strategy based on submaps not only enhances mapping efficiency but also ensures high precision and consistency in the generated maps.

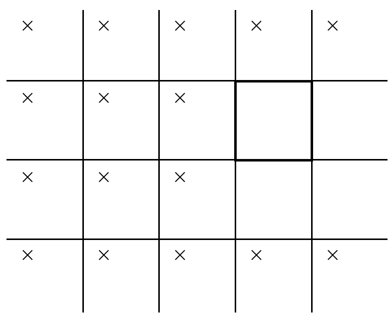
3.2.4 Local optimisation

Local optimisation refers to the process of constructing submaps. The initial scan point is set as the origin (0, 0), and the scan points are denoted as $H = \{h_k\}$, where $k = 1, 2, 3 \ldots k$. The transformation matrix T_ξ represents the pose vector ξ that transforms a scan frame into the submap frame. Thus, the transformation of a scan point p_ξ into the submap frame can be expressed as:

$$T_\xi p_\xi = \begin{bmatrix} \cos\xi_\theta & -\sin\xi_\theta \\ \sin\xi_\theta & \cos\xi_\theta \end{bmatrix} p_\xi + \begin{bmatrix} \xi_x \\ \xi_y \end{bmatrix}$$

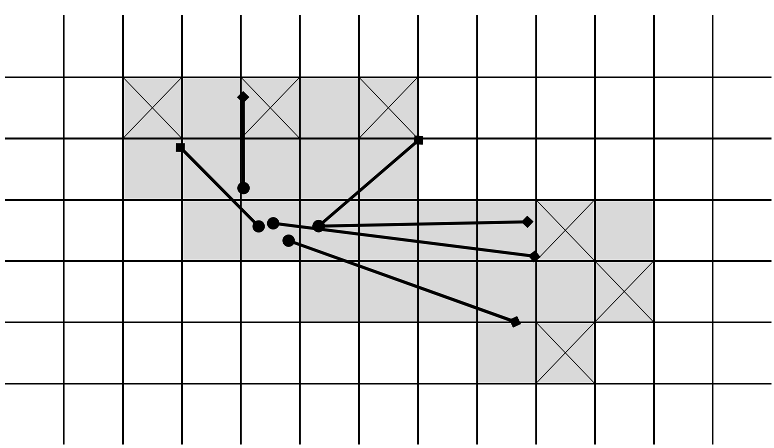
Through several iterations, continuous scan frames are used to construct submaps, which are represented as probability grids with resolution r, as shown in Figure 3.

Figure 3 Pixels and grid points



Whenever a scan is inserted into the probability grid map, the sets of hit points (points with LiDAR data) and miss points (points without LiDAR data) are determined, as illustrated in Figure 4.

Figure 4 Hit and miss-related scans and pixels



For each hit point (shaded and marked with ×), adjacent grid points are added to the hit set. For each miss point (shaded area), grid points along the line from the LiDAR origin to the scan point, excluding those in the hit set, are added to the miss set. For unobserved grids, a default probability value p_{hit} or p_{miss} is assigned (typically 0.5, indicating uncertainty about grid occupancy). For observed grids, the probability odds are updated as:

$$odds(p) = \frac{p}{1-p}$$

The update formula for the hit probability of each grid is:

$$M_{new}(x) = clamp\left(odds^{-1}\left(odds\left(M_{old}(x)\right) \cdot odds\left(phit\right)\right)\right)$$

Before inserting a scan frame into the submap, the pose of the scan frame is optimised using scan matching based on the Ceres library. The goal is to find an optimal pose that maximises the probability of scan points matching the submap. This problem can be formulated as a nonlinear least squares optimisation:

$$\arg\min_{\xi} \sum_{k=1}^{K} \left(1 - M_{smooth}\left(T_{\xi} h_k\right)\right)^2$$

Here, the function M_{smooth}: $\mathbb{R}^2 \to \mathbb{R}$ transforms points into a smoothed probability value in the submap, using a bicubic interpolation function.

3.2.5 Global optimisation

Global optimisation is achieved through loop closure detection, with the primary goal of reducing the accumulated errors during the mapping process. In the cartographer algorithm, each scan frame is matched with submaps, but over time, this matching process can lead to error accumulation. To address this issue, cartographer employs a sparse pose adjustment (SPA) strategy. This strategy optimises the global pose relationships, effectively minimising error accumulation and ensuring map consistency and accuracy. Through this approach, cartographer can generate high-precision maps in large-scale environments, providing a reliable foundation for subsequent path planning and navigation tasks.

3.2.6 Introduction to the A* algorithm

The A* algorithm is a widely used path planning method that builds upon the foundation of Dijkstra's algorithm. In this study, A* was selected as the global path planning method for the robot. Compared to Dijkstra's algorithm, A* introduces a heuristic function that combines the actual distance traveled with an estimated distance to the goal, significantly improving computational efficiency and goal-directedness. This characteristic enables A* to quickly find the optimal path from the start to the goal in complex environments while minimising unnecessary computations.

3.2.7 Introduction to the TEB algorithm

The TEB algorithm is a local path planning method that optimises both the robot's pose sequence P_i and the time intervals ΔT_i between adjacent poses (Cui et al., 2022). The core idea is to generate a smooth and dynamically feasible trajectory by simultaneously optimising the spatial and temporal components of the robot's motion.

- *Mathematical formulation:*

  1 *Pose sequence:* a sequence of kkk poses is represented as:

  $$P = \{P_i\}_{i=0,1,\cdots,k-1}, k \in \mathbb{N}$$

  2 *Time interval sequence:* the corresponding time intervals between poses are represented as:

  $$\tau = \{\Delta T_i\}_{i=0,1,\ldots,k-1}$$

  3 Trajectory representation: the combined pose and time interval sequence is denoted as:

  $$B := (P, \tau)$$

- *Optimisation objective:*

  The TEB algorithm aims to find the optimal trajectory B* by minimising a cost function f(B), which is a weighted sum of various constraint functions:

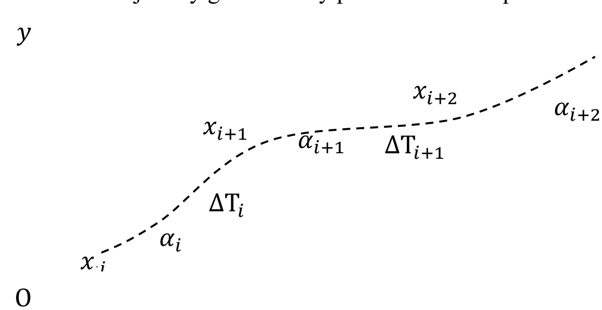
  $$\begin{cases} f(B) = \sum_k \gamma_k f_k(B) \\ B^* = \dfrac{\arg\min f(B)}{B} \end{cases}$$

  where γ_k is the weight coefficient for the k^{th} constraint function. $f_k(B)$ represents individual constraint functions, such as velocity, acceleration, and obstacle avoidance.

- *Trajectory generation:*

  The optimisation process generates a trajectory that balances spatial smoothness and temporal efficiency. The resulting trajectory, represented as a sequence of poses and time intervals, is illustrated in Figure 5.

Figure 5 Pose information trajectory generated by pose and time sequences



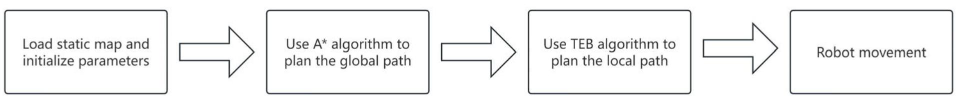
3.2.8 Hybrid path planning with A and TEB algorithm integration*

This study proposes a hierarchical path planning framework that combines the A* algorithm for global path planning with the TEB algorithm for local trajectory optimisation. This integrated approach enables dynamic obstacle avoidance while enhancing both navigation safety and path quality in robotic systems.

The implementation consists of two main phases: First, a feasible global path is generated from the pre-built environmental map using the A* algorithm. Subsequently, key waypoints are extracted from this global path and converted into pose sequences with corresponding time intervals. These parameters serve as inputs for the TEB algorithm, which performs iterative optimisation to generate the optimal local trajectory. The final output includes velocity and steering angle commands, which are published via ROS topics for communication with the low-level controller.

The complete workflow is illustrated in Figure 6.

Figure 6 Hybrid algorithm flowchart

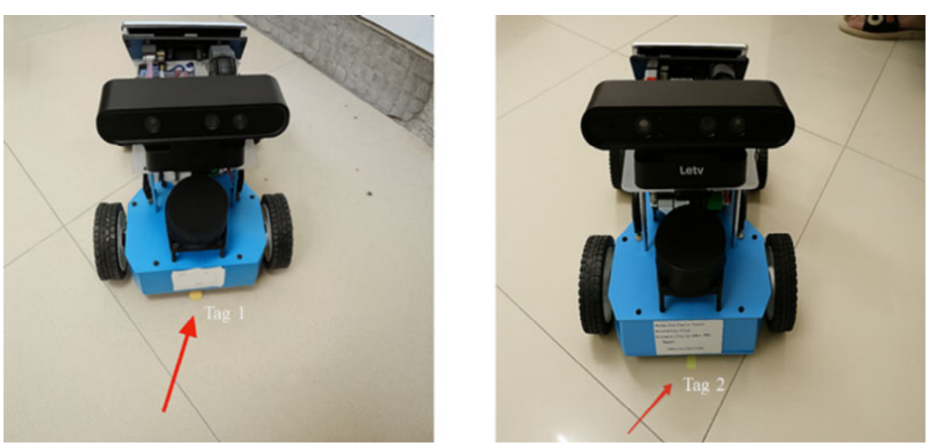


4 Experiments and results analysis

4.1 Motion distance error experiment

The experiment was conducted with the robot's frontal centre point as the reference position, which was marked as the measurement origin. The robot's movement was controlled through a keyboard teleoperation node while simultaneously recording odometry data from the ROS /odom topic. The experimental procedure is illustrated in Figure 7.

Figure 7 Motion distance error experiment procedure (see online version for colours)



Following each movement, the theoretical travel distance was calculated from the odometry data, while the actual distance was measured physically between marked points. To ensure statistical reliability, the experiment was repeated 10 times under identical conditions. The complete error data is presented in Table 2.

Table 2 Summary of motion distance errors

Trial	*X-error (cm)*	*Y-error (cm)*	*Trial*	*X-error (cm)*	*Y-error (cm)*
1	1.9	0.9	6	0.3	0.4
2	1.6	1.7	7	0.2	0.9
3	0.4	1.3	8	0.1	–0.3
4	0.6	0.9	9	2.4	–1.3
5	0.3	0.6	10	0.7	0.9

4.2 Mapping test

In this experiment, the cartographer algorithm was evaluated for its mapping performance using an Ackermann-steering mobile robot. The experimental procedure was as follows: First, the robot chassis was activated and the cartographer package was launched. The robot was then manually guided along the perimeter of the testing environment to collect sufficient LiDAR scan data. Upon completion of the mapping process, the generated map was saved by executing the terminal script bash save_map.sh.

Figure 8 illustrates a comparison between the physical layout of the testing environment and the resulting map. The right panel of the figure clearly depicts the structural features of the environment, including walls, tables, chairs, and other obstacles. This outcome demonstrates the cartographer algorithm's capability to accurately reconstruct complex spatial layouts, confirming its effectiveness in real-world mapping scenarios.

Figure 8 Experimental mapping results (see online version for colours)

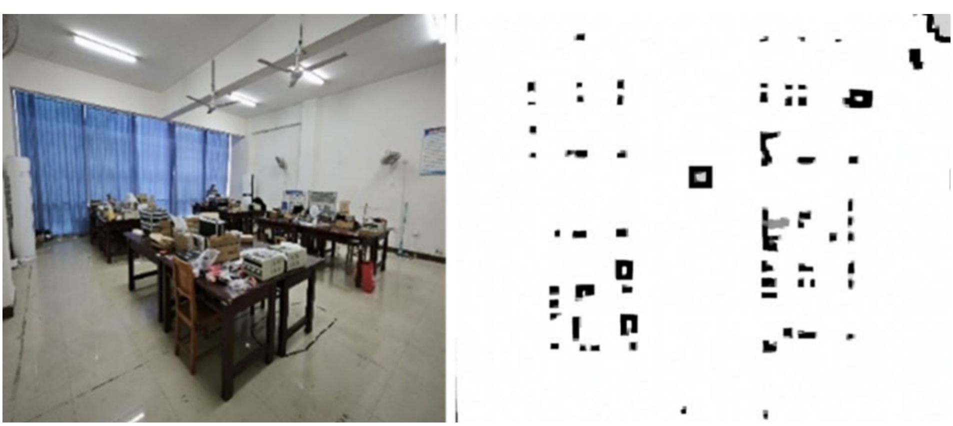
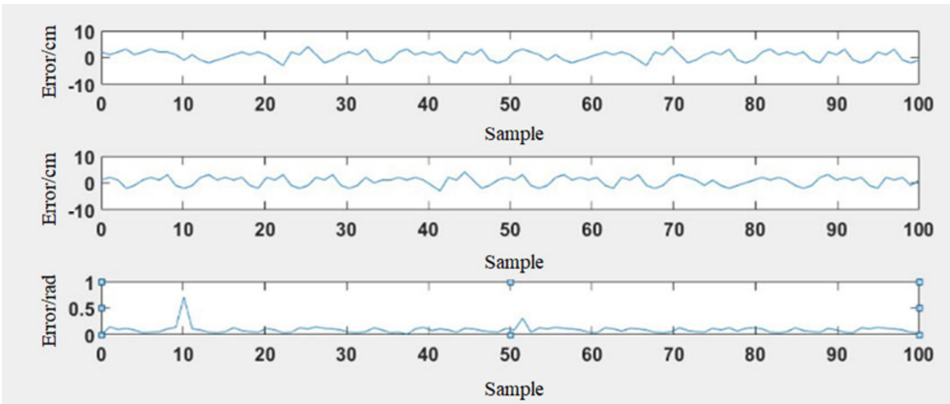


Figure 9 presents the error estimation during the mapping process. By comparing the actual robot positions with their corresponding locations on the constructed map, it is evident that the majority of the mapping errors are localised in specific regions. These discrepancies are likely attributable to LiDAR signal reflections or the presence of dynamic objects in the environment. Nonetheless, the overall mapping error remains within acceptable limits, underscoring the robustness and reliability of the cartographer algorithm in dynamic environments.

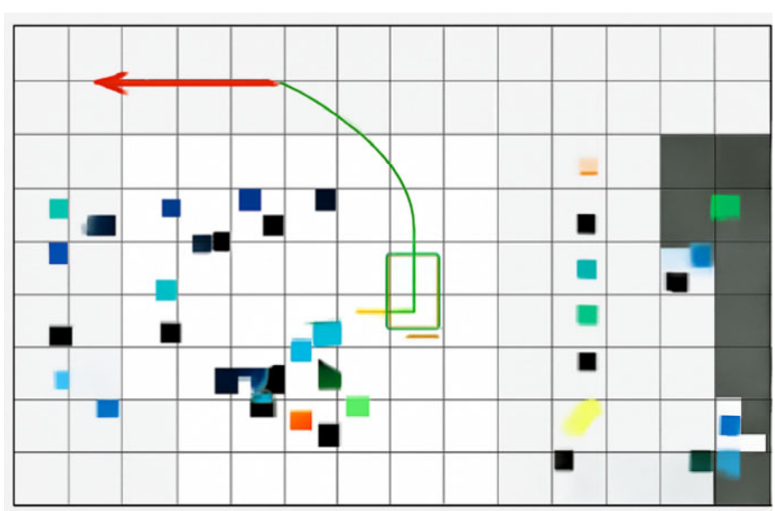
Figure 9 Mapping error estimation (see online version for colours)



4.3 Navigation test

Following the successful construction of the environment map, the navigation package was launched and the previously saved map was loaded to enable path planning and autonomous navigation. The experimental results are shown in Figure 10. In the figure, the green rectangle represents the mobile robot, the large white square denotes the local perception area, the green line indicates the global path, and the brown line shows the local path. The close alignment of the local path with the global path suggests that the path planning algorithm effectively guides the robot toward the designated target.

Figure 10 Navigation test results (see online version for colours)



The red arrow represents the predefined target point. Upon issuing the target command and activating the motor, the robot commenced its navigation task. The experimental outcomes demonstrate that the mobile robot is capable of autonomous navigation and dynamic obstacle avoidance, thereby validating the effectiveness and reliability of the proposed navigation system.

4.4 Complex multi-scenario environments

To comprehensively assess the performance of the IMR in diverse and complex environments, mapping and navigation tests were conducted in multiple scenarios, including an indoor warehouse, an office area, and an outdoor garden path, see Table 3.

- *Indoor warehouse:* the warehouse environment is characterised by dense shelving units and stacked goods, resulting in a complex spatial layout with numerous narrow aisles. During the mapping process, the cartographer algorithm accurately identified the contours of the shelves and the orientation of the aisles, generating a map that clearly reflects the structural layout. However, during navigation, the reflective surfaces of the metallic shelves occasionally interfered with the LiDAR signals, causing temporary localisation errors in certain regions. To mitigate this issue, sensor data were filtered and fused with IMU data, significantly improving localisation accuracy and ensuring successful path planning for material handling tasks.
- *Office area:* the office environment features irregularly arranged furniture, glass partitions, and frequent human movement. During mapping, the robot was able to clearly distinguish between tables, walls, and glass structures. However, dynamic human activity introduced fluctuations in the LiDAR data, particularly in crowded zones (De Guzman et al., 2024). To address this, a dynamic object detection and filtering mechanism was implemented to exclude interference from moving individuals during the data processing stage, thereby enhancing mapping stability. In navigation tests, a hybrid A* and TEB algorithm was used, allowing real-time path adjustments based on the detected positions of individuals. This enabled effective obstacle avoidance and precise arrival at target locations, demonstrating the system's adaptability to dynamic environments.
- *Outdoor garden path:* this scenario involved natural terrain variations and the presence of vegetation such as shrubs and trees, introducing additional mapping challenges. Low vegetation often obstructed or scattered LiDAR beams, reducing mapping accuracy. To address this, data from visual sensors were integrated with LiDAR input. Visual imagery was used to identify and segment the boundaries of vegetation, thereby supplementing the mapping process and enhancing environmental representation. During navigation, terrain undulations required the robot to dynamically adjust its posture for stable movement. Real-time analysis of IMU data was employed to modulate the chassis height and motor speed, ensuring safe and steady traversal across uneven garden paths (Fang, 2023).

Table 3 Challenges and countermeasures in multi-scenario mapping and navigation

Scenario	*Key characteristics*	*Mapping challenges*	*Mapping solutions*	*Navigation challenges*	*Navigation solutions*
Indoor warehouse	Numerous shelves and stacked goods, complex spatial layout, narrow aisles	LiDAR signal interference due to reflective metal surfaces on shelves	Filtering of sensor data and fusion with IMU measurements	Localisation errors caused by LiDAR reflections from metallic surfaces	Filtering of sensor data and fusion with IMU measurements
Office area	Irregular furniture arrangement, glass partitions, frequent human movement	Fluctuating LiDAR scans due to dynamic human activity	Implementation of dynamic object detection and filtering mechanism	Need for real-time path adjustments to avoid moving individuals	Hybrid A* and TEB algorithm enables real-time path adjustment based on human positions
Outdoor garden path	Natural terrain undulations, presence of plants and trees	Occlusion and scattering of LiDAR data by low-lying vegetation	Integration of visual sensor data to identify vegetation boundaries and assist mapping	Terrain-induced instability requiring real-time posture adaptation	Real-time IMU analysis to adjust chassis height and motor speed

5 Discussion and application scenario analysis

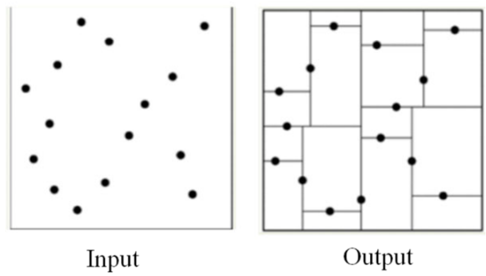
5.1 *Optimisation of cartographer algorithm performance*

While the cartographer algorithm has demonstrated outstanding performance in map construction and is capable of generating highly accurate maps in standard environments, it still presents room for improvement when applied to more complex scenarios. These include environments with numerous irregular obstacles, frequent dynamic object interference, and large-scale settings such as expansive industrial facilities or multi-story commercial complexes. To meet the increasing demands of real-world applications for IMRs, we implemented a multi-dimensional optimisation of the cartographer algorithm to further enhance mapping efficiency and accuracy.

One critical area of improvement lies in the scan matching phase. Traditional scan matching techniques require exhaustive point-to-point comparison across massive LiDAR point cloud datasets, resulting in significant computational overhead and prolonged mapping times (Guan and Li, 2025). To address this limitation, we introduced a feature-based keypoint extraction method that rapidly selects a subset of representative points for matching. For example, in scenarios involving tens to hundreds of thousands of point cloud data points, this approach can reduce the dataset to just 10–20% of its original size.

Furthermore, by integrating a k-d tree (KD-tree) data structure – illustrated in Figure 11 – we reduced the time complexity of keypoint matching from $O(n)$ to $O(\log n)$. This substantially accelerates the matching process while maintaining a high level of accuracy. The combined effect of these enhancements significantly shortens mapping duration and improves responsiveness, making the algorithm more suitable for applications requiring real-time performance.

Figure 11 Establishment of KD tree

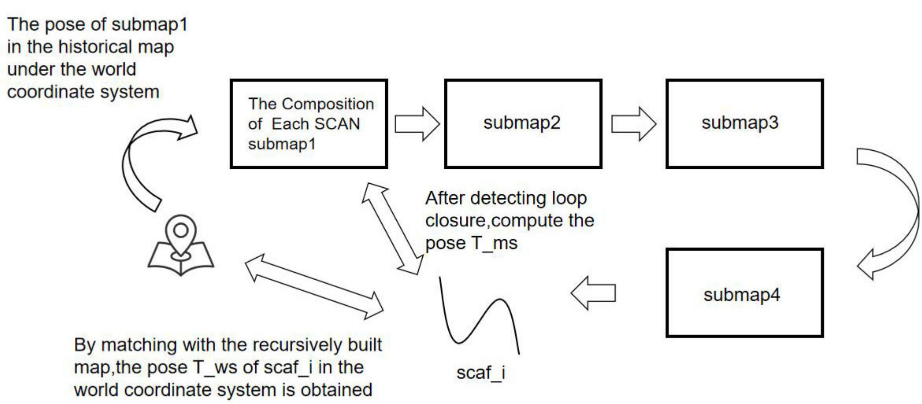


In the loop closure module, the original SPA strategy employed by cartographer presents certain limitations in large-scale map construction, particularly due to its fixed detection frequency and the accumulation of pose estimation errors. These issues often lead to map distortion and misalignment. To address this, we propose an adaptive loop closure detection mechanism that dynamically monitors the mapping extent and the degree of accumulated error (Herrero et al., 2024).

This approach involves a comprehensive analysis of the robot's pose variations and the continuity of scan data. Based on this analysis, an appropriate error threshold is defined. When the accumulated error exceeds the threshold, the system automatically increases the frequency of loop closure detection to promptly correct pose estimation drift and rectify map deviations. Figure 12 illustrates the pose optimisation process enabled by this mechanism.

Experimental validation conducted in a large indoor parking facility demonstrates that the optimised cartographer algorithm reduces mapping errors by approximately 20%. The resulting improvements in map consistency and accuracy significantly enhance the reliability of downstream tasks such as navigation and path planning.

Figure 12 Pose optimisation through adaptive loop closure



5.2 Performance analysis of the A and TEB hybrid path planning algorithm

To comprehensively evaluate the performance of the hybrid A* and TEB algorithm in path planning, we conducted systematic assessments based on several key metrics, including path planning time, path length, and obstacle avoidance success rate.

- *Path planning time:* extensive testing across environments of varying scales reveals that the global path planning time of the A* algorithm increases linearly with the size of the map. This is attributed to the algorithm's inherent design, which involves exhaustive node traversal in the search for a globally optimal path. As the map expands, the number of searchable nodes grows, directly extending planning time. For instance, in compact indoor environments, the A* algorithm can generate a global path within tens of milliseconds. However, in large-scale environments such as commercial complexes – where node counts can increase by an order of magnitude – the planning time may extend to several hundred milliseconds or even seconds. In contrast, the TEB algorithm, responsible for local trajectory planning, exhibits comparatively stable performance. Since TEB focuses solely on the robot's immediate surroundings, its computational load primarily depends on the complexity of local obstacles. In relatively simple settings, TEB can swiftly adjust the global path provided by A*, producing a feasible trajectory that satisfies real-time motion requirements (Inner Mongolia Mobile, 2023). Even in complex, cluttered environments where more computational resources are required for local adjustments, algorithmic optimisations and efficient resource allocation allow the hybrid system to maintain acceptable planning latencies, thereby ensuring real-time responsiveness essential for practical mobile robotics applications (Ni, 2023).
- *Path length:* in terms of path length, the hybrid A* and TEB approach generally produces slightly longer paths compared to using the A* algorithm alone. This increase arises from TEB's dynamic obstacle avoidance and its adherence to the robot's kinematic constraints, such as turning radius and acceleration limits. For example, in the presence of unexpected obstacles, TEB may reroute the robot, resulting in additional travel distance. Nevertheless, statistical analysis across various scenarios shows that the path length increases by only 5–10%. Given the algorithm's significantly improved obstacle avoidance and safety performance, this moderate increase in path length represents a reasonable trade-off between operational robustness and path efficiency.

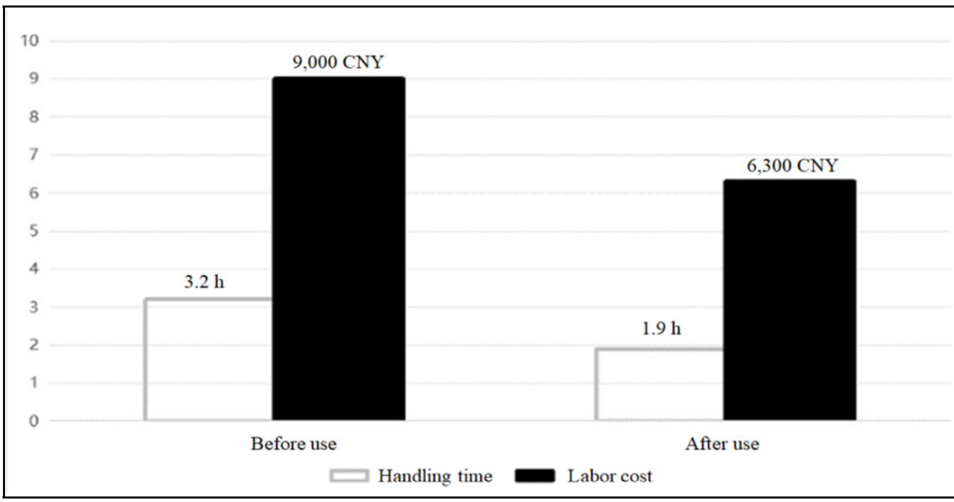
5.3 Applications in the logistics and warehousing sector

In the logistics and warehousing industry, IMRs are emerging as a transformative force, driving automation and operational efficiency. By deploying robots powered by the ROS, modern warehouses can automate core processes including goods transport, storage, and sorting (Xia et al., 2019). These robots function as highly coordinated 'logistics assistants', capable of executing task commands from warehouse management systems with precision. Leveraging high-fidelity maps and advanced path planning algorithms, they efficiently determine optimal routes and navigate to target locations with high localisation accuracy.

Whether retrieving goods from high storage racks or collecting scattered parcels from corners of the facility, these robots can execute tasks with speed and reliability. In large-scale warehouse settings, multiple IMRs operate collaboratively through ROS's distributed communication framework, forming an intelligent logistics fleet (Ni, 2023).

For instance, in a mega-warehouse operated by a leading e-commerce enterprise, the adoption of IMRs led to significant performance improvements. As illustrated in Figure 13, compared to traditional manual handling, robotic operations eliminated efficiency fluctuations caused by human fatigue and increased transport speed by approximately 40%. Simultaneously, labour costs were reduced by around 30% (Shen, 2023). Moreover, thanks to precise motion control, damage rates during handling decreased markedly, contributing to overall improvements in operational efficiency and economic performance. These advancements demonstrate the substantial commercial value that intelligent robotics bring to the logistics and warehousing industry.

Figure 13 Operational efficiency comparison before and after robot deployment



5.4 Applications in the service robotics domain

In the service robotics sector, IMRs are increasingly being deployed in diverse scenarios such as hotel hospitality and medical care, offering customers and patients efficient and thoughtful service experiences.

- *Hotel applications:* in hotel environments, IMRs perform a wide range of service tasks. These robots can warmly greet guests, assist with transporting heavy luggage, guide visitors to their rooms, and promptly deliver amenities to fulfil customer needs. Through deep integration with the hotel's information management systems, robots are able to access real-time customer service requests. Equipped with advanced autonomous navigation and obstacle avoidance capabilities, they can navigate seamlessly through complex hotel lobbies and narrow corridors, providing guests with a smooth and convenient service experience. The deployment of such robots enhances the overall quality of hospitality services and strengthens the hotel's brand image.

- *Healthcare and nursing applications:* in the field of healthcare, IMRs play an increasingly vital supporting role. They can assist medical staff by handling repetitive logistical tasks such as delivering medications and transporting medical equipment (Xia et al., 2019). Their value becomes particularly evident during public health emergencies such as pandemics, where minimising human contact is critical. Robots help reduce direct person-to-person interactions, significantly lowering the risk of cross-infection.

For example, in a pilot program at a major hospital, the implementation of IMRs resulted in the successful execution of over 80% of medication delivery tasks. These robots adhered strictly to predefined routes and delivery schedules, ensuring both the timeliness and accuracy of medication administration. This not only improved the efficiency and reliability of medical services but also ensured that patients received medications promptly. Furthermore, by taking over routine logistical responsibilities, robots helped alleviate the workload of healthcare professionals, allowing them to focus more on essential clinical and patient care activities.

6 Outlook

As we have discussed, advancing robotics and automation to the next level requires overcoming a wide range of barriers, from technical integration to societal ethics. To visualise this complex landscape more effectively, Table 4 organises and maps the key future directions against their most significant challenges and proposed solutions.

Table 4 The future of robotics and automation

Future direction	*Key challenges*	*Proposed solutions and strategies*
Enhanced autonomy and AI	• Robots struggle with unpredictable, ‘edge case’ scenarios.	• *Reinforcement learning:* training robots in simulation to handle millions of scenarios.
	• Ensuring safety and reliability of complex AI decisions.	• *Explainable AI (XAI):* making robot decision-making processes transparent and verifiable.
	• High computational power requirements.	• *Edge computing:* processing data directly on the robot to reduce latency and increase speed.
Human-robot collaboration	• Ensuring absolute safety in shared physical workspaces.	• Advanced sensors (proximity, force-torque) that allow robots to react instantly to human presence.
	• Creating intuitive interfaces for seamless communication.	• ***No-code/low-code interfaces:* allowing non-expert workers to task robots using simple commands or graphical interfaces.
	• Building human trust and acceptance.	• Designing robots with predictable behaviours and clear visual/auditory cues.

Table 4 The future of robotics and automation (continued)

Future direction	*Key challenges*	*Proposed solutions and strategies*
Advanced manipulation and dexterity	• Replicating the sensitivity and adaptability of the human hand. • Grasping a wide variety of object shapes, sizes, and materials. • High cost of sophisticated grippers and sensors.	• *Soft robotics & biomimetic grippers:* developing flexible, adaptive grippers inspired by nature. • *AI-powered vision systems:* using deep learning to instantly identify objects and calculate the optimal grasp strategy. • *Advanced tactile sensing:* equipping grippers with a 'sense of touch' to handle delicate items.
Interoperability and connectivity	• Lack of standardisation; robots from different vendors cannot communicate. • Cybersecurity threats to connected robotic fleets. • Managing massive data streams from thousands of sensors.	• *Universal communication standards:* industry-wide adoption of protocols like VDA 5050 or OPC-UA. • *'Defense-in-depth' cybersecurity:* implementing multi-layered security protocols for robot networks. • *Fleet management software:* using cloud-based platforms to orchestrate, monitor, and analyse entire robot fleets.
Democratisation and scalability	• High upfront investment cost (CapEx) for small and medium-sized businesses (SMBs). • Shortage of skilled personnel for programming and maintenance. • Difficulty integrating robots into existing, non-automated workflows.	• *Robotics-as-a-service (RaaS):* a subscription-based model that lowers the initial cost barrier. • *Modular and reconfigurable robots:* creating flexible systems that can be easily adapted to new tasks. • Developing standardised integration modules for legacy systems.
Ethical and societal integration	• Public concern over job displacement. • Establishing clear legal and ethical guidelines for autonomous actions. • Data privacy concerns with robots operating in sensitive environments like hospitals.	• *Focus on reskilling and upskilling:* creating training programs to transition the workforce to new roles (e.g., robot supervisor, maintenance technician). • *Developing new legal frameworks:* working with policymakers to define liability and responsibility. • Implementing strict data encryption and anonymisation protocols.

With the increasing deployment of IMRs across diverse domains such as service, logistics, and inspection, there is a growing demand for enhanced autonomous navigation capabilities, particularly in dynamic environments. This study presents an improved hybrid SLAM system that integrates cartographer and the TEB-based path planning algorithm. The proposed enhancements demonstrate promising feasibility and effectiveness in real-world scenarios, particularly with respect to mapping accuracy, planning efficiency, and adaptive navigation.

Building on the current research findings, future investigations can further explore the following key directions:

1 Robust perception in dynamic environments

Although the proposed algorithm improves robustness to dynamic objects to a certain extent, challenges remain in highly dynamic or densely populated environments. Future work may integrate deep learning-based approaches for real-time semantic segmentation and tracking of dynamic entities. Such methods could enable more refined modelling of dynamic scenes and enhance the SLAM system's ability to identify and adapt to non-static regions in the environment.

2 Multimodal sensor fusion and redundancy mechanism

Reliance on a single sensor modality increases vulnerability to occlusions, noise, and unexpected failures. Future SLAM systems should incorporate robust fusion of data from multiple sensors – including LiDAR, RGB-D cameras, IMUs, and ultrasonic sensors – through adaptive weighting mechanisms. This would significantly improve system resilience and fault tolerance in complex operational conditions. Moreover, leveraging edge computing technologies for real-time processing of multimodal data will be a key area of future focus.

3 Algorithm lightweighting and edge deployment optimisation

As mobile robots increasingly demand real-time responsiveness and computational efficiency, lightweight design of SLAM and path planning algorithms becomes imperative. Future work can explore sparse graph optimisation, incremental computation frameworks, and graph neural networks (GNNs). Additionally, optimisation for embedded platforms will be essential to enable high-performance SLAM and planning on edge devices with limited resources.

4 Human-robot collaboration and interactive navigation

As robots are expected to operate more frequently alongside humans in shared environments, the development of predictive and collaborative navigation mechanisms will become a critical research direction. Intelligent robots should be capable of anticipating human intentions and trajectories, dynamically adjusting their own paths to enable safer and more natural interaction.

5 Long-term autonomy and environmental adaptability

Conventional SLAM systems typically rely on short-term, high-quality data collection. To enable long-term autonomous operation, systems must evolve to adapt to environmental changes, such as interior modifications or furniture relocation. Techniques such as experience replay and change detection based on historical map data will be crucial to maintaining long-term stability and operational reliability.

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Declarations

All authors declare that they have no conflicts of interest.

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