Indoor Navigation: A Comparative Study of Traditional and Machine Learning Algorithms

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Abstract

Indoor navigation has turned into a critical area for research on account of its applications across multiple fields, along with robotics, healthcare, as well as smart buildings. Compared with outdoor navigation, interior settings pose some special problems such as fewer GPS signals, detailed arrangements, and moving impediments. This paper provides a detailed look at multiple methods used for finding routes in indoor spaces, like graph-based methods, probabilistic methods, and machine learning methods. We evaluate these algorithms based on their own accuracy, computational efficiency, scalability, and robustness across multiple indoor scenarios. The paper discusses the strengths and limitations with each approach and provides understandings into future research directions within the field.

Keywords

Indoor navigation, graph-based methods, probabilistic methods, machine learning methods.

1. Introduction

Nowadays navigation is an important task that is embedded in every aspect of our daily routines. Navigation is generally defined as the process of directing the movements of a vehicle, nave, plane, and people from one place to another [1]. Although there are different types of navigation, one that faces the most challenges is indoor navigation due to the non – existence of the GPS signal, complexity in indoor layouts, moving obstacles like people and furniture, and the need for alternative technologies like Wi-Fi, Bluetooth, and sensors.

Indoor navigation i.e., localization, is the process of determining the location and orientation of a person or object inside a building and guiding them to a place of interest in that location. Applications for this technology range from autonomous robots to assistance technologies for visually impaired people to navigation in smart buildings [2].

With satellite-based devices currently available for precise position data, outside navigation is far easier. However, indoor navigation presents a unique set of challenges that call for a different approach. For instance, while GPS performs exceptionally well outdoors, it may not work well indoors because to elements including signal attenuation, multipath, and dynamic spillway development [3].

Thus, indoor navigation has received much interest, especially in the scenarios of smart buildings, healthcare facilities, and commercial spaces. Due to the failure of GPS-based localization to work indoors, different solutions have been developed, using Wi-Fi fingerprinting, Bluetooth, and sensors [4].

The subject of the study was to compare different algorithm types and summarize their pros and cons, as well as best practices in environments suitable for different solutions. To solve these

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problems, indoor navigation systems were evaluated using a systematic approach that incorporates advanced localization technologies and algorithmic frameworks, as outlined in the subsequent section.

1. Methodology

This study adopts a narrative review approach to explore and synthesize the current state of research concerning traditional and machine learning algorithms for indoor navigation. A narrative review is a recognized methodology for providing a comprehensive and critical overview of a research topic without the rigid procedural constraints typical of systematic reviews or bibliometric analyses. It is particularly suited to fields where the literature is heterogeneous in terms of methodologies, outcomes, and technological focus, as is the case for indoor navigation.

The literature considered in this review was identified through searches conducted in major academic databases, including Google Scholar, ScienceDirect, and Web of Science [5][6]. Keywords such as "indoor navigation," "traditional algorithms," "SLAM," "deep reinforcement learning," and "machine learning for localization" guided the selection process. No formal systematic protocol—such as PRISMA guidelines or a predefined inclusion/exclusion matrix—was applied, given the exploratory nature of the investigation [8][9]. The objective was not to exhaustively catalog all available studies but rather to capture the main trends, strengths, and limitations emerging from significant and representative contributions to the field.

While care was taken to prioritize peer-reviewed journal articles and recent conference proceedings [10], this narrative review does not claim to be exhaustive or to eliminate all potential selection biases. Instead, it aims to offer an informed, critical, and structured discussion of the topic based on a purposive selection of relevant literature, in line with the objectives and constraints of narrative reviews.

Through this methodological lens, the study seeks to compare the traditional indoor navigation methods—such as SLAM-based approaches and classical path-planning algorithms—with more recent machine learning-based techniques, particularly deep reinforcement learning (DRL), highlighting the relative advantages, limitations, and future research directions.

2. Results and discussion

To achieve indoor navigation that is as seamless as outdoor navigation, the integration of advanced technologies is essential. The primary methods adopted are Wi-Fi-based positioning systems, LiDAR, visual and deep learning enhanced SLAM (Simultaneous Localization and Mapping). At large, these technologies increase the accuracy, robustness, and adaptability of systems in indoor environments, improving overall user experience [11].

To enhance the user experience, these improvements focus on accuracy, robustness, and adaptability in complex indoor environments. For instance, many 3D deep learning methods today aim to leverage technical progress from robotics and autonomous driving to consume less energy and perform in real-time by processing raw point cloud data [12].

Deep Learning neural networks (DNNs) have excelled at the understanding and extraction of a high level of intelligence for outlandish datasets, such as point clouds, which can achieve tasks such as object detection, semantic segmentation, and scene reconstruction [13]. Multimodal fusion techniques (e.g., BubblEX) integrate information across multiple modalities in point cloud data to enhance feature learning and further facilitate understanding of how neighboring points (e.g., cells surrounding a treated patch) contribute to the KM feature extraction process. [feasibility of 5G, lightweight data acquisition strategies in geomatics, smart urbanism etc].

These technologies serve as the foundation for the algorithmic approaches compared in the next section, ranging from traditional SLAM to data driven DRL methods.

3. Algorithms

Indoor navigation presents several challenges; nonetheless, certain algorithms can assist in overcoming these obstacles. These algorithms are categorized into traditional and deep reinforcement learning (DRL)-based algorithms.

4.1. Traditional Algorithms

Traditional methods include SLAM, global planning, and local planning. SLAM (Simultaneous Localization and Mapping) is one of the most common approaches employed in robotic indoor applications, where algorithms create maps of the environment and localize a robot at the same time, using the position information gathered by LiDAR, cameras, Wi-Fi, or Ultra-Wideband (UWB) [11] For instance, LiDAR SLAM is recognized for its accuracy as well as real-time data processing, however it might have problems in closed environments due to its expense as well as its problems with reflections [3].

Visual SLAM, using camera systems, is more affordable and widely used in aerial vehicles and mobile robots, but can suffer from reduced performance in low light or with reflective surfaces [14]. Global planning involves creating a complete map of the environment and then calculating the optimal path from start to finish, while local planning focuses on making decisions based on the immediate surroundings of the robot [11]. These methods are often computationally intensive and may not perform well in dynamic environments. In this manner, SLAM algorithms require significant processing power to handle sensor data and update the map in real-time, and global planning needs a complete and accurate map, which is difficult to maintain in changing environments [15].

Traditional autonomous navigation often employs Simultaneous Localization and Mapping (SLAM) to build a map of the environment while simultaneously estimating the robot's pose within that map. Algorithms like Karto-SLAM, which is based on graph optimization, are used in this process. Global planning then uses this map to find an optimal route from a starting point to a goal, often using algorithms like Dijkstra's algorithm as implemented in the Navfn planner. Local planning, such as with the Dynamic Window Approach (DWA) or Timed-Elastic-Band (TEB), then adjusts this global plan in real-time to avoid obstacles and account for dynamic changes in the environment [11]. In contrast, DRL-based methods replace these individual components with a single agent that learns to navigate directly from sensor inputs to motor outputs, effectively learning a navigation policy.

4.1.1. Strength and limitation of traditional algorithm

Traditional path – planning algorithms, such as Dynamic Window Approach (DWA) and Times Elastic Band (TEB), offer several strengths in indoor navigation. These strengths excel in path planning and efficiency, with DWA providing high temporal efficiency and shorter routes, particularly in environments where line-of-sight (LOS) conditions are sufficient and lastly can provide a quick path calculation in simpler environments [11].

Another strength in traditional algorithms is in the safety features where TEB can generate a route with the least number of collision while maintaining safe distances from obstacles and making it highly effective in static or well-mapped environments [11].

From an implementation point of view, these algorithms are easier to implement than AI-based algorithms, as they do not require extensive training data or high computational resources, ensuring predictable behavior in structured scenarios [16].

They have also been used effectively with pre – existing maps, resulting in reliable performance when precise environmental data are available [16].

These strengths make traditional methods ideal for controlled environments, but their strict dependence on the static maps and limited adaptability in dynamic environments highlight the need for complementary approaches, such as machine learning in more complex scenarios.

Despite their strength, traditional algorithms like DWA and TEB offers limitations in real world environments. One of the most important limitations is the environmental adaptability: these algorithms perform poorly in dynamic environments, struggling with unpredictable obstacles (e.g. sudden pedestrian movement), and cannot generalize well to new situations [15].

Sensor Dependencies further deepens these algorithms to not be more reliable because they are heavily reliant on sensor precision and accuracy, wheel odometer accumulates errors due to slipping, LiDAR suffers in featureless corridors ("corridor effect"), necessitating redundant sensor arrays to maintain line-of-sight (LOS) conditions [15].

Notably, performance degrades in sufficiently complex scenarios: for example, while performing DWA, collision rates increase by ~40% in cluttered environments; and while performing TEB, computational latency increases exponentially with the number of obstacles in a situation.

These algorithms do not learn; they remain inflexible to changes in their environment without being manually recalibrated. Compounding these problems is an infrastructure burden, where specific pre-mapping and regular upkeep increase deployment costs by an order of magnitude of 2–3× versus data-driven alternatives. These constraints highlight the reason why modern systems are moving toward hybrid architectures, merging the interpretability of traditional methods with the flexibility that AI affords to create a balance between stability and flexibility [11][17][18]. Similarly, [19] observed TEB's struggles with actuator constraints in maritime HIL testing, further motivating the exploration of adaptive learning methods like DRL.

4.2 Deep Reinforcement Learning Algorithms

DRL-based approaches employ agents to acquire optimal navigation policies via interaction with the environment, providing adaptability to dynamic changes and intricate circumstances. In mobile robotics, a Deep Reinforcement Learning (DRL) agent can acquire navigation skills within a warehouse setting by getting feedback, either incentives or penalties, contingent upon its actions, such as advancing, turning, or halting [11]. This enables the robot to adjust to environmental alterations, including new impediments or layout modifications, without requiring explicit reprogramming [20].

This adaptability is especially beneficial in intricate situations where conventional rule-based navigation systems may struggle, such as congested surroundings or regions with erratic human behavior [16][12]. Imagine a scenario in which a robot is tasked with bringing packages across a crowded office building. For example, a robot that has been trained in deep reinforcement learning would be able to autonomously avoid collisions with other robots it crosses paths with, navigate through narrow hallways, or even prioritize delivery requests based on their urgency—without requiring explicit instructions to program it for each new case it encounters.

This is distinct from classic approaches that require extensive manual tuning and reprogramming whenever the environment changes. Furthermore, DRL algorithms can utilize transfer learning approaches to expedite the learning process in novel situations. A robot taught to navigate one warehouse can swiftly adjust to a different layout by refining its existing policies instead of starting from the beginning.

4.2.1. Strength and limitation of machine learning algorithm

Deep reinforcement learning algorithms offers several strengths in indoor navigation systems, such as environmental adaptability by learning optimal navigation policies through continuous interaction with both static and dynamic environments without relying on pre − existing maps or precision sensors [11].

A distinguish feature of this algorithm is its ability to effectively integrate and execute complex decision-making task through their trial − and − error, capabilities, utilizing policies, reward, and value function to maximize performance with approaches like Soft Actor-Critic (SAC) showing particularly efficient sample usage and lower collision rates compared to traditional methods [11].

Another feature that deep reinforcement learning algorithms has that the traditional algorithms does not have is the benefit of the performance such as SAC demonstrating efficient sample usage and lower collision rate, has better computational efficiency, achieves higher rewards in testing scenarios, can function effectively in maples environments. [11].

The configurability of DRL architectures allows for both model − free and model − based configurations along with the capability to handle continuous or discrete action spaces and hence allows developers a great deal of flexibility when devising their architectures, depending on their specific application requirements. These qualities allow DRL to perform well in complex, real-world navigation tasks, especially when environmental unpredictability is a major factor [11].

However, while being powerful and adaptable to the environment, DRL algorithms face major obstacles such as exceedingly virtual trial and error paths, unavoidable collision happening in the training process, along with high requirement of calculating resources, resulting in difficulty to implement it in real world problems [11][12].

Moreover, their significant reliance on the large, heterogeneous datasets and the need to collect location-related sensitive information raises privacy and security issues receiving the attention of scholars and practitioners [21]. To alleviate these limitations, researchers recommend the implementation of hybrid systems that integrate DRL with traditional methods, federated learning for the retention of privacy, and constant updates of the system to ensure accuracy [11][21]. For systems functioning in dynamic environments with movable obstacles or where facts regarding maps are false DRL is optimal for this [11]. Continuous research into privacy-preserving technologies as well as hybrid methods will likely continue to improve the applicability and robustness of these DRL-based navigational systems as the field matures.

The flexibility of DRL architectures supports both model – free and model – based designs, with the ability to manage continuous or discrete action spaces, offering developers a broad spectrum of configurations based on specific application needs. These attributes make DRL particularly suitable for complex, real-world navigation tasks, especially where environmental unpredictability is a challenge [11].

Despite their strength and adaptability of the environment, DRL algorithms face significant challenges, including extensive virtual training requirements, inevitable collisions during the training phase, and substantial computational resource demands, which complicate real-world implementation [11][12].

Additionally, their performance depends heavily on large, heterogeneous datasets and raises privacy and security concerns due to the collection of sensitive location information [21]. To mitigate these limitations, researchers advocate for hybrid systems that combine DRL with traditional methods, federated learning to preserve privacy, and regular system updates to maintain accuracy [11][21]. DRL is particularly well-suited for dynamic environments with changing obstacles or where map information is unreliable, making it a powerful tool for adaptive navigation in complex, real-world settings [11]. As the field evolves, ongoing advancements in privacy-preserving techniques and hybrid approaches promise to further enhance the practicality and robustness of DRL-based navigation systems.

In a summarized way comparison of indoor navigation algorithms discussed are presented in table 1.

Table 1
Comparison of Indoor Navigation Algorithms

Algorithm	Accuracy	Computational Cost	Robustness	Best Use Case	Limitations
LiDAR SLAM	High	Very High	Moderate	Static environments	Costly; struggles with reflections
Visual SLAM	Moderate	Moderate	Low	Affordable robotics	Fails in low light
Wi-Fi Fingerprinting	Low-Moderate	Low	High	Large buildings	Requires pre-mapping
DRL-Based	High	High (training)	Very High	Dynamic environments	Needs large training dataset

4. Conclusion

Indoor navigation remains a complex and evolving field, demanding solutions that can navigate challenges such as dynamic environments, occluded signals, and diverse spatial layouts. This study has compared traditional algorithms—such as SLAM, DWA, and TEB—with machine learning-based approaches, particularly Deep Reinforcement Learning (DRL), to highlight their respective strengths and limitations. Traditional methods excel in controlled, static environments with high predictability, offering low-cost, easy-to-implement solutions with high interpretability. However, their dependency on precise mapping and limited adaptability restricts their effectiveness in real-world, dynamic scenarios.

In contrast, DRL-based algorithms demonstrate significant advantages in adaptability and autonomous decision-making by learning from real-time interactions with the environment. Their ability to operate without pre-mapped data and adapt policies through trial-and-error makes them highly suitable for complex and unpredictable settings. Nevertheless, DRL faces considerable implementation challenges, including high training costs, computational demands, and privacy concerns related to data acquisition.

The findings emphasize the growing need for hybrid navigation architectures that blend the robustness and interpretability of traditional algorithms with the flexibility and learning capabilities of AI-based methods. As indoor navigation continues to expand across domains such as smart infrastructure, robotics, and assistive technologies, future research should focus on optimizing hybrid solutions, improving training efficiency, and addressing data privacy through federated learning and secure data management practices. Such advancements will be critical for enabling reliable, scalable, and context-aware indoor navigation systems in the years to come.

Declaration on Generative AI

During the preparation of this work, the author(s) used X-GPT-4 and Gramby in order to: Grammar and spelling check. After using these tool(s)/service(s), the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

References

[1] Darken, Rudolph & Peterson, Barry. (2001): Spatial Orientation, Wayfinding, and Representation. Handbook Virtual Environ. 10.1201/b17360-24

[2] Klein LC, Braun J, Mendes J, Pinto VH, Martins FN, de Oliveira AS, Wörtche H, Costa P, Lima J. A Machine Learning Approach to Robot Localization Using Fiducial Markers in RobotAtFactory 4.0 Competition. Sensors. 2023; 23(6):3128. https://doi.org/10.3390/s23063128

[3] Abacı, H.; Seçkin, A.Ç. Mobile Robot Positioning with Wireless Fidelity Fingerprinting and Explainable Artificial Intelligence. Sensors 2024, 24, 7943. https://doi.org/10.3390/s24247943

[4] Cha K-J, Lee J-B, Ozger M, Lee W-H. When Wireless Localization Meets Artificial Intelligence: Basics, Challenges, Synergies, and Prospects. Applied Sciences. 2023; 13(23):12734. https://doi.org/10.3390/app132312734

[5] Ellegaard, O., & Wallin, J. A. (2015). The bibliometric analysis of scholarly production: How great is the impact? Scientometrics, 105(3), 1809–1831. doi:10.1007/s11192-015-1645-z

[6] Öztürk, O., Kocaman, R. & Kanbach, D.K. 2024: How to design bibliometric research: an overview and a framework proposal. Review of Managerial Science18, 3333–3361 doi.org/10.1007/s11846-024-00738-0

[7] Tanya Millard, Anneliese Synnot, Julian Elliott, Sally Green, Steve McDonald & Tari Turner, 2019: Feasibility and acceptability of living systematic reviews: results from a mixed-methods evaluation. Syst Rev. 2019; 8(1): 325.

[8] Kitchenham B, Charters S. Guidelines for performing systematic literature reviews in software engineering. (EBSE 2007-001). Keele university and Durham university joint report, 2007.

[9] Khan D, Plopski A, Fujimoto Y, Kanbara M, Jabeen G, Zhang Y, Zhang X, Kato H. Surface remeshing: A systematic literature review of methods and research directions. IEEE Trans Vis Comput Graphics 2020;1.

[10] D. Khan, Z. Cheng, H. Uchiyama e tal., Recent advances in vision-based indoor navigation: A systematic literature review. Computers & Graphics (2022), https://doi.org/10.1016/j.cag.2022.03.005.

[11] Arce, D.; Solano, J.; Beltrán, C. A Comparison Study between Traditional and Deep-Reinforcement-Learning-Based Algorithms for Indoor Autonomous Navigation in Dynamic Scenarios. Sensors 2023, 23, 9672. https://doi.org/10.3390/s23249672

[12] Afif, M., Ayachi, R., Said, Y. et al. An indoor scene recognition system based on deep learning evolutionary algorithms. Soft Comput 27, 15581–15594 (2023). https://doi.org/10.1007/s00500-023-09177-7

[13] Matrone, F., Paolanti, M., Frontoni, E., & Pierdicca, R. (2024). Enhancing explainability of deep learning models for point cloud analysis: a focus on semantic segmentation. International Journal of Digital Earth, 17(1). https://doi.org/10.1080/17538947.2024.2390457

[14] Wang, P., Li, C., Cai, F. et al. An improved SLAM algorithm for substation inspection robot based on the fusion of IMU and visual information. Energy Inform 7, 86 (2024). https://doi.org/10.1186/s42162-024-00390-8

[15] Wang, SY., Li, CM., Liong, ST. et al. AGV indoor localization: a high fidelity positioning and map building solution based on drawstring displacement sensors. J Ambient Intell Human Comput 15, 2277–2293 (2024). https://doi.org/10.1007/s12652-024-04755-5

[16] Talaat, F.M., El-Shafai, W., Soliman, N.F. et al. Intelligent wearable vision systems for the visually impaired in Saudi Arabia. Neural Comput & Applic (2025). https://doi.org/10.1007/s00521-025-10987-z.

[17] Stahlke, M., Feigl, T., Kram, S., Ott, J., Seitz, J., Mutschler, C. (2024). Data-driven Wireless Positioning. In: Mutschler, C., Münzenmayer, C., Uhlmann, N., Martin, A. (eds) Unlocking Artificial Intelligence. Springer, Cham. https://doi.org/10.1007/978-3-031-64832-8_10

[18] Deng, Mingyao. (2023). Robot navigation based on multi-sensor fusion. Journal of Physics: Conference Series. 2580. 012020. 10.1088/1742-6596/2580/1/012020.

[19] Tornese, R., Polimeno, E., Pascarelli, C., Buccoliero, S., Carlino, L., Sansebastiano, E., & Sebastiani, L. (2022). Hardware-in-the-loop testing of a maritime autonomous collision avoidance system. Proceedings of MED22. Fincantieri NexTech S.p.A. & University of Salento

[20] Zhou, W., & Zhou, R. (2024). Vision SLAM algorithm for wheeled robots integrating multiple sensors. PloS one, 19(3), e0301189. https://doi.org/10.1371/journal.pone.0301189

[21]Cha K-J, Lee J-B, Ozger M, Lee W-H. When Wireless Localization Meets Artificial Intelligence: Basics, Challenges, Synergies, and Prospects. Applied Sciences. 2023; 13(23):12734. https://doi.org/10.3390/app13231273